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Cellular Neural Networks with Hopfield Neural Networks Considering the Confidence Degree

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Abstract—In this study, we propose cellular neural networks (CNN) with Hopfield neural networks (Hopfield NN) considering the confidence degree. The Hopfield NN works as an associative memory to retrieve one of the embedded patterns from the local data of the input images. The confidence degree means the difference between the retrieved pattern and the input image. When the difference is small the confidence degree is set to be large. The confidence degree works to enhance the CNN operation. By computer simulations, we investigate the basic property of the proposed method and confirm its effectiveness for example of pattern detection.

1. Introduction

Cellular Neural Networks (CNN) [1] were introduced by Chua and Yang in 1988. The idea of CNN was inspired from the architecture of the cellular automata and the neural networks. A different point from the conventional neural networks is that CNN has local connectivity property. Since the structure of CNN resembles the structure of animals' retina, CNN can be used for various image processing applications [2]-[5]. CNN is composed of the basic circuit units called cells. The cell contains linear and nonlinear circuit elements which are typically linear capacitors, linear resistors, linear and nonlinear controlled sources.

In the previous study, we have proposed a space-varying CNN designed using the Hopfield NN. We prepare the Hopfield NN as associative memory to which some patterns are embedded. In that method, the templates of CNN was chosen from some memorized templates according to the retrieved pattern. By using this method, we can perform better image processing depending on the local information of input images. For example, when the retrieved pattern is like white and black image we may use edge template, while for relatively smooth retrieved pattern we may use diffusion template. By this setting, the CNN is expected to detect the edges of the input image with diffusion for smooth area.

In this study, in order to improve the above method, we consider the confidence degree which means the difference between the retrieved pattern and the input image. When the difference is small the confidence degree is set to be large. The confidence degree works to enhance the CNN operation. By computer simulations, we investigate the basic property of the proposed method and confirm its effectiveness for for example of pattern detection.

In Sec. 2, we review the basic of the standard CNN. In Sec. 3, we review the basic of the standard Hopfield neural network. In Sec. 4, we describe the structure of the space-varying CNN designed by Hopfield NN considering the confidence degree. In Sec. 5, simulation results of binary image processing task are shown. Section 6 concludes this article.

2. Cellular Neural Networks [1]

In this section, we describe the basic structure of CNN. CNN has M by N processing unit circuits called cells. Cells are arranged in a reticular pattern to M line by N row. We represent a cell $C(i, j)$ using a variable i which denotes vertical position and a variable j which denotes horizontal position. The cell contains linear and nonlinear circuit elements. CNN is an array of cells. Each cell is connected to its neighborhood cells according to a template. Usually, the same template is used for all the cells except for boundary cells. CNN has the features of time continuity, spatial discreteness, nonlinearity and parallel processing capability.

The state equation and the output equation of the cell $C(i, j)$ are shown as follows.

State equation:

$$\begin{aligned}\frac{dv_{xij}}{dt} &= -v_{xij} + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r} A_{(i,j;k,l)}v_{ykl}(t) \\ &\quad + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r} B_{(i,j;k,l)}v_{ukl}(t) + I. \qquad (1)\end{aligned}$$

Output equation:

$$v_{yij}(t) = \frac{1}{2}(|v_{xij}(t) + 1| - |v_{xij}(t) - 1|). \qquad (2)$$

where v_x, v_y and v_u represent a state, an output and an input of the cell, respectively. In the Eq. (1), A is the feedback template and B is the control template. These templates and threshold value I are collectively called the general template.

The *r-neighborhood* of $C(i, j)$ in CNN is defined by

$$Nr(i, j) = \{C(k,l) \mid \max\{\,|k-i|\,,\,|l-j|\,\} \le r,\quad 1 \le k \le M;\quad 1 \le l \le N\}. \tag{3}$$

where r is a positive integer number. In our study, we fix the value of r as 1.

3. Hopfield Neural Network Working as Associative Memory

In this section, we describe the basic structure of Hopfield Neural Network (Hopfield NN). Associative memory is a system which returns a stored pattern or its reversed pattern that is similar to an inputted pattern. Noisy patterns can be associated or distorted patterns can be recognized by a well-constructed associative memory.

The Hopfield NN is used as an associative memory by exploiting the property that the network has multiple stable states. Namely, if the parameters of the network can be decided in such a way that the patterns to be stored become stable states of the network, the network produces a stored pattern that is similar to an input pattern. The energy function of the Hopfield NN with N neurons and P stored binary patterns is defined by the following equation.

$$E = -\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}x_i x_j + \sum_{i=1}^{N}\theta_i x_i, \tag{4}$$

where w_{ij} is the weight between i-th neuron and j-th neuron, and θ_i is the threshold of the i-th neuron. The weight w_{ij} is given as follows.

$$w_{ij} = \begin{cases} \sum_{p=1}^{P} x_i{}^{(p)} x_j{}^{(p)} & (i \neq j) \\ 0. & (i = j) \end{cases} \tag{5}$$

The weight w_{ij} is 0 when $i = j$, because all the units have combined with all the units of the others except themselves The states of the neurons are asynchronously updated due to the following difference equation:

$$x_i(t+1) = sgn(\sum_{i \neq j} w_{ij}x_j(t)), \tag{6}$$

where *sgn* is an output function as follows:

$$sgn(a) = \begin{cases} 1 & (a \ge 0) \\ -1. & (a < 0) \end{cases} \tag{7}$$

4. Space-Varying Cellular Neural Networks Considering the Confidence Degree

In the previous study, we have proposed space-varying cellular neural networks which is designed by using the ability of the associative memory of Hopfield NN. In general, the design of space-varying systems is not easy. However, we can set one of prepared existing templates on each cell of CNN according to the retrieved pattern by Hopfield NN to which some typical local image structures are embedded. Namely, we need only some existing templates and their associated patterns. The design method is described as follows. Firstly, we prepare some two-dimensional arbitrary patterns for the memory of Hopfield NN and some existing templates related with these patterns, respectively. Secondly, Hopfield NN memorize the some two-dimensional arbitrary patterns. Thirdly, Hopfield NN compare between memorized the some arbitrary patterns and each pixel and its two neighborhood pixels of a input image. Hence, from some arbitrary patterns, Hopfield NN associate the certain arbitrary pattern which is the most similar to the pattern of each pixel and its two neighborhood pixels. Fourth, from the prepared some existing templates, the template of each cell in CNN is designed based on the associated pattern. Finally, input image is processed by using the space-varying CNN designed by Hopfield NN. Each templates are applied to each cell by these steps.

In this study, we propose the developing system by considering the confidence degree to space-varying CNN. We calculate the Hamming difference between the retrieved pattern and the input image. When the Hamming difference is small the confidence degree is set to be large. The confidence degree works to enhance the CNN operation. By using this system, it is possible to detect the some objects by changing the threshold value when several similar objects exist in the input image. The threshold value I_{cd} is defined as following in Eq. 8 and the characteristics of the threshold value I_{cd} with the Hamming distance and the confidence degree is shown in Fig. 1.

$$I_{cd} = \frac{13 \times Confidence\ Degree[\%]}{100(1 + exp(HD))} \tag{8}$$

In Eq. (8), HD is calculated by Eq. (9), and $Confidence\ Degree[\%]$ is a parameter to change the characteristics of the threshold value I_{cd}.

$$HD = \frac{-1 \times Hamming\ Distance + 13}{5} \tag{9}$$

5. Simulation Results

In order to confirm the effectiveness of this proposed method, the CNN application of the object detection is simulated. In this simulation, we use “Logic AND” template. This template reads out the black when input value and initial value are black. The others situation, the output becomes white. Therefore, when the input image and the initial state are same, the output is same with input image. However, if the threshold value of “Logic AND” template

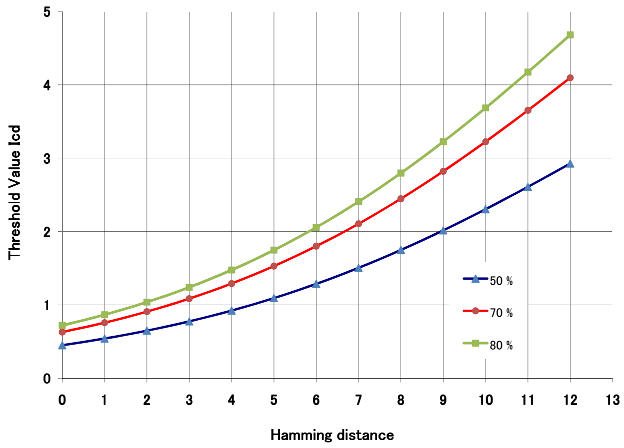


Figure 1: Change of the threshold value I_{cd} by the confidence degree.

is changed smaller than -2.1, CNN outputs white regardless of the input image and the initial state.

In this section, we show some simulation results using the proposed CNN. The input binary image is 4 and its size is 64 by 64. First, we describe the memorized patterns and related templates. And templates are found in [8].

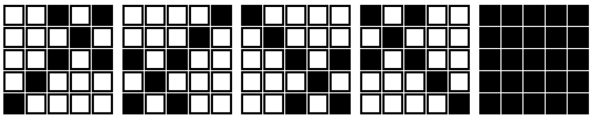


Figure 2: Memorized patterns.

"Logic AND" template:

$$A = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \; B = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \; I = -1. \qquad (10)$$

"White filler" template:

$$A = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \; B = 0, \; I = -4. \qquad (11)$$

This template of Eq. (11) changes all outputs into -1.

The memorized patterns are set as shown in Fig. 2. Four patterns which are Fig. 2 from the left are related with "Logic AND" template. These patterns corresponds to the part of objects in the input image. The rightmost pattern is related with "White Filler" template. This pattern describe the uniform region. By using these patterns, wiring weights of Hopfield NN is decided and each templates are applied to each cells.

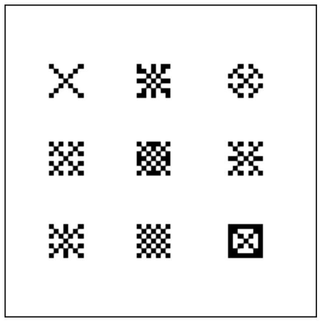
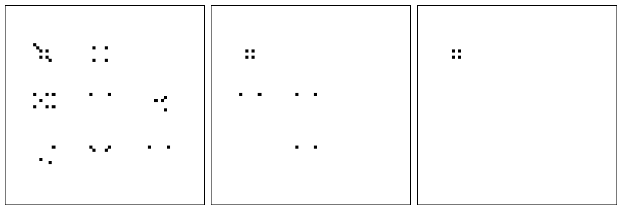


Figure 3: Input binary image to CNN and Hopfield NN.

Moreover, by changing the confidence degree which is 50 [%], 70 [%] and 80 [%], the extra threshold value I_{cd} is decided like Eq. 8 and Fig. 1. State equation of CNN updated is described as follows.

$$\frac{dv_{xij}}{dt} = -v_{xij} + \sum_{k=i-r}^{i+r} \sum_{l=j-r}^{j+r} A_{n(i,j;k,l)} v_{ykl}(t) + \sum_{k=i-r}^{i+r} \sum_{l=j-r}^{j+r} B_{n(i,j;k,l)} v_{ukl}(t) + I - I_{cd}. \qquad (12)$$

By using the extra threshold value I_{cd}, simulation results are changed as shown in Fig. 4 (a), (b) and (c), respectively. Therefore, some points of the object are detected by changing the confidence degree. Additionally, some points which have same pattern with memorized pattern is detected irrespectively the confidence degree.



(a) (b) (c)

Figure 4: Output image by using proposed system. (a) Confidence degree is 50 [%]. (b) Confidence degree is 70 [%]. (c) Confidence degree is 80 [%].

By using this system, we detected some points of each objects. Additionally, by changing the confidence degree, the number of the detected points are changed. Moreover, we carry out "Recall" template with conventional CNN to Fig. 4.

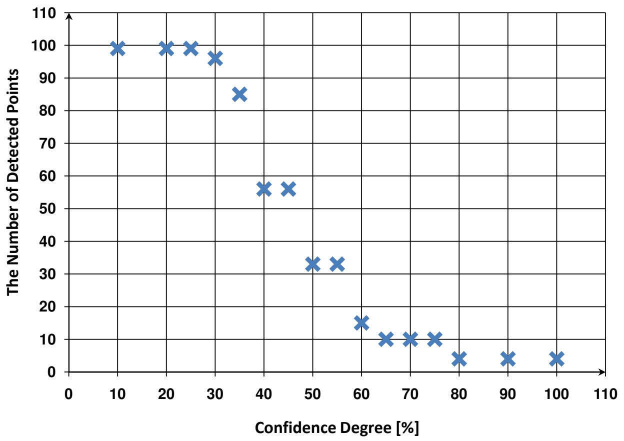
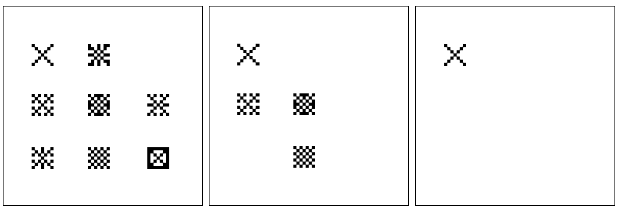


Figure 5: Change of detected points by Confidence degree.

"Recall" template:

$$A = \begin{bmatrix} 0.3 & 0.3 & 0.3 \\ 0.3 & 4 & 0.3 \\ 0.3 & 0.3 & 0.3 \end{bmatrix},\ B = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 5.1 & 0 \\ 0 & 0 & 0 \end{bmatrix},\ I = 0. \tag{13}$$

Simulation results are shown as follows (Fig. 6).



(a) (b) (c)

Figure 6: Output image by applying the "Recall" template with conventional CNN to Fig. 4. (a) Recall the input image in Fig. 4 (a). (b) Recall the input image in Fig. 4 (b). (c) Recall the input image in Fig. 4 (c).

From this simulation results, we can change the type of the detected objects by changing the confidence degree. Additionally, we could detect the object which is including the same pattern with the memorized pattern.

6. Conclusions

In this study, we proposed cellular neural networks (CNN) with Hopfield neural networks (Hopfield NN) considering the confidence degree. The Hopfield NN worked as an associative memory to retrieve one of the embedded patterns from the local data of the input images. The confidence degree meant the difference between the retrieved pattern and the input image. When the difference was small the confidence degree was set to be large. The confidence degree worked to enhance the CNN operation. By computer simulations, we investigated the basic property of the proposed method and confirmed its effectiveness for several examples.

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