Cellular Neural Networks with Effect from Friend Having Most Different Values and Its Friends

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***Abstract*— Generally, in the conventional CNN, each cell is connected to only its neighboring cells according to a template. In this case, the information that a cell can obtain from its neighboring cells is limited. In actual association, we possible to gain different perspectives and grow up by involving different types of friends. Therefore, in this study, we focus on the concept of human relationship in the real world. Then, we propose cellular neural networks with effect from friend having most different values and its friends. The proposed method is the new approach in consideration of the phenomena in such actual society.**

I. Introduction

In recent years, our life teems with information by growth of high information society. Generally, sequential digital circuits are used for many information processing. However, sequential digital circuits cannot perform real time processing. Therefore, the neural networks were devised based on the human's nervous system. The neural networks can design of analog circuit. Additionally, the neural networks can perform expression of nonlinear operating characteristics. Hence, the neural networks can express complicated processing easily. In fact, neural networks are used in every direction, such as an associative memory, pattern recognition, image processing, and so on. Then in 1988, Cellular Neural Networks (CNN) [1] were introduced by L. O. Chua and L. Yang. The idea of the 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. The local connectivity property makes the CNN tailor made for VLSI implementation. Therefore, the CNN has the features of time continuity, spatial discreteness, nonlinearity and parallel processing capability. Furthermore, the structure of CNN resembles that of animals' retina. Therefore, CNN can be used for various image processing applications [2]-[4]. In CNN, each cell is connected to its neighboring cells according to a template. Then, each cell is influenced by neighboring cells and its value is updated.

Generally in the conventional CNN, each cell is connected to only its neighboring cells according to a template. In this case, the information that a cell can obtain from its neighboring cells is limited. Then, in order to increase the information that a cell can obtain from its neighboring cells, there is also an approach of extending size of template. However, this approach has the potential to collapse the local connectivity property of CNN. Additionally, there is not so much template of large than the size of 3×3 matrix. In previous times, method of changing connection of among cells without extending size of template has been proposed. Especially, a method of introduced the concept of small-world network is interesting [5]. Therefore, we focus on the concept of human relationship in the real world. In the previous study, we have adapted the concept of effect from best friend and its friends to network of CNN and proposed new method. As the proverb "Evil communications corrupt good manners" says, we receive a great amount of influence from connected friends. In the case of that we make friends of foreign country, we possible to learn foreign country's values and foreign language. Furthermore in the case of that we make friends of the opposite sex, we possible to re-evaluate one's own greatness from viewpoint of opposite sex. In this way, we grow up by involving different types of friends.

In this study, we adapt the concept of effect from friend with most different value and its friends to network of CNN. Then, we propose the new method in consideration of the phenomena in such actual society, and investigate the effect in image processing. In the proposed method, connections of among cells are decided by the value of each cell. In each cell, a cell with the most different value of center cell is defined as "Different cell" in eight neighboring cells. Hence, the value of each cell is updated receive influences from the different cell and its neighboring cells. Then, we show some simulation results and confirm its effectiveness.

The list of this paper is structured as follows. In Sec. 2, we review the conventional of the standard CNN. In Sec. 3, we propose the new method of CNN. In Sec. 4, some simulation results of the proposed method are shown. The section 5 concludes the article.

II. Cellular Neural Networks

In this section, we explain the conventional structure of the CNN. The CNN has M by N processing unit circuits called cells. The cell contains linear and nonlinear circuit elements which are typically linear capacitors, linear resistors, linear and nonlinear controlled sources. Cells are arranged in a reticular pattern to M line 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 CNN is an array of cells. Each cell is connected to its neighboring cells according to a template. Usually, the template is the

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same for all cells except for boundary cells. The CNN has the features of time continuity, spatial discreteness, nonlinearity and parallel processing capability. The state equation and the output equation of the CNN are shown as follows.

State equation :

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

Output equation :

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

where v_x, v_y and v_u represent a state, an output and an input of cell, respectively. In the Eq. (1), A is the feedback template and B is the control template. These and the constant bias I are collectively called general template. The output equation is a piece-wise linear function. In fact, the output value of CNN is within of -1 to 1. When the CNN is used for image processing, values of black and white are treated as 1 and -1, respectively.

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

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

where r is a positive integer number. Each cell has $(2r + 1)^2$ neighborhood cells. Hence, the size of template is defined by r. If r is 1, the size of template is 3×3 matrix. Additionally, if r is 2, the size of template is 5×5 matrix.

III. Cellular Neural Networks with Effect from Friend Having Most Different Values and Its Friends

In this section, we explain the algorithm of the cellular neural networks with effect from friend having most different values and its friends (DF-CNN). The DF-CNN is the method of constituting new combinations of among cells. In this paper, we consider the local connection of CNN as friendship. Then, in each cell, the neighboring cells are defined as friend cells. Based on this, the algorithm of DF-CNN is described as follows.

A. In The Case of Feedback Template

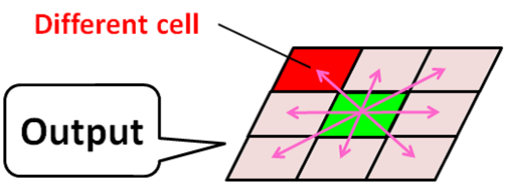

Fig. 1. Search the different cell in output image.

Step 1: In each cell of output image, a cell with the most different of the value of center cell $C(i, j)$ is defined as "Different cell" from eight neighboring cells like Fig. 1.

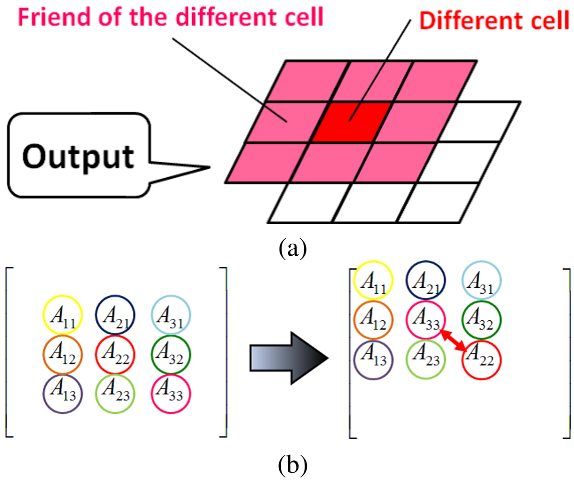

Fig. 2. New combination of feedback template. (a) The combination on centering on the different cell. (b) Elements of new feedback template.

Step 2: The combination centering on a cell $C(i, j)$ is changed into a combination centering on the different cell like Fig. 2(a).

Moreover, the element of the feedback template of the different friend and the center cell are replaced. With this, a new combination is constituted like Fig. 2(b).

Step 3: The value of each cell is updated according to the Eqs. (1) and (2) using the new combinations of feedback templates.

Step 4: Steps 1 to 4 are repeated every 0.0005 [τ].

B. In The Case of Control Template

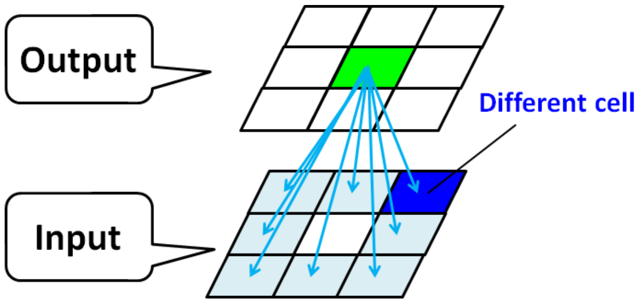

Fig. 3. Search the different cell in input image.

Step 1: In each cell of input image, a cell with the most different of the value of center cell $C(i, j)$ in output image is defined as "Different cell" from eight neighboring cells in input image like Fig. 3.

Step 2: The combination centering on a cell $C(i, j)$ is changed into a combination centering on the different cell like Fig. 4(a).

Moreover, the element of the control template of the different friend and the center cell are replaced. With this, a new

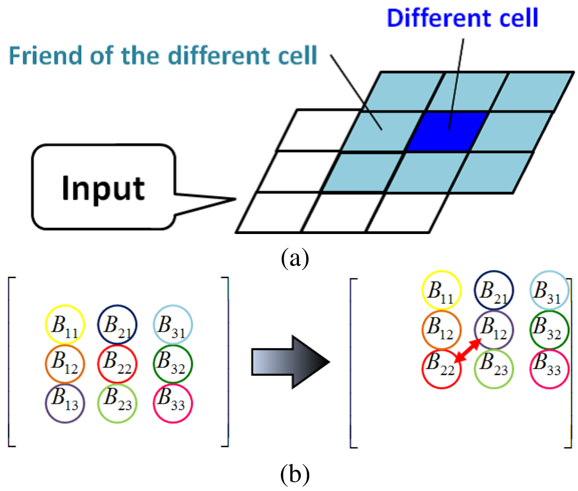

Fig. 4. New combination of control template. (a) The combination on centering on the different cell. (b) Elements of new control template.

combination is constituted like Fig. 4(b).

Step 3: The value of each cell is updated according to the Eqs. (1) and (2) using the new combinations of control templates.

Step 4: Steps 1 to 4 are repeated every 0.0005 [τ].

Therefore, the value of each cell is updated by receiving influences from the different cell and its neighboring cells.

IV. Simulation Results

In this section, we show some simulation results for edge detection and divide domains by using the DF-CNN. In this study, boundary condition is fixed with mirror reflector condition.

A. Edge Detection

In this subsection, we show some simulation results of edge detection by using the DF-CNN. In edge detection, the edge of the indistinct portion is not detected by using "*Edge detection*" template of 3×3 matrix. On the other hand, by using "*Edge detection*" template of 5×5 matrix, we can detect the edge of the indistinct portion. However, by using "*Edge detection*" template of 5×5 matrix, the detected edge becomes bold line and some noises are left. In the DF-CNN, we use only "*Edge detection*" template of 3×3 matrix [6]. "*Edge detection*" templates of 3×3 matrix and 5×5 matrix are described as follows.

Edge detection template of 3×3 matrix :

$$A = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \; B = \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}, \; I = -1. \qquad (4)$$

Edge detection template of 5×5 matrix :

$$\begin{aligned} A &= \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \\ B &= \begin{bmatrix} -1 & -3 & -4 & -3 & -1 \\ -3 & 0 & 6 & 0 & -3 \\ -4 & 6 & 20 & 6 & -4 \\ -3 & 0 & 6 & 0 & -3 \\ -1 & -3 & -4 & -3 & -1 \end{bmatrix}, \\ I &= -1. \end{aligned} \qquad (5)$$

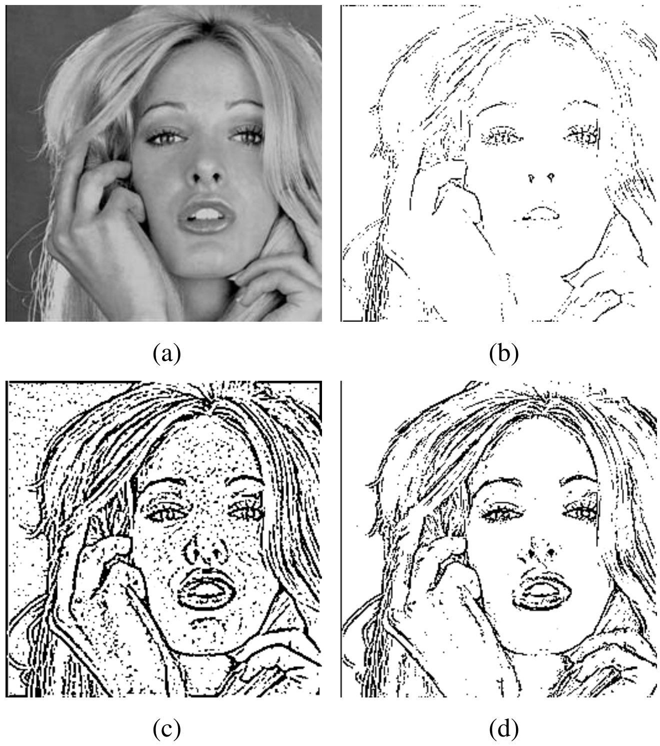

Fig. 5. Edge detection result 1. (a) Input and initial state images (woman). (b) Edge detection result using the conventional CNN with the 3×3 matrix template. (c) Edge detection result using the conventional CNN with the 5×5 matrix template. (d) Edge detection result using the DF-CNN.

Figure 5 shows the edge detection results. The almost edge is not detected using the conventional CNN with the "*Edge detection*" template of 3×3 matrix in Fig. 5(b). On the other hand, the detected edge becomes bold line and many noises are left using the conventional CNN with the "*Edge detection*" template of 5×5 matrix in Fig. 5(c). In Fig. 5(d), by using the proposed method, the edge can be detected more clearly and the detected edge is more fine line than using the conventional CNN.

Figure 6 shows the edge detection results for another input image. Fig. 6(a) contains some indistinct portion. The indistinct portion is not detected using the conventional CNN with the "*Edge detection*" template of 3×3 matrix in Fig. 6(b).

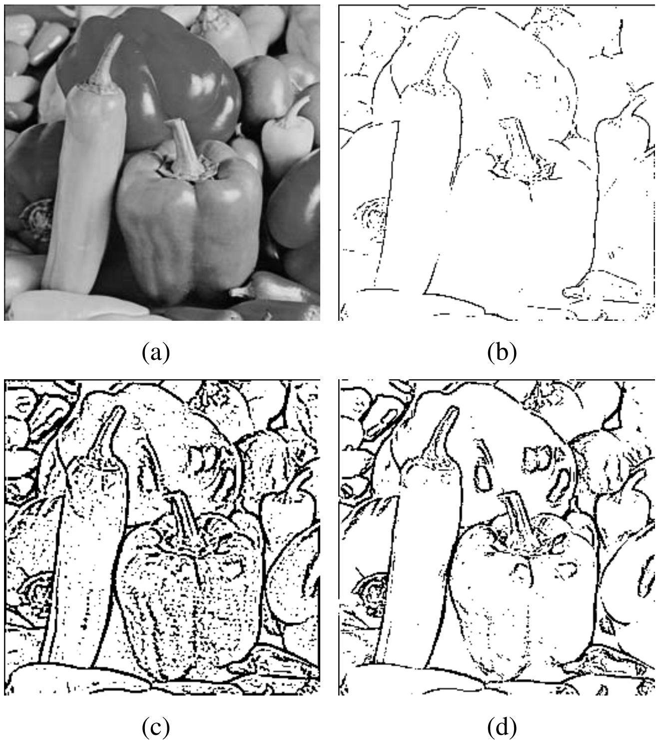

Fig. 6. Edge detection result 2. (a) Input and initial state images (pepper). (b) Edge detection result using the conventional CNN with the 3×3 matrix template. (c) Edge detection result using the conventional CNN with the 5×5 matrix template. (d) Edge detection result using the DF-CNN.

On the other hand, the detected edge becomes bold line and many noises are left using the conventional CNN with the "*Edge detection*" template of 5×5 matrix in Fig. 6(c). Similar to the above results, by using proposed method, the edge can be detected more clearly and the detected edge is more fine line than using the conventional CNN in Fig. 6(d). Also, in comparison to Fig. 6(c), some noises are removed by using the proposed method.

From these results, we can confirm that the proposed method is more effective than the conventional CNN for the edge detection. Also, the proposed method does not depend on the image. This method has broad utility, because this system needs only the value of cell.

B. Divide Domains

In this subsection, we show other application using the DF-CNN. To divide sparse domain from thick domain, we create and use "*Divide domains*" template based on "*Small object remover*" template [6]. The "*Divide domains*" template is shown as follows.

Divide domains template :

$$A = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 1 \\ 1 & 1 & 1 \end{bmatrix}, \; B = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \; I = -1. \qquad (6)$$

Figure 7(b) shows the output image by the DF-CNN using the "*Divide domains*" template. The thick domain of the left

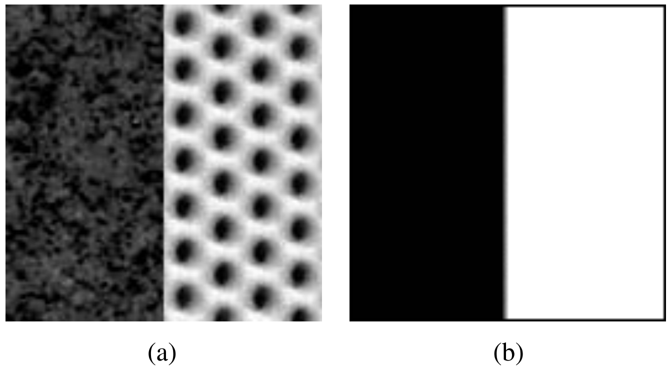

Fig. 7. Divides sparse domain from thick domain result by the DF-CNN. (a) Input and initial state images (image size is 128×128 pixels). (b) Divide domains result by the DF-CNN using the "*Divide domains*" template.

half in the input image remains as a black domain. At the same time, the sparse domain of the right half in the input image remains as a white domain. Thereby, we can see that the thick domain and the sparse domain can be divided with the DF-CNN.

V. Conclusion

In this study, we have proposed cellular neural networks with effect from friend having most different values and its friends. The DF-CNN is the new method in consideration of the phenomena in such actual society which likes "Evil communications corrupt good manners". From some simulation results, we have confirmed that our proposed method is effective for edge detection and dividing sparse domain from thick domain in image. Especially, edge detection results have improved by using simple system and existing template of 3×3 matrix without extending size of template. Also our proposed method is excellent about general versatility, because this system needs only the value of cell. In the future works, we would like to adapt the proposed system to multilayer CNN.

Acknowledgment

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References

[1] L. O. Chua and L. Yang, "Cellular Neural Networks: Theory," *IEEE Trans. Circuits Syst.*, vol. 32, pp. 1257-1272, Oct. 1988.
[2] M. Namba and Z. Zhang, "Cellular Neural Network for Associative Memory and Its Application to Braille Image Recognition," *Proc. of IJCNN'06*, pp. 4716-4721, Jul. 2006.
[3] H. Koeppl and L. O. Chua, "An Adaptive Cellular Nonlinear Network and its Application," *Proc. of NOLTA'07*, pp. 15-18, Sep. 2007.
[4] K. R. Crounse and L. O. Chua, "Methods for Image Processing and Pattern Formation in Cellular Neural Networks: A Tutorial," *IEEE Trans. Circuits Syst.*, vol. 42, no. 10, pp. 583-601, Oct. 1995.
[5] K. Tsuruta, Z. Yang, Y. Nishio and A. Ushida, "Small-world cellular neural networks for image processing applications," *Proc. of ECCTD'03*, vol. 1, pp. 225-228, Sep. 2003.
[6] Cellular Sensory Wave Computers Laboratory Computer and Automation Research Institute Hungarian Academy of Sciences, "Cellular wave Computing Library (Template, Algorithms, and Programs) Version 2.1".