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Application of Two-Layer Cellular Neural Networks for Edge Detection

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Abstract

In this research, we propose the new type two-layer cellular neural networks. In our two-layer cellular neural networks, calculation start time of each layer have difference. In particular, the first layer is calculated in first, and output of the first layer is inputted to the second layer. By using diffusion processing in this structure, we expect that the complex image processing using the CNN is realized. We confirm the characteristics of our two-layer CNN by computer simulation.

1. Introduction

Cellular Neural Networks (CNN) [1] were introduced by Chua and Yang in 1988. The idea of the CNN was inspired from the architecture of the cellular automata and the neural networks. The CNN has local connectivity property. The basic circuit unit of cellular neural networks is called a cell. It contains linear and nonlinear circuit elements, which typically are linear capacitors, linear resistors, linear and nonlinear controlled sources. The structure of cellular neural networks is similar to that found in cellular automata. Unlike the conventional neural networks, the CNN has local connectivity property. Namely, any cell in a cellular neural network is connected only to its neighbor cells. Since the structure of the CNN resembles the structure of animals' retina, the CNN can be used for various image processing application [2]-[4] including medical image processing [5].

Wiring weights of the cells of the CNN are established by parameters called the template. The performance of the CNN is decided by the template. Usually, the templates of all the cells in the CNN are identical and those values do not change during the processing. This is good for implementation but restrict the performance, namely the conventional CNN can not perform image processing based on the local features of input images.

In the previous study, we have proposed improvement of two-layer CNN for edge detection. In order to improve for edge detection using the CNN, we concentrate on the diffusion template. Diffusion template can diffuse the input image. Namely, value of all cells converge to one constant value. We think that this effect is available to the differentiation process. Hence, differentiation process is capable of edge detection performance. By using diffusion template in our two-layer CNN, we obtained the effective edge detection results. However, connection between each layer of our two-layer CNN in the previous study is only from second layer to first layer. From structure that the multiple-layer CNN is mutual coupling, we think that connection between each layer of our two-layer CNN in the previous study change to the mutual coupling.

In this study, we proposed the two layer-CNN for edge detection with mutual coupling. The behavior of two-layer CNN becomes complex by mutual coupling, while we expect the high quality edge detection using our two-layer CNN. Additionally, we apply the threshold types to the coupling template. We show the edge detection results having the certain region by computer simulation.

In the Sec. 2, we review the basic structure of the standard CNN. In the Sec. 3, we review the proposed two-layer CNN model. In the Sec. 4, simulation results using the proposed two-layer CNN are shown. In the Sec. 5, concludes the article.

2. Cellular Neural Networks [1]

In this section, we describe the basic structure of the standard CNN. The CNN has M by N processing unit circuits called cells. 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 cell contains linear and nonlinear circuit elements. The CNN is an array of cells. Each cell is connected to its neighboring cells according to a template. Usually, the template is the 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 cell 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 equation (1), A is the feedback template and B is the control template. These and bias I are collectively called general template.

3. Structure of Two-Layer CNN with Mutual Coupling

In this section, we describe the structure of the proposed two-layer CNN with mutual coupling. The first feature of the proposed two-layer CNN with mutual coupling model is that the calculation start time of each layer have difference, in particular, first layer is calculated in first, and output of first layer is inputted to the second layer. Namely, calculation time of the second layer later than that of the first layer. By applying this effect, we can realize the differentiation processing in CNN, consequently, edge detection performance using CNN is improved. The second feature is the mutual coupling of the proposed two-layer CNN. This means that the behavior of the proposed two-layer CNN becomes complex, whereas we expect that the image processing performance is improved. The third feature is that the using template in the proposed two-layer CNN is simple templates.

The processing structure of the proposed two-layer CNN is described as follow.

STEP 1: Firstly, we input an image to the first layer. The state value calculate in the first layer. The state equation of the cell in the first layer described as follow.

State equation of the first-layer :

$$\frac{dv_{x1ij}}{dt} = -v_{x1ij} + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r} A_1(i,j;k,l) v_{x1kl}(t) + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r} B_1(i,j;k,l) v_{u1kl}(t) + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r} C_1(i,j;k,l) v_{y2kl}(t) + I_1. \quad (3)$$

where C_1 is coupling template from second layer to first layer. The term of C_1 is 0 until the second layer calculation start.

STEP 2: We calculate difference of the output value in the first layer at different times. The difference equation is described as follow.

Difference of output value in the first layer:

$$v_{u2ij} = v_{y1ij}|_{t=\Delta\tau} - v_{y1ij}|_{t=0}. \quad (4)$$

In this equation, $\Delta\tau$ is the time from calculation start of the first layer to input the second layer. In this study, $\Delta\tau$ is set to 0.05.

STEP 3: The calculated value in step 2 is inputed to the second layer. The state equation of the cell in the second layer described as follow.

State equation of the second-layer :

$$\frac{dv_{x2ij}}{dt} = -v_{x2ij} + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r} A_2(i,j;k,l) v_{x2kl}(t) + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r} B_2(i,j;k,l) v_{u2kl}(t) + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r} C_2(i,j;k,l) v_{y1kl}(t) + I_2. \quad (5)$$

where C_2 is coupling template from first layer to second layer

Finally, the first layer and second layer in the proposed our two-layer CNN are influenced each other.

4. Simulation Results

In this section, we show the simulation results using the proposed two-layer CNN. In this simulation, we use the diffusion template. Diffusion template is shown as follow.

Diffusion Template:

$$A = \begin{bmatrix} 0.1 & 0.15 & 0.1 \\ 0.15 & 0 & 0.15 \\ 0.1 & 0.15 & 0.1 \end{bmatrix}, B = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, I = 0.(7)$$

By using this template, input image is diffused without limit.

Next, the edge detection template in the proposed two-layer CNN is shown as follow.

Edge Detection Template in Two-Layer CNN:

The first layer template

$$A_1 = \begin{bmatrix} 0.1 & 0.15 & 0.1 \\ 0.15 & 0 & 0.15 \\ 0.1 & 0.15 & 0.1 \end{bmatrix}, B_1 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, I_1 = 0$$

The second layer template

$$A_2 = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 3 & 1 \\ 1 & 1 & 1 \end{bmatrix}, \quad B_2 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad I_2 = -0.1$$

Coupling template

$$C_1 = \begin{bmatrix} 0.05 & 0.05 & 0.05 \\ 0.05 & -0.4 & 0.05 \\ 0.05 & 0.05 & 0.05 \end{bmatrix},$$

$$C_2 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & a & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad \begin{cases} a = 3 & if \ \ v_{y1ij} \geq \mathrm{Th} \\ a = 0 & otherwise \end{cases}. \qquad (8)$$

We set that the template of the first layer in our two-layer CNN is "Diffusion" template as template (8), furthermore template of the second layer in our two-layer CNN have the effect that the grayscale image is converted to the binary image. Moreover, we describe the coupling templates C_1 and C_2, and the coupling template C_2 is threshold type. This means that if output value of the first layer V_{y1ij} is larger than a threshold value Th, a becomes 3, if V_{y1ij} is smaller than the threshold value Th, a becomes 0, namely, the first layer has not influence to the second layer.

Next, in order to compare the original CNN with the proposed two-layer CNN in edge detection performance, we carry out the edge detection processing using original CNN. The "Edge Detection" template is shown as follow.

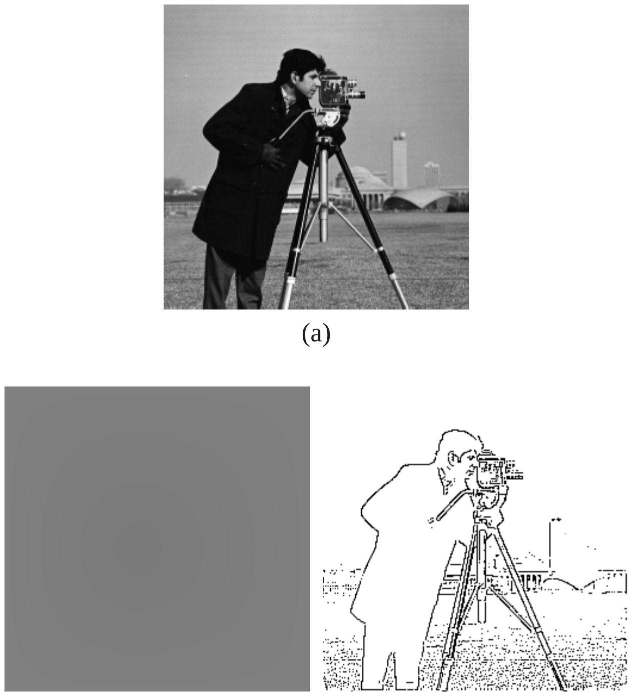
Edge Detection Template in original CNN:

$$A = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}, B = \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}, I = -1. \qquad (9)$$

By using this template, edge of input binary image is detected.

Figure 1 shows the simulation results using "Diffusion" template (7) and "Edge Detection" template (9) in original CNN. Figure 1(a) is an input image. This input image have indistinct portion of the edge. Figures 1(b) and (c) shows the simulation results using "Diffusion" template (7) and "Edge Detection" template (9) in the original CNN. We can see in Fig. 1(a), input image have indistinct portion of the edge. Also, we can see in Fig. 1(c), indistinct portion of the edge as building of background can not be detected in original CNN.

Figures 2(a) and (c) shows the simulation results using "Edge Detection" template (8) in first layer of the proposed two-layer CNN. While Figs. 2(b) and (d) show the simulation results using the template (8) in second layer of the proposed two-layer CNN. In Fig. 2, edge of input image as Fig. 1(a) is detected more effective than the edge detection result as Fig. 1(c) using original CNN. Moreover, certain domain in output image as Fig. 2 becomes black. This certain domain is depend on the threshold value Th. In particular, when the threshold value Th is 0.2 as Figs. 2(a) and (b), face of human in the input image as Fig. 1(a) become black. While the threshold value Th is 0.8 as Figs. 2 (c) and (d), face of human in the input image as Fig 1(a) become white. By this effect, we obtained the edge detection result having the certain region using the proposed our two-layer CNN. Additionally, background of output image as Figs. 2(a) and (c) have certain density. This density represent to the diffused color of background in the input image as Fig 1(a). From these results, we can obtained the two type output images by influencing each other, first type output image have the effects of edge detection having certain region and diffusion performance, second type output image have the effect of the edge detection having the certain region. Namely, first type output image have some information more than second type output image. Therefore, we decided that the conclusive output image from the proposed two-layer CNN is first type output image (output image in the first layer of the proposed two-layer CNN).



(a) (b) (c)

Figure 1: Simulation results using templates (7) and (9) in original CNN. (a) Input image (Cameraman). (b) Diffusion result using "Diffusion" template (7) in original CNN. (c) Edge detection result using "Edge Detection" template (9) in original CNN.

Figure 3 shows the simulation results for different input image with the same "Edge Detection" template. Similar to the case of the previous results, we can obtain the two types output images.

5. Conclusions

In this research, we have proposed the new type two-layer cellular neural networks. In our two-layer cellular neural net-

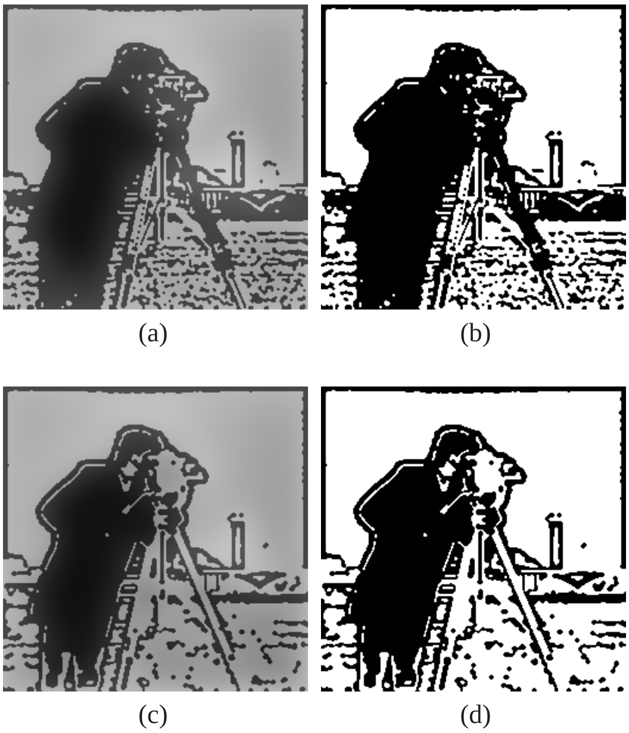


Figure 2: Simulation results using template (8) in the proposed two-layer CNN. (a) Output image of the first layer in the proposed two-layer CNN (Th=0.2). (b) Output image of the second layer in the proposed two-layer CNN (Th=0.2).(c) Output image of the first layer in the proposed two-layer CNN (Th=0.8). (d) Output image of the second layer in the proposed two-layer CNN (Th=0.8).

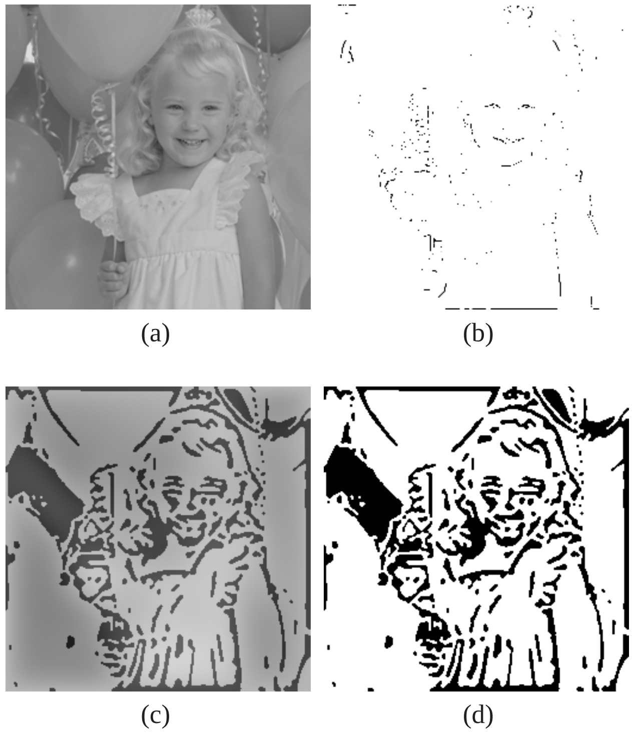


Figure 3: Simulation results using template (8) in the proposed two-layer CNN. (a) Input image (Balloon). (b) Edge detection result using "Edge Detection" template (9) in original CNN. (c) Output image of the first layer in the proposed two-layer CNN (Th=0.2). (d) Output image of the second layer in proposed two-layer CNN (Th=0.2).

works, calculation start time of each layer have difference. In particular, first layer is calculated in first, and output of first layer is inputted to the second layer. By using diffusion processing in this structure, we obtained the two type output images from the proposed two-layer CNN, and conclusive output image have the edge of input image and certain region. We feel that the output image using the proposed two-layer CNN is available to the region extraction.

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