Edge Enhancement of Color Image by Three-Layer Cellular Neural Network Considering Three Primary Colors

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Abstract—In this study, we propose the three-layer cellular neural network considering three primary colors. In our propose three-layer cellular neural network, the connections between the three layers play an important role. Namely, the three layers do not operate independently but all the outputs influence to the other layers. In this research, we show some edge enhancement more effectively than the original cellular neural networks 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. Unlike the conventional neural networks, the CNN has local connectivity property. 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 character extractions [5][6]. Further, the CNN can be utilized to produce some kinds of pattern generation [7][8].

The humans retina have an ability distinguishing colors and consist of three types of cells called "cone" responding to the three primary colors and a cell called "rod" responding to the amount of light. The humans can recognize colors by the function of the cone cells. Roska et al. have proposed a concept using a three-layer CNN processing the three primary colors in [9]. They have confirmed that the three-layer CNN could produce half-toned images of color images. However, after their pioneering work, there have not been many researches on the CNN dealing with three primary colors of the image effectively.

In this study, we propose the three-layer cellular neural network considering three primary colors (RGB-CNN). Before the processing, a color image is divided into three primary colors and they are converted to three gray-scale images corresponding to red value, green value, and blue value. This preprocess corresponds to the function of the cone cells of the retina. These three images are inputted to the proposed three-layer cellular neural networks. In our RGB-CNN, the connections between the three layers play an important role. Namely, the three layers do not operate independently but all the outputs influence to the other layers.

In this study, we concentrate on the edge enhancement of color images. Preparing the edge detection template for each layer of the RGB-CNN, we confirm that the RGB-CNN can enhance the edges of color images more effectively than the regular processing by using the original CNN.

In Sec. 2, we propose the RGB-CNN. In Sec. 3, we show the algorithm using the RGB-CNN for the edge enhancement of color images. In Sec. 4, we show some computer simulated results. Section 5 concludes the article.

2. RGB-CNN

In the original CNN, color images are converted to gray-scale images before the processing. The gray-scale images do not have color information. Therefore, the conventional CNN is impossible to consider color information. The proposed RGB-CNN is the three-layer CNN considering the three primary colors of light.

2.1. Red-Green-Blue

The Red-Green-Blue is called the three primary colors of light and all colors can be represented by combining these three colors. The mechanism of the three primary colors of light is shown in Fig. 1. In Fig. 1, "R", "G" and "B" represent red, green and blue, respectively. The color becomes black when all Red-Green-Blue values are minimum. Also, the color becomes white when all Red-Green-Blue values are maximum.

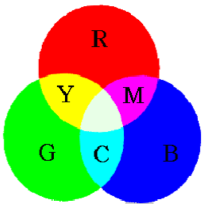


Figure 1: Mechanism of three primary colors of light.

2.2. Three-layer CNN

Figure 2 shows the structure of the proposed three-layer CNN. The three-layer CNN consists of three single-layer CNNs. Each layer is coupled to another layer with the connection template (CR, CG, CB). Because of these connection templates, the red layer has a direct influence to the green layer. Also, the green layer has a direct influence to the blue layer, and the blue to the red. We can say that all layers have mutual influences each other.

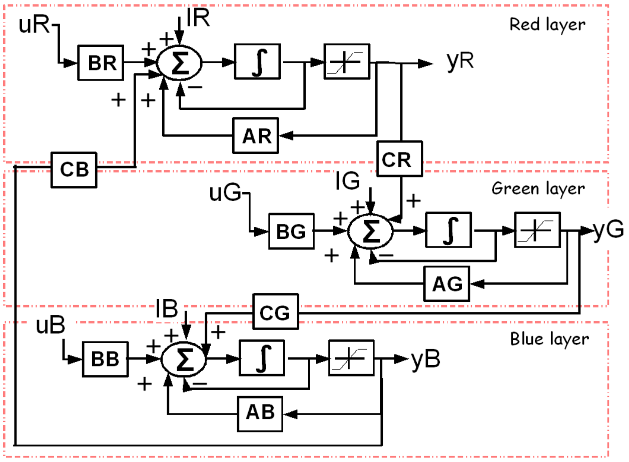


Figure 2: Structure of three-layer CNN.

The dynamical system equations associated with the three-layer CNN are described by the following equations: (1) Three first-order state differential equations:

$$\begin{aligned}\frac{dv_{xR,ij}}{dt} = {} & -v_{xR,ij} + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r} AR_{(i,j;k,l)}v_{yR,kl}(t)\\ & + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r} BR_{(i,j;k,l)}v_{uR,kl}(t)\\ & + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r} CB_{(i,j;k,l)}v_{yB,kl}(t) + IR \qquad (1)\end{aligned}$$

$$\begin{aligned}\frac{dv_{xG,ij}}{dt} = {} & -v_{xG,ij} + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r} AG_{(i,j;k,l)}v_{yG,kl}(t)\\ & + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r} BG_{(i,j;k,l)}v_{uG,kl}(t)\\ & + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r} CR_{(i,j;k,l)}v_{yR,kl}(t) + IG \qquad (2)\end{aligned}$$

$$\begin{aligned}\frac{dv_{xB,ij}}{dt} = {} & -v_{xB,ij} + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r} AB_{(i,j;k,l)}v_{yB,kl}(t)\\ & + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r} BB_{(i,j;k,l)}v_{uB,kl}(t)\\ & + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r} CG_{(i,j;k,l)}v_{yG,kl}(t) + IB \qquad (3)\end{aligned}$$

(2) Three output equations:

$$v_{yR,ij}(t) = \frac{1}{2}(|v_{xR,ij}(t) + 1| - |v_{xR,ij}(t) - 1|) \qquad (4)$$

$$v_{yG,ij}(t) = \frac{1}{2}(|v_{xG,ij}(t) + 1| - |v_{xG,ij}(t) - 1|) \qquad (5)$$

$$v_{yB,ij}(t) = \frac{1}{2}(|v_{xB,ij}(t) + 1| - |v_{xB,ij}(t) - 1|) \qquad (6)$$

where v_x, v_y, and v_u represent a state, an output and an input of cell, respectively. In the equations (1), (2) and (3), A is the feedback template and B is the control template. These and bias I are collectively called general template. In addition, C are the connection templates introduced to couple the three layers.

Figure 3 shows the structure of the RGB-CNN. Before the processing, a color image is divided into three primary colors and they are converted to three gray-scale images corresponding to red value, green value and blue value. These three images are inputted to the three-layer CNN as v_{uR}, v_{uG}, and v_{uB}, Finally, we can obtain three possible output images from the three-layer CNN.

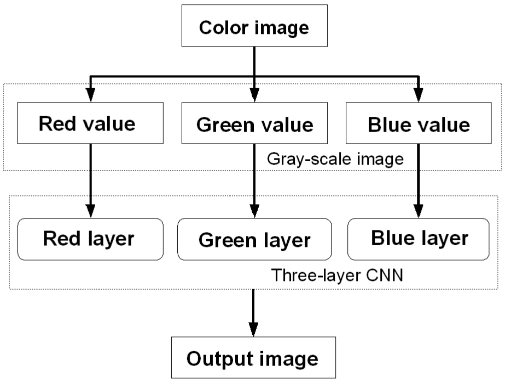


Figure 3: Structure of RGB-CNN.

3. Edge Enhancement Using RGB-CNN

In this section, we design the RGB-CNN for edge enhancement of color images. For the edge detection of a color image, we sometimes face the difficulty if we process the task after converting the image to a gray-scale image. Because some edges enhanced by the difference of the colors may disappear by the conversion.

3.1. Edge Detection Template in Conventional CNN

The template (7) is the convectional edge detection template. By using the template (7), edges in binary images can be detected. However, edges in color images cannot be detected sufficiently.

$$A = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}, B = \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}, I = -1. \qquad (7)$$

3.2. Edge Enhancement Template in RGB-CNN

The template (8) is the edge enhancement template for RGB-CNN.

$$AR = AG = AB = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$BR = BG = BB = \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

$$CR = \begin{bmatrix} 0 & 0 & 0 \\ 0 & b & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad \begin{cases} b = 2 & if \ v_{yRij} \geq 0 \\ b = 0 & otherwise \end{cases}$$

$$CG = \begin{bmatrix} 0 & 0 & 0 \\ 0 & b & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad \begin{cases} b = 2 & if \ v_{yG,ij} \geq 0 \\ b = 0 & otherwise \end{cases}$$

$$CB = \begin{bmatrix} 0 & 0 & 0 \\ 0 & b & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad \begin{cases} b = 2 & if \ v_{yB,ij} \geq 0 \\ b = 0 & otherwise \end{cases}$$

$$IR = IG = IB = -1. \tag{8}$$

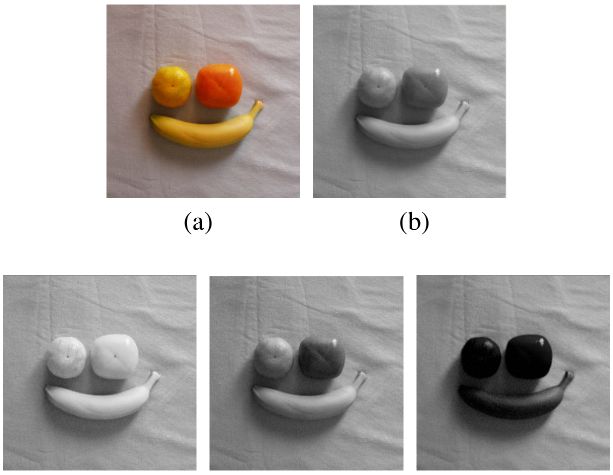
In Eq. (8), A, B and I are the same as those in Eq. (7). For the connection template CR, CG and CB, we consider the nonlinear (threshold-type) function to make the effect of each layer more significantly. Namely, for CR, if the output value of the red layer is lager than zero, b becomes 2 and the output influences to the green layer. By using this nonlinear template, the outputs of the three layers enhance each other. It should be mentioned that the three output images of the three layers become the same, although three outputs of the three-layer CNN usually different.

4. Simulation Results

In this section, we show some effective edge enhancement results using RGB-CNN. Figure 4 shows an example of the conversion of a color image to gray-scale images. Figures 4(a) and (b) are the original color image and the gray-scale image converted from the color image directly. Also Figs. 4(c), (d) and (e) are the gray-scale images corresponding to the red, green and blue values of the color image, respectively.

4.1. For Fruit Image

Figure 5 shows the simulation results for the fruit image in Fig. 4. Figure 5(a) shows the result for the input image in Fig. 4(b). We cannot detect the edges effectively. Figures 5(b), (c) and (d) show the results for the input images in Figs. 4(c), (d) and (e). We can see that the edge on the banana can be detected by using the red color while the edge on the persimmon can be detected by using the blue color. Even if we combine these three outputs, the edges are not visible clearly as Fig. 5(e). On the other hand, the proposed edge-detection RGB-CNN produce the output image in which all the edges are enhanced and also the shaded area remains as like a half-toned image.


(a) (b)

(c) (d) (e)

Figure 4: Example of conversion of color image to gray-scale images. (a) Color image. (b) Gray-scale image. (c) Gray-scale image for red value. (d) Gray-scale image for green value. (e) Gray-scale image for blue value.

4.2. For Monster Image

Figure 6 shows the simulation results for monster image. We can see that the proposed RGB-CNN can detect the edges of the image more effectively than the conventional CNN.

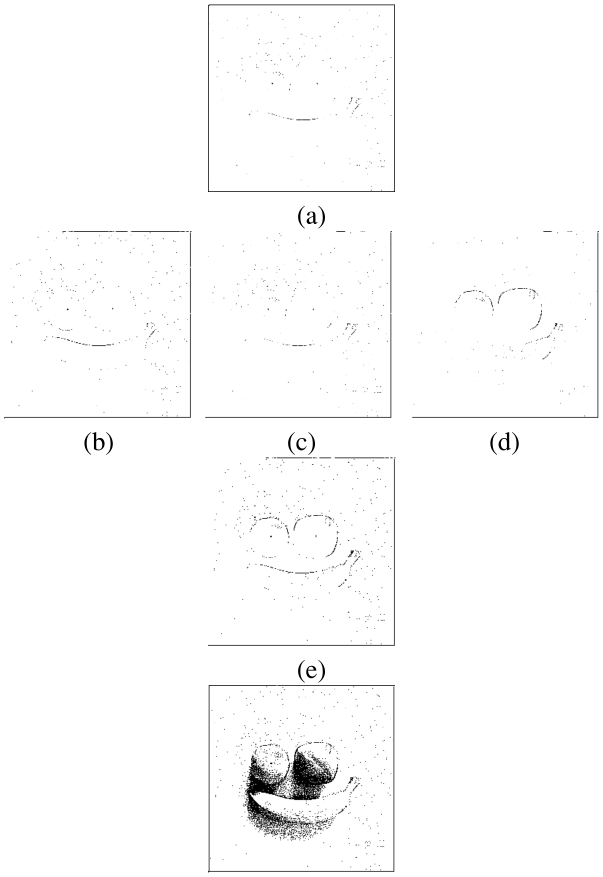
4.3. For Castle Image

Figure 8 shows the simulation results for castle image. In this result, we can obtain the output image in which the shaded area is enhanced as well as all the edges can be detected. We feel that this effect is useful for that human recognize the edges in color input images.

5. Conclusions

In this study, we have proposed the three-layer CNN considering the three primary colors. By computer simulations of edge detection tasks for a color image, we have confirmed that the RGB-CNN could enhance the edges of color images more effectively than the regular processing by using the original CNN. We feel that the RGB-CNN is available to various image processings.

Also, we can see that output images using RGB-CNN have the effect of half-toning. In the future work, we should investigate about this effect.



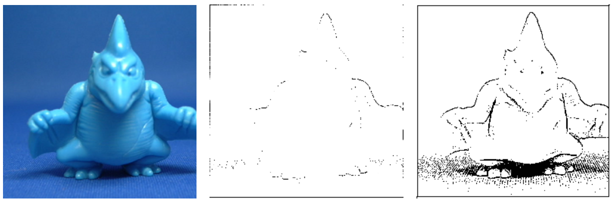
(a)

(b) (c) (d)

(e)

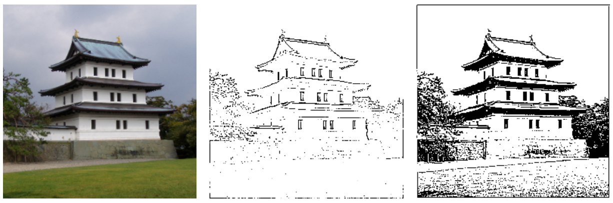
(f)

Figure 5: Edge enhancement of fruit image. (a) Output image using the conventional CNN for the input image in Fig. 4(b). (b) Output image using the conventional CNN for the input image in Fig. 4(c). (c) Output image using the conventional CNN for the input image in Fig. 4(d). (d) Output image using the conventional CNN for the input image in Fig. 4(e). (e) Output image combining the outputs in Figs. 5(b), (c) and (d). (f) Output image using the edge-enhancement RGB-CNN for the input image in Fig. 4(a).



(a) (b) (c)

Figure 6: Simulation result for monster image. (a) Input image (color). (b) Output image using the conventional CNN for the input converted to gray-scale image. (c) Output image using the edge-enhancement RGB-CNN.



(a) (b) (c)

Figure 7: Simulation result for castle image. (a) Input image (color). (b) Output image using the conventional CNN for the input converted to gray-scale image. (c) Output image using the edge-enhancement RGB-CNN.

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