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A Method of Edge Detection Using Small World Cellular Neural Network

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Abstract

A few years ago, Tsuruta et al. have proposed Small World Cellular Neural Networks (SWCNN). SWCNN is the system that shortcut connections are introduced into the original CNN and can be applied to some image processing tasks. We have investigated the performance of the SWCNN by changing the structure of the network keeping the number of all branches same and have clarified that the SWCNN can realize edge detection of gray scale images. In this article, we propose a new SWCNN system for better edge detection of gray scale images.

1. Introduction

Studies of network map are very important, because they help us to understand the basic features and requirements of various systems. So far many connection topologies of network assumed to be either completely regular or completely random have been studied in the past. Cellular Neural Network (CNN) model invented by Chua and Yang in 1988 [1] is a typical of those completely local connectivities, which is presented as a preferred implementation of locally and regularly coupled neural networks. The CNN has been successfully used for various high-speed parallel signals processing applications such as image processing, pattern recognition as well as modeling of various phenomena in nonlinear systems. However, in many cases in real life, many network topologies such as biological, technological and social networks are known to be not completely random nor completely local but somewhere in between. This was modeled in an interesting work by Watts and Strogatz in 1998 [2] as the small-world model. The model is a network consisting of many local links and fewer long range shortcut. Therefore, it has a high clustering coefficient like regular lattices and a short characteristic path length of typical random networks. Interesting examples are shown by collaboration of movie stars, connectivity of Internet web pages or neural nets, etc.

Recently, Tsuruta et al. have proposed the Small World Cellular Neural Network (SWCNN) [3][4]. They have reported that several kinds of image processing (e.g. edge detection, small object removers, etc.) come to learn to react more adaptable. We have clarified that we could control the performance of the SWCNN by changing the characteristics of the shortcuts (the length, the number, and the direction) in the SWCNN [5].

In this article, we propose a new SWCNN system for better edge detection of gray scale images. We investigate the characteristics of our SWCNN by applying them to edge detection of gray scale images and show some interesting results. Further, we propose some improvements of the method.

2. Original CNN and edge detection

The edge detection is one of very important image processing tasks. By using CNN, we can realize to conduct the task on analog processing. Our proposed system has the same base of the original CNN. In this section, we describe the structure of the original CNN and the simulation results for gray scale images.

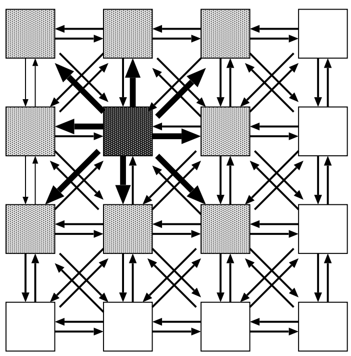


Figure 1: Structure and basic network topology of CNN.

The CNN has nonlinear processing units 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 state equation of the cell is represented as follow.

$$\dot{x}_{ij}(t) = -x_{ij}(t) + I + \sum_{C(k,l)\in Nr(i,j)} A(i,j;k,l)y_{kl}(t) + \sum_{C(k,l)\in Nr(i,j)} B(i,j;k,l)u_{kl}(t) \quad (1)$$

$$y_{ij}(t) = \frac{1}{2}(|x_{ij}(t)+1| - |x_{ij}(t)-1|)$$
$$i = 1,2,....,M, \quad j = 1,2,....,N. \quad (2)$$

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

In the state equation, x, y and u are state, output, and input, respectively. And, $A(i,j;k,l)$, $B(i,j;k,l)$ and I are constant parameters and we call them the template.

CNN can conduct various kinds of image processing tasks by setting the values of the template. The template for edge detection designed for binary images is as follows.

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

Figure 2(b) shows the result of the edge detection using the original CNN with the template (4). We can say that the result is not good. A simple method to improve the performance is changing the threshold value. Figures 2(c) and (d) show the results for different threshold values I. We can obtain the improved results. However, at the same time much noise appears. As a major factor of this phenomenon, it was thought that the cells in the CNN only have the connection to adjoin cells. In gray scale images, the edges included in the image have a margin of obscurity, therefore the difference between adjoin cells existing in the obscure edge does not become larger than the expected value. For this reason, the performance of the edge detection by using the original CNN is not good.

3. Network topology of SWCNN

To solve the above problem, we must spread the neighboring connections of the cell. However, if we spread the neighboring connections, then the wirings in the CNN become very complex. So we propose a new SWCNN system which is the CNN with a few shortcut connections. In our SWCNN system, shortcut connections can be made one per one direction Therefore, the shortcut connections of one cell can be eight at the maximum. If a shortcut connection is made, then the

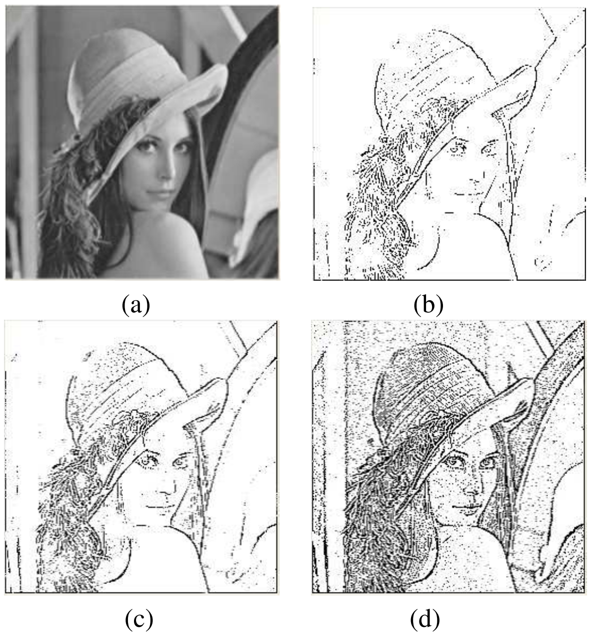


Figure 2: Edge detection of a gray scale image using the original CNN with different threshold values I. (a) Input image. (b) $I = -1.0$. (c) $I = -0.8$. (d) $I = -0.3$.

neighboring connection with the same direction must be cut. We assume that the length of the shortcut connections is the same and is denoted by the parameter Lm.

The shortcut connections of $C(i,j)$ can be made, if the inputs of neighboring cells included in $N_r(i,j)$ in Eq. (3) satisfy the below condition (5).

$$u_{min} \leq |u_{ij} - u_{kl}| \leq u_{max} \quad (5)$$

The neighboring set $N_r(i,j)$ is modified to $N'_r(i,j)$ by removing the neighbor cell $C(k,l)$ and adding the destination cell $C(a,b)$, which is the cell located Lm away from $C(i,j)$ to the same direction as $C(k,l)$.

The state equation is rewritten as follows:

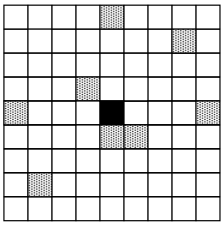
$$\dot{x}_{ij}(t) = -x_{ij}(t) + I + \sum_{C(k,l)\in Nr'(i,j)} A'(i,j;k,l)y_{kl}(t) + \sum_{C(k,l)\in Nr'(i,j)} B'(i,j;k,l)u_{kl}(t) \quad (6)$$

where $A'(i,j;a,b) = A(i,j;k,l)$ and $B'(i,j;a,b) = B(i,j;k,l)$. $A'(i,j;k,l)$ and $B'(i,j;k,l)$ are the parameters corresponding to the shortcuts. Note that the distance between $C(a,b)$ and $C(i,j)$ when $C(k,l)$ is in diagonal position is calculated by $1/\sqrt{2} \times Lm$.

Figure 3 shows an example of $N'_r(i,j)$ with an input for the parameters $u_{min} = 0.1$, $u_{max} = 0.2$ and $Lm = 4$. For example, since the input of the left upper neighboring cell

-0.1	0.4	0.1
0.2	0.3	0.5
0.4	0.3	0.6

(a)



(b)

Figure 3: Network topology example (b) of $N'_r(i,j)$ with an input (a) for the parameters $u_{min} = 0.1, u_{max} = 0.2$, and $Lm = 4$.

dose not satisfy the condition (5), the connection to the neighboring cell is preserving. However, since the input of upper neighboring cell satisfies the condition (5), the connection to the neighboring cell was cut and reconnected to the cell Lm away by a shortcut.

Figure 4: Output image of the proposed SWCNN with $I = -1.0, u_{min} = 0.001, u_{max} = 0.2$, and $Lm = 4$

Figure 4 shows the result using the proposed SWCNN with parameters $I = -1.0$, $u_{min} = 0.001$, $u_{max} = 0.2$, and $Lm = 4$. In this result, the obscure edges are detected well with less noise.

4. Difference input system

In the case of gray scale input images, we should consider that the edges in the image have some kinds of obscurity. Therefore, there is a possibility that the fourth term of the state equation (6) approaches zero though the cell exists on the edges. If the absolute values of the differences are inputted by the feedback, this problem will be solved. Hence, we modify our SWCNN as follows:

$$\dot{x}_{ij}(t) = -x_{ij}(t) + I + \sum_{C(k,l)\in N'r(i,j)} A'(i,j;k,l)y_{kl}(t) - \sum_{\substack{C(k,l)\in N'r(i,j) \\ C(i,j)\notin Nr(i,j)}} B'(i,j;k,l) \times |u_{ij} - u_{kl}| \quad (7)$$

Figure 5: Output image using the SWCNN system with difference inputs. The parameters are $I = -0.53$, $u_{min} = 0.001$, $u_{max} = 0.2$ and $Lm = 4$.

Figure 5 shows the simulation result using the above system with parameters $I = -0.53, u_{min} = 0.001, u_{max} = 0.2$, and $Lm = 4$. From the result, the detected edges are very thick. To solve the problem, we further improve the state equation as follows.

$$\begin{aligned}\dot{x}_{ij}(t) = -x_{ij}(t) + I + \sum_{C(k,l)\in N'r(i,j)} A'(i,j;k,l)y_{kl}(t) \\ - \sum_{\substack{C(k,l)\in Nr(i,j) \\ C(i,j)\notin Nr(i,j)}} B'(i,j;k,l) \times |u_{ij} - u_{kl}| \\ - C_0 \times \left| \sum_{\substack{C(k,l)\in N'r(i,j) \\ C(i,j)\notin Nr(i,j)}} B'(i,j;k,l)u_{kl}(t) \right|. \quad (8)\end{aligned}$$

The state equation has an additional fifth term newly. The new term can thin down the thick detected edges.

Figure 6: Output images of the SWCNN (8).

Figure 6 shows the result using the above state equation (8). However, the once-detected edges which correspond to clear edges in the input image disappear. To solve this problem, we change the network characteristic of the cells existing near clear edges. So, we define that the shortcut connections are not made, if the characteristics of the input satisfy the below condition.

$$|u_{ij} - u_{kl}| < u_{all}, \qquad \forall Nr(i,j) \tag{9}$$

Figure 7: Output images of the SWCNN using condition (9) with $u_{all} = 0.3$.

Figure 7 shows the result using the condition (9). In this results, the proposed system realizes to detect the edges of both of obscure edges and high tone edges successfully.

5. Conclusions

In this article, we have proposed new network topology of SWCNN and have investigated the features and the usefulness. We have applied the proposed SWCNN to edge detection of gray scale images and have confirmed its efficiency.

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