Analysis of Edge Detection Using Direction-Preserving Small World Cellular Neural Networks

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Abstract

A few years ago, Tsuruta et al. have proposed Direction-Preserving Small World Cellular Neural Networks (DP-SWCNN). They investigated the performance of the network by changing structure of the network keeping the number of all branches. In this article, we propose an improved DP-SWCNN with new network topology and investigate the availability for 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 [1][2]. 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 [3] 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 Direction Preserving Small World Cellular Neural Network (DP-SWCNN) [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.

In this article, we improve network topology of this DP-SWCNN to find useful characters. Differences between Tsuruta's DP-SWCNN [4] and our DP-SWCNN are described in Section 2. We investigate the characteristic of our DP-SWCNN by applying them to edge detection of gray scale images and show some interesting results.

2. Network topology of proposed DP-SWCNN

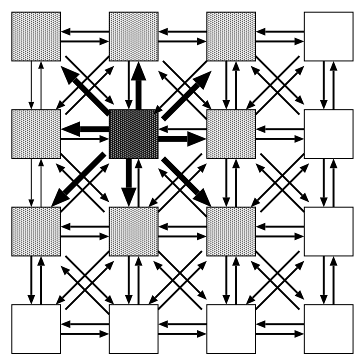


Figure 1: Structure and network topology of CNN.

In this section, we describe network topology of the proposed SWCNN with a two-dimensional M by N array structure. First, we explain structure of CNN simply. CNN has $M \times N$ cell circuits as Fig. 1. 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. Differences between Tsuruta's DP-SWCNN [4] and our DP-SWCNN are as follows.

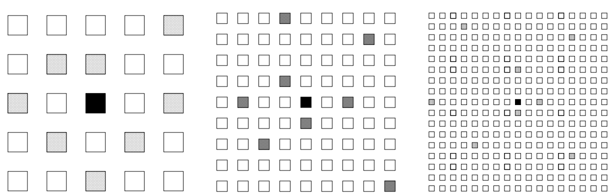
- The number of shortcuts of each cell is seven or less. (In the case of the boundary cells, the number is five, and in the case of the corner cells, the number is three.)
- The neighboring connections of both cells connected by a shortcut are cut if they have the same direction as the shortcut.

- The distance between two cells connected by a shortcut has a limitation length Lm.

The probability p is defined by the following equation.

$$p = \frac{\textit{total number of shortcuts}}{\textit{total number of connections}} \qquad (1)$$

The number of shortcuts of the cells have are almost even. Namely, if the value of p equals 0.5, the number of shortcuts of the cells is almost four. (if it equals 0.25, the number is almost two, and if it equals 0.125, the number is almost one.) Figure 2 shows some examples of the network topology of $C(i,j)$.



(a) (b) (c)

Figure 2: Examples of network topology of $C(i,j)$. Black cell represents $C(i,j)$. Gray cells represent the connected cell with $C(i,j)$. (a) $p = 0.5$, $Lm = 2$. (b) $p = 0.25$, $Lm = 4$. (c) $p = 0.125$, $Lm = 8$.

Next, in order to investigate the feature of the network, we calculated the characteristic path length $L(p)$ and the clustering coefficient $C(p)$ as varying p. The characteristic path length $L(p)$ is defined as the number of edges in the shortest path between two vertices, averaged over all pairs of vertices. The clustering coefficient $C(p)$ is defined as follows; Supposes that a vertex v has k_v neighbors; then at most $k_v(k_v-1)/2$ edges can exist between them. Let C_v denote that fraction of these allowable edges that actually exist. Define $C(p)$ as the average of C_v over all v. The results are shown in Fig. 3.

Next, we show the state equation of each cell $C(i,j)$: A, B, and I are real constants called as feedback template, control template and current, respectively; $x_{ij}, y_{i,j}$, and $u_{i,j}$ denote the state, input and output of the cell, respectively.

$$\begin{aligned}\dot{x}_{ij}(t) = -x_{ij}(t) + I + &\sum_{C(k,l)\in Nr(i,j)} A(i,j;k,l)y_{kl}(t)\\ &+ \sum_{C(k,l)\in Nr(i,j)} B(i,j;k,l)u_{kl}(t)\\ + \sum_{g_{ij}} A(i,j;a,b)y_{ab}(t) &+ \sum_{g_{ij}} B(i,j;a,b)u_{ab}(t) \qquad (2)\end{aligned}$$

$$\begin{aligned} y_{ij}(t) &= \frac{1}{2}(|x_{ij}(t)+1| - |x_{ij}(t)-1|)\\ i &= 1,2,....,M, \quad j = 1,2,....,N. \qquad (3)\end{aligned}$$

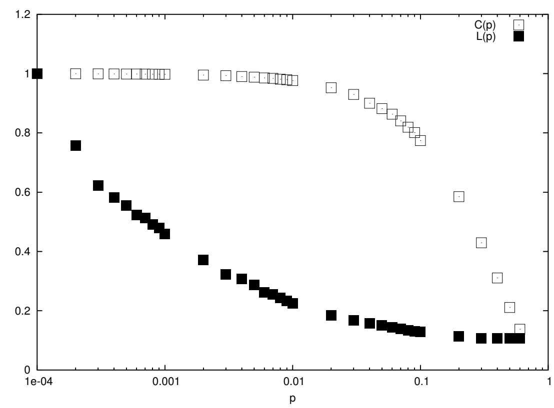


Figure 3: Characteristic path length $L(p)$ and clustering coefficient $C(p)$ of proposed DP-SWCNN.

In equation (2), $N_r(i,j)$ are neighboring connected cells of $C(i,j)$, while g_{ij} denotes the cells connected by shortcuts to $C(i,j)$. a and b represent the positions of shortcuts.

3. Simulation

Image processing is one of important applications of the CNN. Edge detect operation is one of them. In this section, we investigate the effect of applying the proposed DP-SWCNN to edge detection.

3.1. Edge detection template

The edge detection extracts edges of objects in a binary image where each black pixel with at least one white nearest neighbor is defined to be an edge cell. Equation (4) is the template which is designed for the original CNN to perform edge detection of binary images.

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

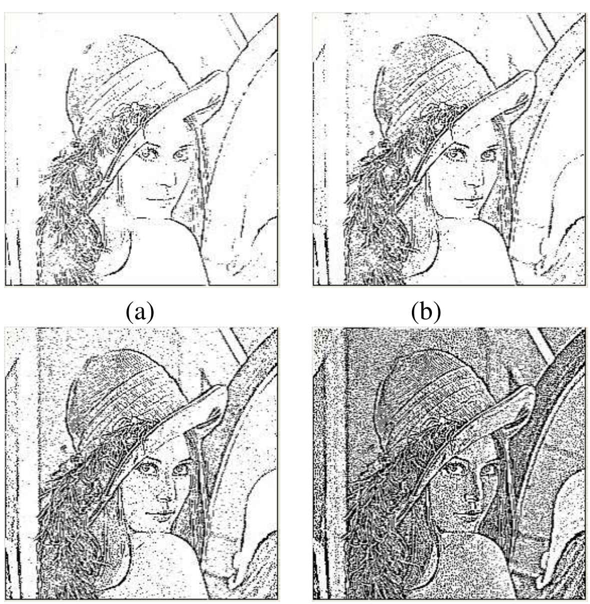
3.2. Original CNN

Figure 4 shows the simulation results of edge detection of a gray scale image using the original CNN with the template

(4). Figure 4(a) is input image and (b) is output image. From Fig. 4, it is clear that this processing is weak for the gray scale image. Because, the template (4) is designed to work well for binary input images only. We can obtain different outputs for different values of the threshold I in the template (4). Figure 5 shows the output images when the threshold I is changed. As increases I, the edges are extracted clearer. However, many noises are also extracted.

(a) (b)

Figure 4: Input image and output image of original CNN. (a) Input image. (b) Output image.



(a) (b) (c) (d)

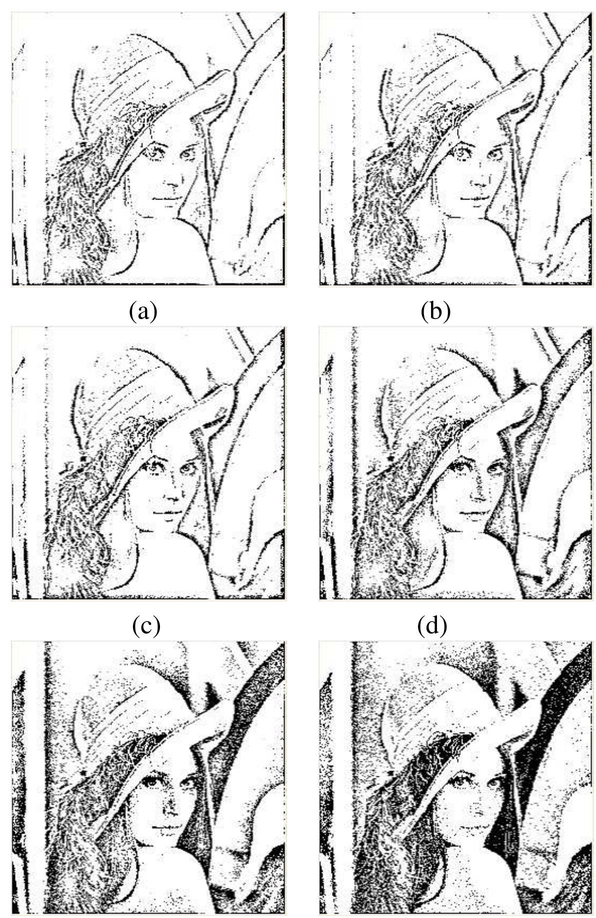
Figure 5: Output images of original CNN with changing threshold I. (a) $I = -0.8$. (b) $I = -0.5$. (c) $I = -0.3$. (d) $I = -0.1$.

3.3. DP-SWCNN

We apply the same template to the proposed DP-SWCNN with different probability p and limitation length Lm. p and Lm are parameters which characterize the DP-SWCNN. Figure 6 shows the simulation results with different Lm where p is fixed to 0.5. From the results, we can say that the performance of the DP-SWCNN is better than the original CNN, because fuzzy edges which the original CNN cannot extract are able to be extracted. However, when Lm increases, the output image include more noises.

Figure 7 shows the simulation results with different p where Lm is fixed to 4. From the results, we may say that higher p gains better performance.

Next, Fig. 8 shows the simulation results with changing threshold I where $p = 1$ and $Lm = 4$. From the results, more fuzzy edges are extracted as I decreases, but a lot of noises are also extracted.



(a) (b) (c) (d) (e) (f)

Figure 6: Output images of DP-SWCNN with changing Lm. (a) $Lm = 2$. (b) $Lm = 3$. (c) $Lm = 4$. (d) $Lm = 8$. (e) $Lm = 20$. (f) $Lm = 50$.

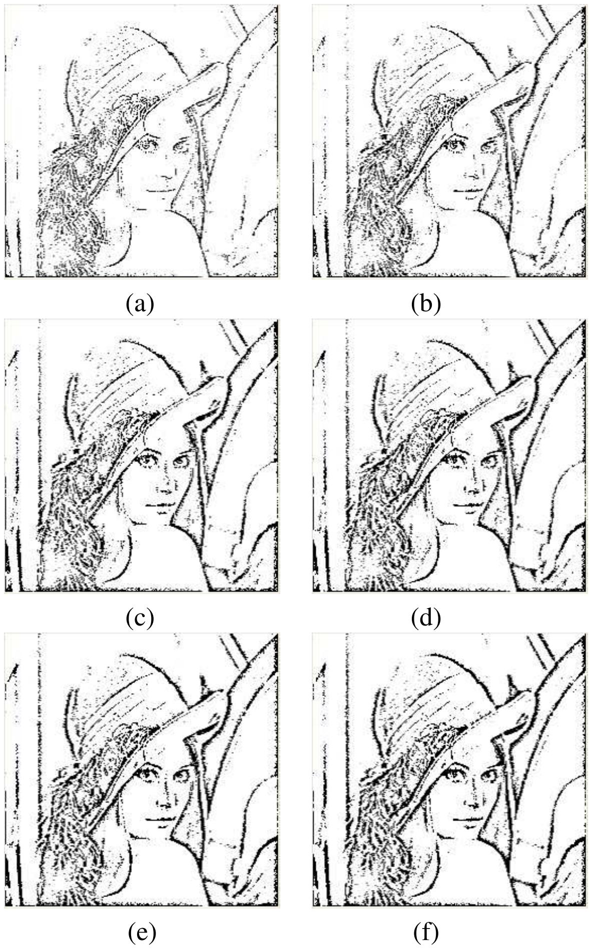


Figure 7: Output images of DP-SWCNN with changing p. (a) $p = 0.125$. (b) $p = 0.25$. (c) $p = 0.37$. (d) $p = 0.5$. (e) $p = 0.67$. (f) $p = 1$.

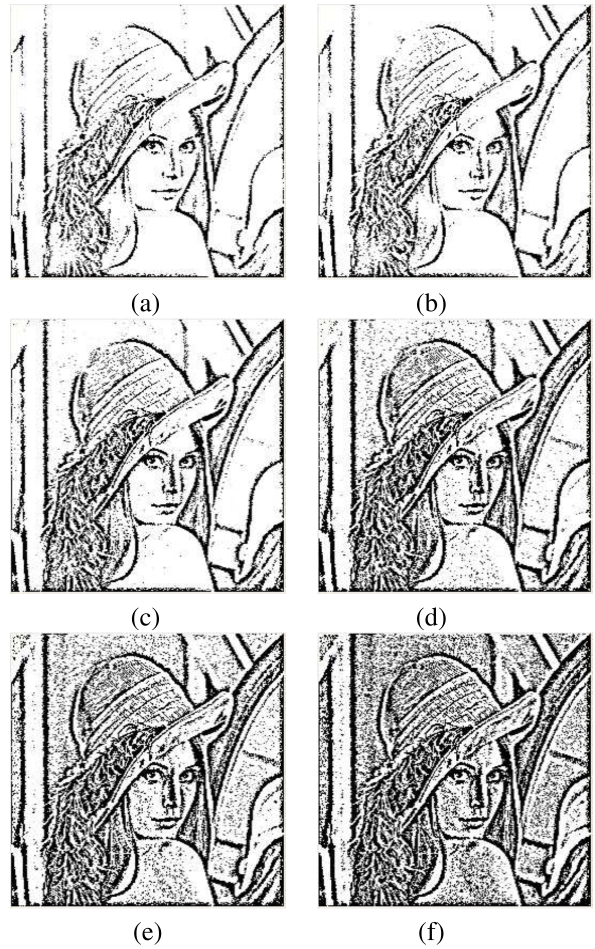


Figure 8: Output images of DP-SWCNN with changing threshold I where $p = 1$ and $Lm = 4$. (a) $I = 0.8$. (b) $I = 0.6$. (c) $I = 0.4$. (d) $I = 0.2$. (f) $I = 0.1$.

4. Conclusions

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

References

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