ECCTD'03 - European Conference on Circuit Theory and Design, September 1-4, 2003, Cracow, Poland

Small-World Cellular Neural Networks for Image Processing Applications

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***Abstract* — In this paper, we propose a Small-World Cellular Neural Network (SWCNN) model, which is constructed by introducing some random couplings between cells to adding to the original Chua-Yang CNN. Applying this SWCNN model to some applications of image processing such as small object remover, edge detecttiom, etc. are investigated. We found from numerical simulations that the SWCNN can improve the results of the image output in a certain content.**

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]–[6]. 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 [7] as the small-world model. The model is a network consisting of many local links and fewer long range 'short cuts'. 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. Up to the present, many phenomena of synchronous chaos in networks with samll-world interactions have been investigated [8] – [10].

In this paper, we propose a Small-World CNN (SWCNN) model to investigate the middle ground between regular and random networks by introducing the concept of connection topology of small-world network in CNN. By applying the SWCNN to the existing CNN image processing applications such as small object remover, grey-scale to binary encoding and edge detection of grey-scale image, some interesting results are given.

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2 SMALL-WORLD CNN STRUCTURE

In this section, we describe the connection topology of the SWCNN composed of a two-dimensional M by N array structure. Basically, the SWCNN is obtained by adding some random couplings between cells in the original Chua-Yang CNN. Here, we introduce a probability p_c, which means what percentage of the cells in the CNN occur to random coupling to another cell. We assume that, besides its local couplings, each cell in the array is only permitted a maximum of one random coupling to another cell, moreover, the coupling is bidirectional. Thereby, for a $M \times N$ array, it has a maximum P_c of $M \times N/2$ pairs of cell couplings. Figure 1 shows a sketch map of the SWCNN consisting of 4×4 cells. Obviously, when $p_c = 0$, the SWCNN is completely the same with the original CNNs, and the maps correponding to $0 < p_c < 1$ and $p_c = 1$ are respectively shown in the middle part and the right hand side of the Fig.1. The state equation of each cell $c(i,j)$ of the SWCNN is formulated by Eq. (1), and the output equation is defined by Eq. (2).

$$\begin{aligned}\dot{x}_{ij}(t) = -x_{ij}(t) + I \\ + \textstyle\sum_{c(k,l)\in N_r(i,j)} A(i,j;k,l)y_{kl}(t) \\ + \textstyle\sum_{c(k,l)\in N_r(i,j)} B(i,j;k,l)u_{kl}(t) \\ + W_c M(i,j;p,q)y_{pq}(t)\end{aligned} \tag{1}$$

$$y_{ij}(t) = \frac{1}{2}(|x_{ij}(t)+1| - |x_{ij}(t)-1|) \tag{2}$$

$$i = 1,2,...,M, \quad j = 1,2,...,N.$$

where $N_r(i,j)$ denotes the neighbor cells of radius r of a cell $c(i,j)$; A, B, and I are real constants called as feedback template, control template and bias current, respectively; x_{ij}, y_{ij}, u_{ij} denotes the state, input and output of the cell, respectively; $M(i,j;p,q)$ describes the small-world map that is randomly created by program with indicating the probability p_c in advance, if there is a coupling between one cell $c(i,j)$ and another cell $c(p,q)$, then the $M(i,j;p,q)$ is equal to 1, otherwise is zero; and W_c stands for the coupling weight between the randomly coupled cells.

Now, we apply the SWCNN to invesigate its abilities in image processing applications.

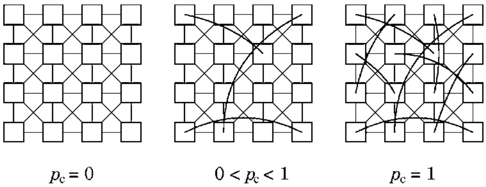


Figure 1: A two-dimensional SWCNN architecture with different probability p_c.

3 APPLYING TO IMAGE PROCESSING APPLICATIONS

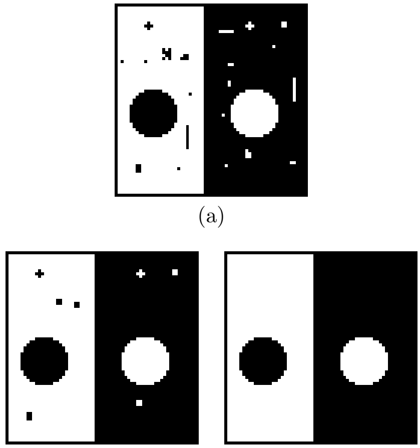
Image processing is one of important applications of the CNN. As well known, many templates and algorithms used for this purpose have been developed. In this section, we investigate the effect of applying the SWCNN to existing image processing application, such as small object remover, grey-scale to binary encoding and grey-scale edge detection.

3.1 Small object remover

This task is to delete noise in binary image. Here, we consider a SWCNN array consisting of 64×64 cells. If we use the SWCNN with the randomly coupled probability $p_c = 0$ (i.e. the SWCNN is the same with the Chua-Yang original CNN), then the SWCNN can filter those isolated black/white dots or lines with one pixel width by adopting the following template (3).

$$\mathbf{A} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 1 \\ 1 & 1 & 1 \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad I = 0 \tag{3}$$

The simulation result is shown in Fig. 2, where Fig. 2(a) is the input image and Fig. 2(b) is the result for the original CNN. In this simulation, the boundary condition is set as zero-flux and the initial state of the network is initialized by the input image. We can see that some bigger objects remain in the output image yet. If we applying the SWCNN with the probabilty $p_c = 1$ to the above problem, those bigger objects can be deleted as well as shown in Fig. 2(c). The randomly coupled weight $w_c = 2.0$, the other template parameters hold unchanged.



(a)

(b) (c)

Figure 2: An simulation example for small object remover in binary image, where (a) is the input and the initial state image, (b) is the output result of the SWCNN with $p_c = 0$, and (c) is the output result of the SWCNN with $p_c = 1.0$.

3.2 Grey-scale to binary encoding

In general, this task is defined as changing a grayscale image into a binary image. The black (white) pixels in the output image correspond to the locations in the gray-scale image where the average of pixel intensities over the local coupling radius r feedback convolution window is positive (negative). If we do not consider the average concept, then the task can be simply obtained by adopting the following template (4).

$$\mathbf{A} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 4 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad I = 0 \tag{4}$$

The simulation result is shown in Fig. 3, where Fig. 3(a) is the input gray-scale image and Fig. 3(b) is the output binary image for the original CNN. Now, we investigate the effect by appling the SWCNN to this problem with the various different probabilities p_c. Figures 3(c)-(f) show the simulation results that respectively correspond to the probability p_c adopted by 0.1, 0.3, 0.5 and 1.0. In all these cases, the coupling weight is

$$w_c = 1.0. \tag{5}$$

These simulation results show that, by using the SWCNN, the binary output images are to use the density of black pixels in certain area to represent the gray-scale of the input image. Comparing with the result Fig. 3(b). The quality of their output images is optimized by human visualisation. With the probability increasing, the density increases. The better visual effect is shown in Fig. 3(d) obtained by $p_c = 0.3$. The SWCNN does the work as the Halftoning CNN does in the original CNN model. Moreover, we confirmed that the speed of the convergence is improved.

3.3 Gray-scale edge detection

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. The template (5) is designed to work well for binary iuput images only.

$$\mathbf{A} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix},$$

$$I = -1. \tag{6}$$

If the input image is a gray-scale image, the output may not be a binary image, and will in general be gray-scale where black pixels correspond to sharp edges, near-black pixels correspond to fuzzy edges, and near-white pixels correspond to noise. The simulation result is shown in Fig. 4(b). Figure 4(a) is the input gray-scale image. Similarly, we apply the SWCNN model with different random coupling probabilities to this problem. Under the above template (6) and the random coupling weight $w_c = -0.5$, the simulation results are shown in Figs. 3(c)-(f), which correspond to the coupling probabilities $p_c = 0.1, 0.3, 0.5$ and 1.0, respectively.

we observe from the simulations that the SWCNN can detect some edges such as the pillar in the left hand side of the image, the pattern of the hat, the face characters, etc. that can not be detected by the original CNN by using the SWCNN. Moreover, the ability of the edge detection become higher with the probability increases. The better result shown in Fig. 4(f) is obtained by $p_c = 1.0$. Therefore, we can conclude from these simulation results that the application of the SWCNN to the gray-scale edge detection problem could improve the efficiency of the original CNN.

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

Figure 3: An example for gray-scale image to binary encoding by using SWCNN. (a) is the input and initial state image, (b) is the binary output image for the original CNN, (c)-(d) are the binary output images obtained by using the SWCNN with the probability $p = 0.1, 0.3, 0.5$ and 1.0, respectively.

4 CONCLUSIONS

In this study, we have proposed a SWCNN model, and preliminary discussed the image processing applications of the SWCNN such as small object remover, gray-scale to binary encoding and grey-scale edge detection. Although these problems can be solved by the original CNN, we found from our simulation results that the application of the SWCNN to these problems permit to improve the quality of these results with the same parameters of the templates A, B and I. Due to introducing the random coupling between the cells in the SWCNN, we will try to analysis the SWCNN in statistical method and find more applications in the future works.

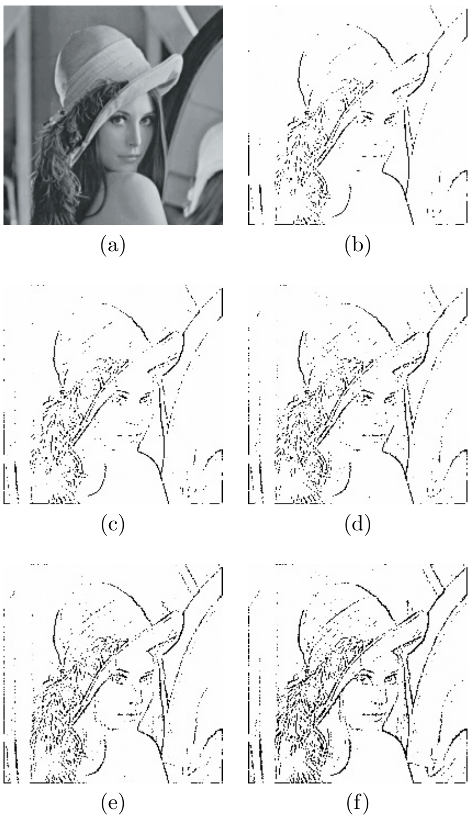


Figure 4: An example for gray-scale edge detection by using SWCNN. (a) is the input and initial state image, (b) is the edge output image for the original CNN, (c)-(d) are the binary output images obtained by using the SWCNN with the probability $p = 0.1, 0.3, 0.5$ and 1.0, respectively.

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