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Restoration of Road Network Information by Using Cellular Neural Network

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Abstract

In this study, we propose an algorithm for estimation of the original road from the hidden road by using cellular neural networks (CNN). Our proposed algorithm is composed of two steps that is flowchart to detect the road and to connect the road. From some simulation results, we are able to expect the original road by various satellite images, hence we confirm that the effectiveness of the proposed algorithm.

1. Introduction

The Cellular Neural Networks (CNN) [1] were introduced by Chua and Yang in 1988. The idea of CNN was inspired from the architecture of the cellular automata and the neural networks. A different point from the conventional neural networks is that CNN has local connectivity property. Since the structure of CNN resembles the structure of animals' retina, CNN can be used for various image processing applications [2]-[5]. CNN is composed of the basic circuit units called cells. The cell contains linear and nonlinear circuit elements which are typically linear capacitors, linear resistors, linear and nonlinear controlled sources. Wiring weights of the cells are established by parameters called the template. The template of CNN consists of three elements as the feedback template A, the control template B and the threshold value I. The performance of CNN is decided by these templates.

In the image processing applications, the various images like the medical image are used as an input image. The satellite image is also the one, it is used for the route search application. However, the road is sometimes hidden by the hurdle like a cloud, it is bad effect for obtaining correct results.

In this study, we propose how to prospect the original road from the hidden road in the satellite image including obstacle by using CNN. Our algorithm for estimation of the original road is composed by two steps; the detection of the road and the connection of the road. In the first step of our algorithm, the hidden road by the obstacle is detected from the satellite image as an input. In the second step, the detected road in the first step is connected. Finally, we can make estimation the original road in the satellite image including the obstacle.

In the Sec. 2, we describe the conventional CNN. In the Sec. 3, we propose an algorithm for estimation. In the Sec. 4, we show some computer simulation results using the proposed algorithm. The Section 5 concludes the article.

2. Cellular Neural Networks [1]

In this section, we describe the basic structure of CNN. CNN has M by N processing unit circuits called cells. Cells are arranged in a reticular pattern to M line by 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. CNN is an array of cells. Each cell is connected to its neighboring cells according to a template. Usually, the same template is used for all the cells except for boundary cells. CNN has the features of time continuity, spatial discreteness, nonlinearity and parallel processing capability.

The state equation and the output equation of the cell $C(i, j)$ are shown as follows.

State equation:

$$\begin{aligned}\frac{dv_{xij}}{dt} &= -v_{xij} + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r} A_{(i,j;k,l)} v_{ykl}(t) \\ &\quad + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r} B_{(i,j;k,l)} v_{ukl}(t) + I. \qquad (1)\end{aligned}$$

Output equation:

$$v_{yij}(t) = \frac{1}{2}(|v_{xij}(t) + 1| - |v_{xij}(t) - 1|). \qquad (2)$$

where v_x, v_y and v_u represent a state, an output and an input of the cell, respectively. In the Eq. (1), A is the feedback template and B is the control template. These templates and threshold value I are collectively called the general template.

The *r-neighborhood* of $C(i, j)$ in CNN is defined by

$$\begin{aligned}Nr(i, j) = \{C(k, l) \mid \max\{|k-i|, |l-j|\} \le r,\\ 1 \le k \le M;\quad 1 \le l \le N\}. \qquad (3)\end{aligned}$$

where r is a positive integer number. In our study, we fix the value of r as 1.

3. Proposed algorithm

In this section, we describe the proposed algorithm for estimation of the original road from the hidden road. Our proposed algorithm is composed of two steps that is flowchart to detect the road and to connect the road. Additionally, there are two kinds of flowcharts to detect the road. We have to use both the flowcharts as the situation demands. One is the case that the color of the road is different from the color of the obstacle. The other is the case that the color of the road is same with the color of the obstacle.

3.1. How to detect the hidden road

In this subsection, we describe two kinds of flowcharts how to detect the roads.

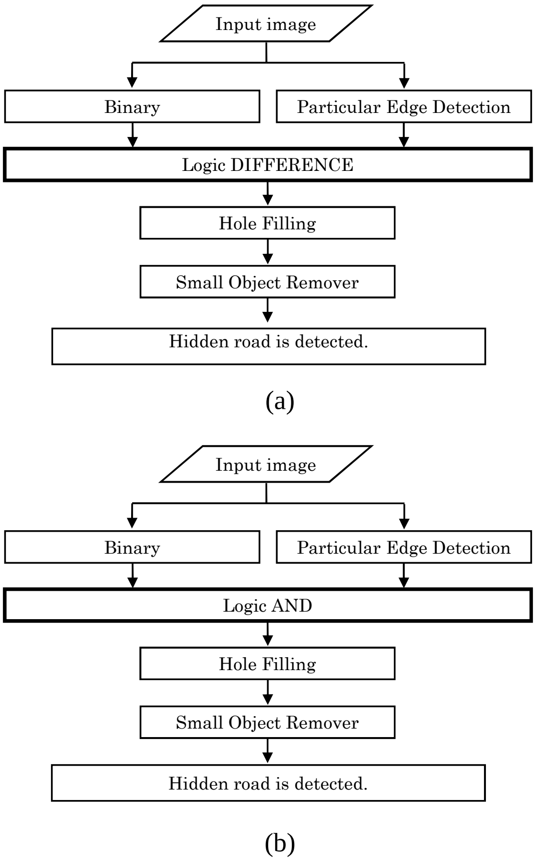

Figure 1: Flowchart to detect the hidden road. (a) Flowchart 1; The color of the road and of the obstacle are same. (b) Flowchart 2; The color of the road and of the obstacle are different.

The different point between these flowcharts is that the third processing is Logic AND or Logic DIFFERENCE. We have to use both these flowcharts as the situation demands.

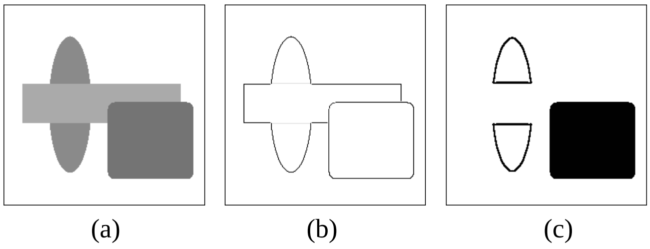

Figure 2: Edge detection. (a) Input image containing alternating layers of gray scale objects. (b) Output image obtained by the conventional "Edge Detection" template. (c) Output image obtained by the proposed "Particular Edge Detection" template.

3.1.1. *Used templates*

We propose new template described as following equation.

Particular Edge Detection template:

$$A_1 = \begin{bmatrix} -2 & -0.3 & -2 & -0.3 & -2 \\ -0.3 & 1 & 7 & 1 & -0.3 \\ -2 & 7 & 14 & 7 & -2 \\ -0.3 & 1 & 7 & 1 & -0.3 \\ -2 & -0.3 & -2 & -0.3 & -2 \end{bmatrix}, \ B = 0, \ I = I. \quad (4)$$

This template detects the edge of a object with a specified density by changing a threshold value I. For example, we consider an image containing three objects with different densities shown in Fig. 2(a). The conventional "Edge Detection" template detects all the edge of the three objects as Fig. 2(b). Moreover, by using the conventional template, the two edges of two overlapped objects, whose densities are similar, are detected as one edge. In contrast, "Particular Edge Detection" template detects a edge of the specific density object and a black object as Fig. 2(c). This is because that by changing the threshold value I, the proposed template can detect only the edge of the object with the specified density even if the objects with the similar densities are overlapped. Furthermore, the gray object with larger density than the threshold value I is converged to black as the object on the right corner in Fig. 2(c), and the object with smaller density than I is converged to white as the square object on the center.

Additionally, the convergence time of "Particular Edge Detection" template is overwhelmingly shorter than the conventional "Edge Detection" template. The output image as Fig. 2(c) is not obtained whatever any templates are applied, as far as we know. From these behaviors, we think that "Particular Edge Detection" template is appropriate to detect the hidden road.

Hole Filling template:

$$A = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 3 & 1 \\ 0 & 1 & 0 \end{bmatrix}, \ B = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 4 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \ I = 1. \quad (5)$$

This is a propagating template [6]. By using this template, white will spread from the boundary of the image, and the area surrounded by white will be filled. In this study, we suppose that the satellite image contains three objects; the obstacle such as a cloud, the road hidden by the obstacle and the unnecessary objects such as buildings. We use this template to remove the unnecessary objects. Please note that most roads are connected with the boundary of the image. If a boundary value is set as black, the unnecessary objects, which is not connected with a boundary of the image, will be filled with white.

By carrying out "Flowchart 1" or "Flowchart 2", the road hidden by the obstacle is detected from the satellite input image.

3.2. How to connect the hidden road

In this subsection, we propose the flowchart how to connect the road hidden by the cloud as the obstacle.

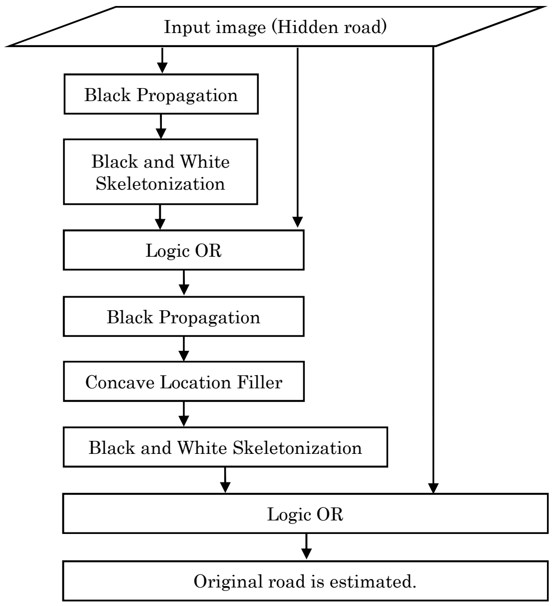

Figure 3: Flowchart 3: Flowchart to connect the hidden road.

3.2.1. *Used templates*

First, make detected road temporarily thick by "Black Propagation" template to connect hidden road [6].

Black Propagation template:

$$A = \begin{bmatrix} 0.25 & 0.25 & 0.25 \\ 0.25 & 3 & 0.25 \\ 0.25 & 0.25 & 0.25 \end{bmatrix}, \; B = 0, \; I = -1. \tag{6}$$

This template extends black to every directions.

Secondly, the gap between the two thick lines is filled by "Concave Location Filler" template [6].

Concave Location Filler template:

$$A = \begin{bmatrix} 0.5 & 0.5 & 0.5 \\ 0.5 & 3 & 0.5 \\ 0.5 & 0.5 & 0.5 \end{bmatrix}, \; B = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \; I = 3.25. \tag{7}$$

The template transforms all the objects to solid black concave polygons with vertical, horizontal and diagonal edges only.

Thirdly, the contour of a black object is gradually cut down with "Black and White Skeltonization" template [6].

Black and White Skeltonization template:

SKELBW1

$$A = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \; B = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}, \; I = -1.$$

SKELBW2

$$A = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \; B = \begin{bmatrix} 2 & 2 & 2 \\ 0 & 9 & 0 \\ -1 & -2 & -1 \end{bmatrix}, \; I = -2.$$

$$\cdots$$

SKELBW8

$$A = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \; B = \begin{bmatrix} 2 & 0 & -1 \\ 2 & 9 & -2 \\ 2 & 0 & -1 \end{bmatrix}, \; I = -2. \tag{8}$$

This template carries out the thinning process, hence the output image has only one pixel line.

Flowchart 3 connects the hidden road which is detected by "Flowchart 1" or "Flowchart 2".

4. Simulation results

In this section, we carry out two simulations. One is the case that the colors of the obstacle and of of the roads are same, and another is the case that it is different.

4.1. Case 1: Same colors

Figure 4(a) is an input image. The road is hidden by the cloud which exists on the center of the image. Figures 4(b) and (c) are an output images obtained by applying "Flowchart 1" to Fig. 4(a) and "Flowchart 3" to Fig. 4(b), respectively. Figure 4(d) shows the expected original road. From Fig. 4(d), we can see the little error in the expected road. However, the proposed algorithm could interpolate the hidden road. Therefore, we think that the proposed algorithm is enough for estimation of the original road.

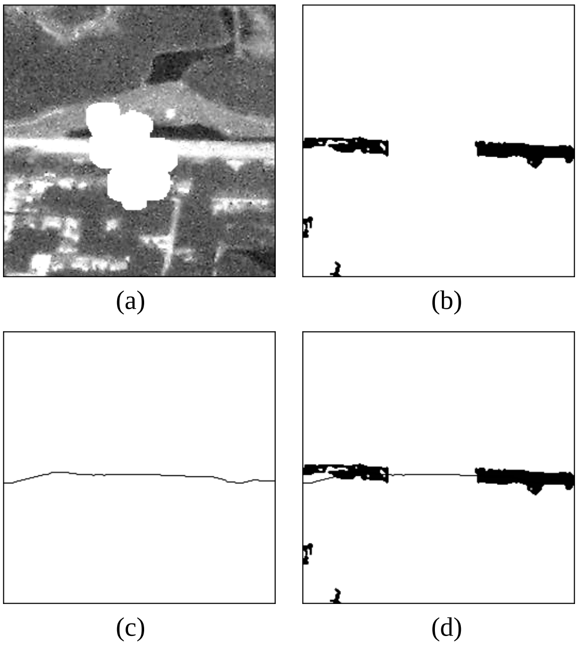

Figure 4: Simulation for an image including the obstacle whose color is same as the hidden road. (a) Input image. (b) Output image obtained by "Flowchart 1." (c) Output image obtained by "Flowchart 3." (d) Output image which is added Fig. 4(c) to Fig. 4(b).

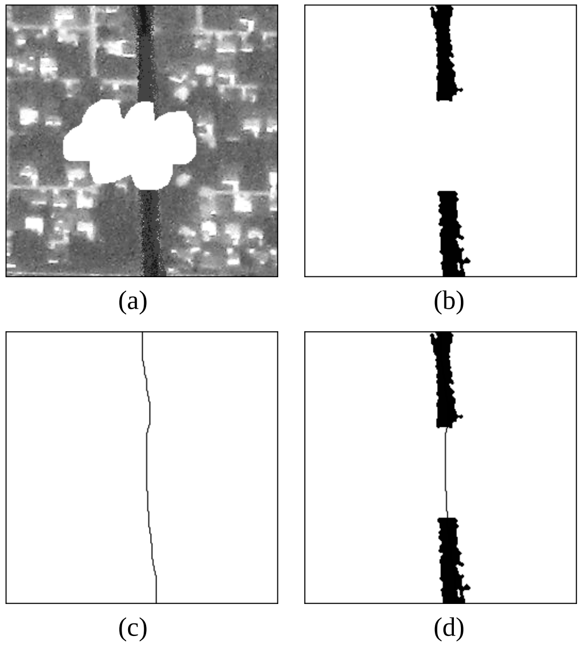

Figure 5: Simulation for an image including the obstacle whose color is different as the hidden road. (a) Input image. (b) Output image obtained by "Flowchart 2." (c) Output image obtained by "Flowchart 3." (d) Output image which is added Fig. 5(c) to Fig. 5(b).

4.2. Case 2: Different colors

Figure 5(a) is an input image. The road is hidden by the cloud whose color is different from the road. Figures 5(b) and (c) shows output images obtained by applying "Flowchart 2" to Fig. 5(a) and "Flowchart 3" to Fig. 5(b), respectively. Figure 5(d) shows the expected original road. From Fig. 5(d), we think the proposed algorithm could expect the original road. According to our simulation, our proposed algorithm is effective for estimation of the original road in various satellite images including the obstacle.

5. Conclusions

In this study, we have proposed an algorithm for restoration of road network information by using CNN. We were able to make estimation the original road by various satellite images. From simulation results, we have confirmed that our proposed algorithm is effective in the actual satellite images. In the future work, we should be selected the one of Flowcharts 1 and 2 automatically. Additionally, the anticipated road are one pixel line unlike the real road. Therefore, we would like to size a line to the width of the real road.

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