LETTER

Detecting Lung Cancer Symptoms with Analogic CNN Algorithms Based on a Constrained Diffusion Template

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SUMMARY In this article, a new type of diffusion template and an analogic CNN algorithm using this diffusion template for detecting some lung cancer symptoms in X-ray films are proposed. The performance of the diffusion template is investigated and our CNN algorithm is verified to detect some key lung cancer symptoms, successfully.

key words: *cellular neural networks, image processing, diffusion, X-ray films*

1. Introduction

Cellular neural networks (CNNs) [1], [2] were introduced by L.O. Chua et al. in 1988. In cellular neural networks, nonlinear information processing elements called cells are regulary arranged on a two or three-dimensional grid. Each cell is interconnected only to its neighbors p and the cells that are not directly connected affect each other indirectly through propagation effect. The state and output equations at cell (i, j) are described by

$$\frac{dv_{xij}}{dt} = -v_{xij}(t) + \sum_{m=i-p}^{i+p} \sum_{n=j-p}^{j+p} A(i,j;m,n) v_{ymn}(t) + \sum_{m=i-p}^{i+p} \sum_{n=j-p}^{j+p} B(i,j;m,n) v_{umn} + I_{ij} \quad (1)$$

$$v_{yij}(t) = \frac{1}{2}\left(|v_{xij}(t)+1| - |v_{xij}(t)-1|\right) \quad (2)$$

$$1 < i < M, \quad 1 < j < N \quad .$$

where M, N mean the scale of CNN, v_{xij} the state-variable and v_{umn} the input. The connection pattern of the cells is the same on a grid at any cell, so (A, B, I) is called the cloning template. The operation of CNNs is determined by the cloning templates. A simple cell, when implemented as a VLSI circuit, consists of a linear capacitor, nonlinear voltage controlled current sources and linear resistors. Since the structure of CNNs is similar to the structure of the vertebrate retina and the visual system, CNNs are appropriate for image processing [3]–[5]. Using the CNN Universal Machine, CNN analogic (analog and logic) algorithms can be developed [8]. Applications in image processing using cellular neural networks have many varieties. Binary image processing problems have been researched for rather a long time. At present, gray-scale image processing has become important and are researched actively in various fields [3]–[7].

On the other hand, X-ray films are widely used for the detection of cancers in the stomach, lung and so on. Furthermore, because of their cost performance, X-ray films are usually used for screening-type medical examinations. If doubtful regions are detected in X-ray films, the patient will be examined by CT or MRI in detail. Therefore, it is of crucial importance to detect doubtful regions in X-ray films. However, X-ray films have delicate intensity gradient and doctors have to check a large number of films for screening-type examinations. Hence, it is very helpful for doctors to develop systems detecting doubtful regions in X-ray films.

In this study, we propose a constrained diffusion template and an analogic CNN algorithm based on this template capable of detecting some key lung cancer symptoms in the X-ray film having delicate gradient of intensity. At first, we introduce different diffusion templates and examine their performance by computer simulations. Next, the algorithm using the constrained diffusion template to detect the boundary of a lung cancer symptom in medical X-ray films, is developed. We carry out computer simulations and verify that our algorithm can successfully detect the specific area of lung cancer.

2. Constrained Diffusion Template

The operation of cellular neural networks is determined by the cloning template (A, B, I) corresponding to the weights of the connections. We can execute various im-

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age processing methods using different CNN templates.

At first we discuss the *constrainted diffusion template* given by

$$A = \begin{bmatrix} 0.1 & 0.15 & 0.1 \\ 0.15 & 0 & 0.15 \\ 0.1 & 0.15 & 0.1 \end{bmatrix}$$
$$B = \begin{bmatrix} 0.1 & 0.15 & 0.1 \\ 0.15 & 0 & 0.15 \\ 0.1 & 0.15 & 0.1 \end{bmatrix}$$
$$I = 0. \tag{3}$$

The original template with $B = 0$ and $I = 0$ called a simple diffusion template are obtained from discrete space approximations of the two dimensional heat conduction equation, and therefore executes the heat diffusion. The image data is supplied to the initial conditions and allowed to diffuse for a specified time. During the process, the data is smoothed—the effect of the diffusion template can be explained as a low-pass filtering with a time dependent transfer characteristics [1]. If the stopping time is increased, the original image is progressively more low-pass filtered. We have found that the performance of the simple diffusion template is not satisfactory enough to be used in pre-processing steps, since it blurs the image in an uncontrolled manner. Therefore, a robust and image structure sensitive algorithm can not be based on this template. The performance and structure sensitivity can be greatly improved by introducing an additional B term (the control operator), e.g. with the same weights as in feedback operator A as given by Eq. (3).

When using the constrained diffusion template the B term ensures a nontrivial steady state, since it "forces" the output to stay close to the initial condition. The image is structure sensitively filtered and the solution is robust (there is no need to define an exact stopping time—an important argument from implementation point of view). We performed computer simulations of this template for various gray-scale images. We made the following observations. This template diffuses the input image in each area divided by three gray levels, namely black, gray and white areas. An example of computer simulated results is shown in Fig. 1. In this figure the outputs using a non-constrained and constrained diffusion are shown. It can be clearly seen that in case of the latter one, the term B constrains diffusion driven by the term A. It is also verified that after some extent of time, the network output stabilizes close to the initial condition.

(a) (b) (c)

Fig. 1 Example of computer simulated results using the Non-constrained and Constrained Diffusion Template. Running time = 100 and time step = 0.01. (a) Input image. (b) Output of the non-constrained diffusion. (c) Output of the constrained diffusion.

3. Analogic CNN Algorithm for Detecting Lung Cancer Symptoms

In this section, we introduce an analogic CNN algorithm to detect boundaries of some lung cancer symptoms. This might be one of the promising applications using the constrained diffusion template proposed in the previous section. This algorithm, consisting of several templates, can capture the hidden area of lung cancer symptoms in X-ray films and can detect their boundary.

It is hard to characterize the geometry of lung cancer symptoms we want to detect in these experiments. Note that the areas of cancers correspond to the closed domains with small inhomogeneities in the X-ray film, because the tissues in these areas are destroyed by the cancer, so that they are slightly different from the normal ones. Therefore, they appear as patches with irregular boundaries in the background. We have found that the average gradient intensity at the boundaries falls within a considerably narrow interval and this information from initial measurements can be exploited in algorithm design.

The algorithm can be divided into three parts and the flow-chart is shown in Fig. 2. Let us explain this algorithm according to the flow-chart. First, block A is the most important part, since pre-filtering and area detection are completed in this phase. The input image of the first-layer is shown in Fig. 4 (b). This is the magnification of the left-upper corner in the original X-ray film in Fig. 4 (a)†.

A.1 The input image and its inverted image are processed in parallel. By using the *constrained diffusion template* (2), the input image and its inverted image are smoothed (Fig. 4 (c), (d)).

A.2 The parts with large gradient are detected by the *gradient template* (A· 1). After the gradient detection, the parts surrounded by black pixels are filled with blacks by the *hole template* (A· 2) (Fig. 4 (e), (f)).

A.3 Since the first constrained diffusion (2) usually magnifies the boundaries, the objects in images are peeled one pixel from the boundaries by the *peel template* (A· 3). By executing AND (logical opera-

†Typical templates are given in the Appendix.

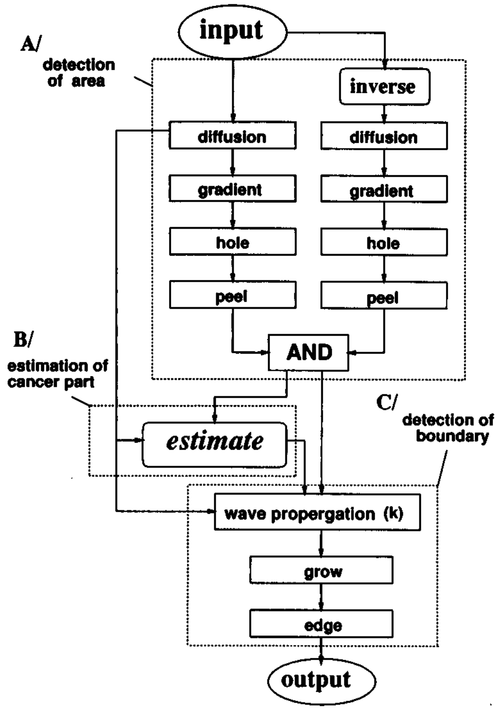

Fig. 2 Flow-chart of the analogic CNN algorithm detecting boundaries of a lung cancer symptom.

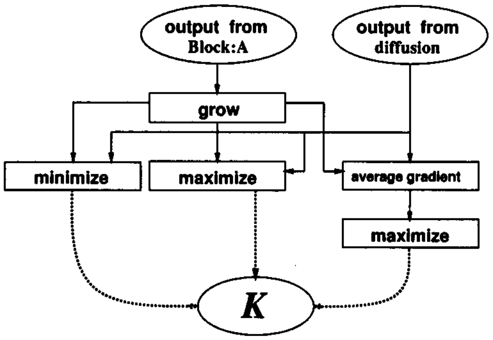

Fig. 3 Flow-chart of the estimation algorithm.

tion), we can find the area of lung cancer symptoms (Fig. 4 (g)).

As a result of this block, we obtain a binary image where locations of lung cancer symptoms are marked with black patches.

There are many kinds of X-ray films such as whiter and/or blacker ones depending on the film processing, so that our algorithm should be applicable to the detection of cancers in any kind of film. Firstly, we estimate the inhomogeneity K in the cancer area by measuring the maximum and minimum values of the pixels in the domains detected by the block A. The *wave-propagation template* (A·4) changes all the pixels to black when the difference between the neighbors is less than K, and furthermore, the propagation will continue to the boundary [4]. Therefore, the gradient at the boundary needs be taken account for the estimation of K, which is decided by measuring the maximum value of the average gradient (A·5) (K is usually chosen to have a value of approximately 0.2). The flow-chart of the block B is shown in Fig. 3.

Finally, the algorithm in block C detects the boundary of lung cancer symptoms.

First, we choose a starting point in the cancer area detected by the block A, and set the pixel value equal to 1 (black). Then, the *wave-propagation template* changes all of the pixels in the cancer area to black, and the propagation will be stopped at the boundary, whose output image is given by Fig. 4 (h). To detect the boundary, we apply the grow (A·6) and edge detection (A·7)

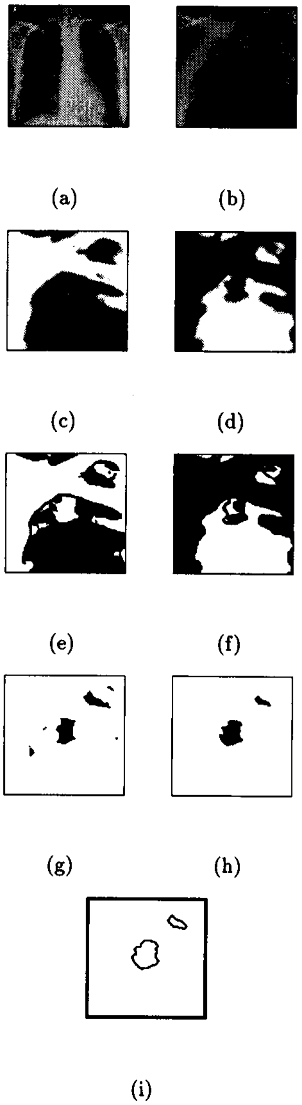

Fig. 4 Example 1. (a) Original X-ray film. (b) Input image. (c) Constrained-smoothed image 1. (d) Constrained-smoothed image 2. (e) Gradient image 1. (f) Gradient image 2. (g) Output image of AND. (h) Area of lung cancer symptom. (i) Boundary of lung cancer symptom, where 1 means original image and 2 inverted image.

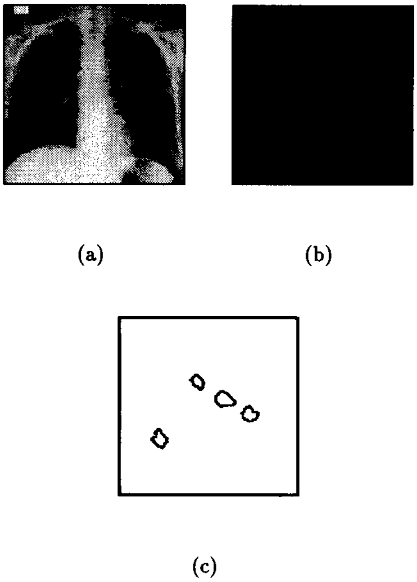

Fig. 5 Example 2. (a) Original X-ray film. (b) Input image. (c) Output image.

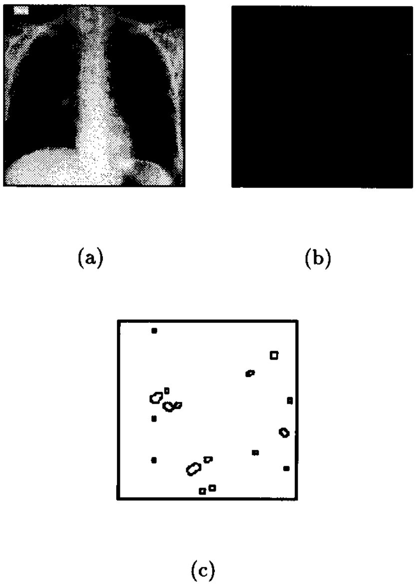

Fig. 6 Example 3. (a) Original X-ray film. (b) Input image. (c) Output image.

template. Thus, we can see that the boundary of the lung cancer was successfully detected Fig. 4 (i). The flow chart is shown by the block C.

Similarly, we applied this algorithm to other X-ray films which have many small bubbles of metastatic lung cancer. Computer simulated results are shown in Figs. 5 and 6. We can see that even small bubbles can be detected. We performed all simulations with the *constrained diffusion template* (2) using the step size of 0.01 for Fig. 4, Fig. 5 and Fig. 6. We can conclude that although in these examples it is very difficult to recognize the area of lung cancer symptoms even for a human expert, our algorithm can detect the boundary.

4. Conclusions

In this study, we proposed a new type of diffusion template called the constrained diffusion template. We also synthesized an analogic CNN algorithm based on this template which is capable of detecting lung cancer in X-ray films. We investigated the performance of the constrained diffusion template and verified that our CNN algorithm can successfully detect the lung cancer.

The constrained diffusion template proposed in this article is expected to have many useful applications for various gray-scale images, for example, in diagnoses of diseases in medical images such as CT and MRI, forecasting weather conditions from aerial photographs, and so on. However, detailed investigation and mathematical characterization of constrained diffusion template is our future research.

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Appendix: Typical Templates

A.1 The *gradient template* detects pixcels having larger value than a specified threshold I.

$$A=\begin{bmatrix}0&0&0\\0&1&0\\0&0&0\end{bmatrix}\quad B=\begin{bmatrix}a&a&a\\a&a&a\\a&a&a\end{bmatrix}$$

$$I=-\text{threshhold}(0.3-0.7)$$

$$a=\left.\begin{matrix}|v_{uij}-v_{ukl}|, & |v_{uij}-v_{ukl}|<2\\ 0, & \text{otherwise}\end{matrix}\right\}\qquad\text{(A· 1)}$$

A.2 The *hole template* changes all the pixels surrounded by a black boundary to black.

$$A=\begin{bmatrix}0&1&0\\1&2&1\\0&1&0\end{bmatrix}\quad B=\begin{bmatrix}0&0&0\\0&4&0\\0&0&0\end{bmatrix}$$

$$I=-1\qquad\text{(A· 2)}$$

A.3 The *peel template* peels one pixcel located at the boundary.

$$A=\begin{bmatrix}0&0&0\\0&2&0\\0&0&0\end{bmatrix}\quad B=\begin{bmatrix}0.25&0.25&0.25\\0.25&2&0.25\\0.25&0.25&0.25\end{bmatrix}$$

$$I=-4.8\qquad\text{(A· 3)}$$

A.4 The *wave-propagation template* is given by

$$A=\begin{bmatrix}0.25&0.25&0.25\\0.25&3&0.25\\0.25&0.25&0.25\end{bmatrix}\quad B=\begin{bmatrix}b&b&b\\b&b&b\\b&b&b\end{bmatrix}$$

$$I=2.75$$

$$b=\left\{\begin{matrix}0, & |v_{uij}-v_{ukl}|<2K\\ -7, & \text{otherwise}\end{matrix}\right\}\qquad\text{(A· 4)}$$

A.5 The *average gradient template* measures the average of gradients.

$$A=0\quad B=\begin{bmatrix}b&b&b\\b&0&b\\b&b&b\end{bmatrix}\quad b=1/8|v_{uij}-v_{ukl}|$$

$$I=0\qquad\text{(A· 5)}$$

A.6 The *grow template* fattens one pixel at the boundary.

$$A=\begin{bmatrix}0&0&0\\0&2&0\\0&0&0\end{bmatrix}\quad B=\begin{bmatrix}0&0.3&0\\0.3&0&0.3\\0&0.3&0\end{bmatrix}$$

$$I=2\qquad\text{(A· 6)}$$

A.7 The *edge template* detects a boundary.

$$A=\begin{bmatrix}0&0&0\\0&2&0\\0&0&0\end{bmatrix}\quad B=\begin{bmatrix}-0.25&-0.25&-0.25\\-0.25&2&-0.25\\-0.25&-0.25&-0.25\end{bmatrix}$$

$$I=-1.5\qquad\text{(A· 7)}$$