



A Shift-Invariant Neural Network for the Lung Field Segmentation in Chest Radiography

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Received October 10, 1996; Revised July 10, 1997

Abstract. We have developed a computerized method using a neural network for the segmentation of lung fields in chest radiography. The lung is the primary region of interest in routine chest radiography diagnosis. Since computer is expected to perform disease pattern search automatically, it is important to design appropriate algorithms to delineate the region of interest. A reliable segmentation method is essential to facilitate subsequent searches for image patterns associated with lung diseases. In this study, we employed a shift invariant neural network coupled with error back-propagation training method to extract the lung fields. A set of computer algorithms were also developed for smoothing the initially detected edges of lung fields. Our preliminary results indicated that 86% of the segmented lung fields globally matched the original chest radiographs. We also found that the method facilitates the development of computer algorithms in the field of computer-aided diagnosis.

1. Introduction

Chest radiography is one of the most primary and most widely used techniques in diagnostic imaging. With the advent of digital radiology, digital medical image processing techniques for digital chest radiographs have attracted considerable attention, and several studies on computer-aided diagnosis (CADx) as well as on conventional image processing techniques for chest radiographs have been reported [1–12]. In the automatic diagnostic process for chest radiographs, it is important to delineate the areas of the lungs, the heart, and the diaphragm. This is because the original chest radiograph is composed of important anatomic structures and, without knowing exact positions of the organs, the automatic diagnosis may result in unpredictable results. Since a part of an organ can be

superimposed on another organ in projection chest radiograph, some parts of lung boundaries are not clearly observed.

The automatic extraction of an anatomical structure from digital chest radiographs can be a useful tool for (a) the evaluation of heart size [1], (b) automatic detection of interstitial lung diseases [2–5], (c) automatic detection of lung nodules [6–10], (d) automatic detection of pneumothorax [11], (e) evaluation of interval changes of the chest radiographs [12], and (f) data compression, etc. Based on the clearly defined boundaries of heart area, rib spaces, rib positions, and the extracted rib cage, one should be able to use this information to facilitate the tasks of the CADx on chest radiographs. A number of techniques for the segmentation of lung fields have been developed by several investigators: (a) using features analysis extracted by a commercial package [13, 14], and (b) using profile analysis and edge tracking techniques [15–17]. The second category intends to segment the lung field automatically, which is also the goal of this study. In these studies, investigators focus on the chest radiograph on

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which a $14'' \times 17''$ (or $17'' \times 14''$) adult posterior-anterior (PA) view X-ray image is formed using a conventional screen/film or a modern digital technique [18].

An artificial neural network is a tool that can estimate unknown function from certain pairs of input-output samples. Theoretically, a neural network can approximate arbitrary functions if it has at least one hidden layer consisting of sufficient units [19]. In addition, it is easy to emulate neural networks on special hardware, such as massively parallel processors, because the processing of each unit is quite simple. Because of these attractive capabilities, there has recently been an increase in reported studies on diagnostic applications of neural networks in radiology [20–23]. In almost all of these studies, fully connected feed-forward neural networks based on the error back propagation algorithm [24] have been used.

A shift-invariant neural network model is a simplified version of the vision system in vertebrate animals. Its signal propagation is based on the discrete convolution like in the traditional image processing. The most significant characteristic of the shift-invariant neural network is that it can automatically learn and extract image features, which is necessary to the assigned tasks, during its training process. Because of this characteristic, manual design of image processing kernel is not necessary. The kernels obtained by the neural network training are not always understandable. However, mathematical optimization of an image processing task based on a neural network training system can be made much more appropriate than manually designed approach. Because of the optimized image processing kernels, it is expected that the shift-invariant neural network has the better performance than methods based on manually selected kernels.

The shift-invariant neural network is considered to be an extended version of the basic model of the neocognitron initiated by Fukushima et al. [25]. By the combination of the shift-invariant structure and error back propagation algorithm, the several potential applications could be considered. Until now, this model was applied to zip code recognition [26], lung nodule detection [8, 9], microcalcification detection [9, 27], and classification of benign and malignant processes associated with microcalcifications [28].

In this paper, we present an automatic scheme for the detection of lung fields on chest radiographs by using a shift-invariant neural network. In addition, a smoothing algorithm is presented to delineate the boundaries of the lung fields.

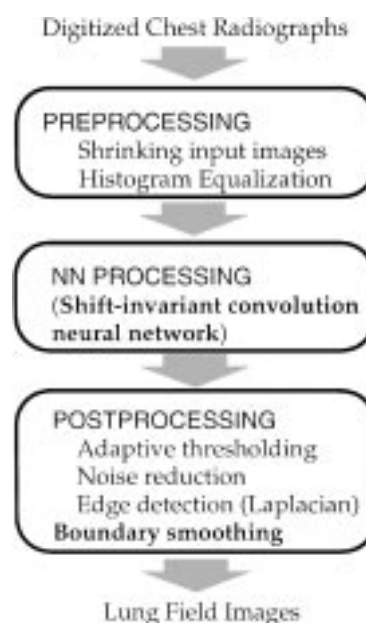


Figure 1. Flow chart of computer algorithms for the detection of lung fields.

2. Algorithm for Detection of Lung Structures

The algorithm used for the detection of lung region is shown in Figure 1. Our method consists of three sections: preprocessing for background adjustment, the convolution neural network to extract the rib cage, and post-processing to smooth the boundaries and reduce the noise. In general, a $14'' \times 17''$ film can be digitized by a film digitizer in $2048 \times 2500 \times 12$ bits of computer information (each image pixel represents $180 \mu\text{m}$ square). We averaged and subsampled the image by a factor of eight because (a) the processing time can be reduced from several hours to approximately 2–3 minutes for an image and (b) there is not necessary to segment the lung with high resolution chest radiography. Hence, the images are formatted in $256 \times 312 \times 12$ bits as one of the preprocessing procedures. The miniaturized chest images are then processed by the histogram equalization algorithm which adjusts the gray tone distribution of the input image in order to provide similar qualities of for the neural network. The images are then processed by a trained neural network to enhance the boundaries of lung fields. In the post-processing, the lung boundaries are extracted by an adaptive thresholding method incorporated with the Laplacian filter and a noise reduction techniques. The detected boundaries, however,

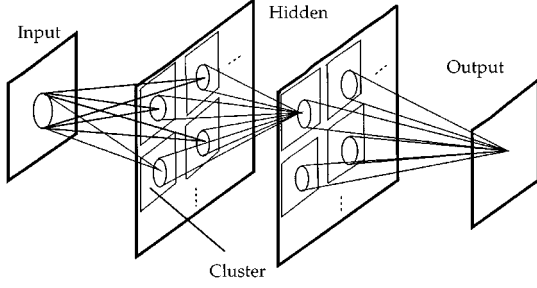


Figure 2. A shift-invariant convolution neural network architecture.

are eroded mainly due to the superimposed collarbones and posterior ribs on the lung. To smooth the boundaries, we used a novel smoothing method based on the change of the tangent at each point of the roughly detected boundaries. In the following sections we describe the shift-invariant neural network and the boundary smoothing method.

2.1. Shift-Invariant Neural Networks

The shift-invariant neural network with two hidden layers is shown in Figure 2 [26, 29]. The network model is a multi-layered feed-forward network which consists of neuron-like units with semi-linear activation functions, namely a sigmoid function. Units in a single layer are divided into clusters. Each unit in the higher layer is connected to several units in every cluster of the lower layers. Each unit has a limited receptive field and the interconnections between units are constrained to be locally shift-invariant.

The signal processing and the learning algorithms of the neural network are quite similar to the standard multilayer perceptron neural network trained by the generalized delta rule method [24], except that a set of the weighting factors are shared by a group of neurons residing in the next layer. Let $N_p^l(x, y)$ and $O_p^l(x, y)$ represent the net input and the output, respectively, of the unit (x, y) in the p th cluster of the l th layer. Let the pattern of connectivity between the units in the p th cluster of the l th layer and the unit (x, y) in the q th cluster of the $(l + 1)$ th layer be $W_{p,q}^l(x, y)$ where $l = (1, 2, \dots, L)$, $p = (1, 2, \dots, P^l)$, and $q = (1, 2, \dots, P^{l+1})$. The input to units on the subsequent layers of the network is

$$N_q^{l+1} = \sum_{p=1}^{P^l} (O_p^l * W_{p,q}^l)(x, y) + b_q^{l+1}, \quad (1)$$

where b_p^l represents the bias in p th cluster of the l th layer and the symbol $*$ denotes the convolution operation. The output of the units can be written as,

$$O_q^{l+1} = f(N_q^{l+1}(x, y)), \quad (2)$$

where $f(x)$ is a sigmoidal function to denote the point-wise thresholding, written by

$$f(x) = \frac{2}{1 + \exp(-x)} - 1. \quad (3)$$

Let the t th change of the weight be $\Delta W_{p,q}^l(t)$ and the t th change of the bias be $\Delta b_p^l(t)$. The error function is defined as

$$E = \frac{1}{2} \sum_i \sum_{x,y} (T^i(x, y) - O_1^{L,i}(x, y))^2, \quad (4)$$

where $T^i(x, y)$ and $O_1^{L,i}(x, y)$ denote the components of the desired output image and the actual output image of the network for the training input image i , respectively. Based on Eqs. (3) and (4), the error back propagation algorithm in this model can be modified as follows:

$$\Delta W_{p,q}^l(t+1) = \eta(\delta_q^{l+1} * O_p^l)(x, y) + \alpha \Delta W_{p,q}^l(t), \quad (5)$$

$$\Delta b_p^l(t+1) = \eta \sum_i \sum_j \delta_p^l(i, y) + \alpha \Delta b_p^l(t), \quad (6)$$

$$\begin{aligned} \delta_p^l &= f'(N_p^l(x, y)) \sum_q [(\delta_q^{l+1} * \tilde{W}_{p,q}^l)(x, y)], \\ \tilde{W}_{p,q}^l(x, y) &= W_{p,q}^l(-x, -y), \end{aligned} \quad (7)$$

and, in the case of the last layer,

$$\delta_1^L = f'(N_1^L(x, y))(T - O_1^L)(x, y), \quad (8)$$

where $f'(x)$, η , α , and $T(x, y)$ denote the derivative of $f(x)$, the learning rate, the constant factor of the momentum term, and the desired output image, respectively.

Specifically, Eq. (1) computes the forward signal propagation from a set of front image (i.e., matrix nodes) to the next layer. Equations (2) and (3) modulate the collective signals held in each node of the hidden layer. Equation (5) and its associated functions

(i.e., Eqs. (6)–(8)) were used to change the weighting factors of kernels based on error backpropagation techniques. The forward signals at the output node (i.e., $O_1^{L,i}(x, y)$) are compared with the target signal $T(x, y)$. The backpropagation algorithms would modify the kernel weights at each layer. This back and forth process is repeatedly used for all training samples until the error converges a small value.

2.2. Boundary Smoothing Method

The smoothing method is based on the analysis of the tangent change at each point on the boundary in clockwise. The change of the tangents at eroded areas is large, although the change at smooth areas is small. We can find eroded areas by detecting a large change in absolute value of the tangents. The threshold value determining large change of the tangent is obtained empirically. In Figure 3, a typical boundary image delineated by the neural network and some examples of tangent lines are shown.

The algorithm of the boundary smoothing method is as follows:

- (a) Calculate tangent at each point from a starting point clockwise,

$$\theta(t) = \tan^{-1} \left(\frac{Y(t) - Y(t-1)}{X(t) - X(t-1)} \right), \quad (9)$$

where $X(t)$ and $Y(t)$ denote the horizontal and vertical positions of t th point, respectively.

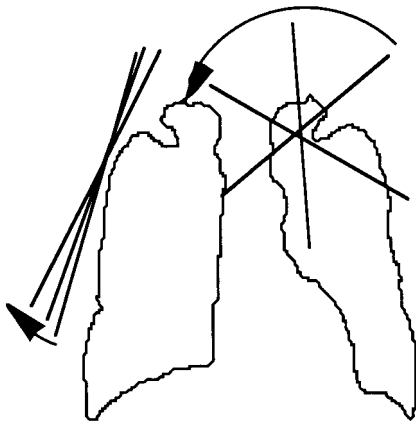


Figure 3. Changes of tangent at smoothed and eroded boundary segments.

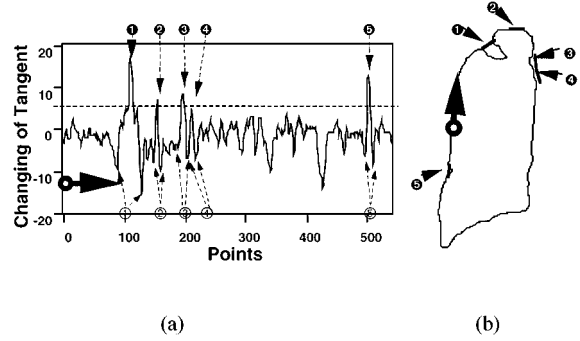


Figure 4. Boundary smoothing method: (a) thresholding of smoothed changes; (b) eroded lung boundary and its correction.

- (b) Smooth the tangent,

$$\begin{aligned} \bar{\theta}(t) &= \frac{\theta(t-n) + \theta(t-n+1) + \cdots + \theta(t+n-1) + \theta(t+n)}{2n+1}, \end{aligned} \quad (10)$$

where n was 5 in our experiment;

- (c) Calculate the change of smoothed tangents,

$$d(t) = \frac{\bar{\theta}(t+1) - \bar{\theta}(t-1)}{2}. \quad (11)$$

- (d) Smooth the changes of the boundary,

$$\begin{aligned} \bar{d}(t) &= \frac{d(t-n) + d(t-n+1) + \cdots + d(t+n-1) + d(t+n)}{2n+1}. \end{aligned} \quad (12)$$

- (e) Find peak values larger than a threshold (i.e., ①, ②, ③, ④, and ⑤ in Fig. 4(a)).
 (f) Find the two smallest points from both sides in an interval (i.e., ①, ②, ③, ④, and ⑤ Fig. 4(a)).
 (g) On the lung image, connect the corresponding two points with straight line (Fig. 4(b)).
 (h) repeat steps (e)–(g).

3. Experiment and Results

The neural network used in the experiment had four layers. The input and output layers consisted of 255×255 and 231×231 neurons, respectively. The first hidden layer consisted of three 251×251 -neuron clusters and the second layer consisted of two 241×241 -neuron clusters. There are three 5×5 kernels between the input and the first hidden layer, two 11×11 kernels between the first and the second hidden layer, and two

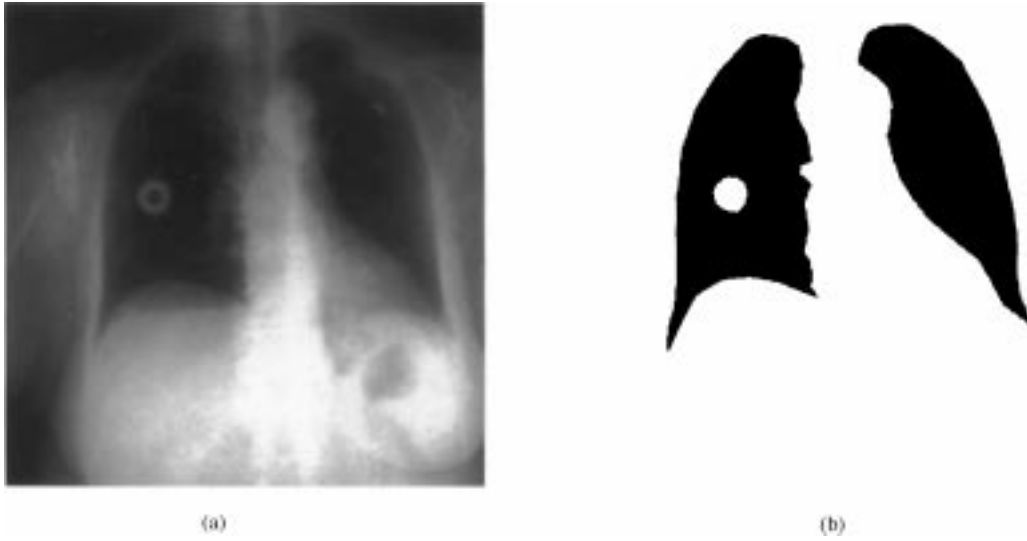


Figure 5. A pair training set images: (a) histogram-equalized image and (b) its target image.

11×11 kernels between the second and the output layer. Each neuron on the hidden layers and the output layers has a bipolar sigmoidal function defined as

$$f(x) = \frac{2}{1 + \exp(-x)} - 1, \quad (13)$$

and each neuron on the input layer has the following transfer function:

$$O_1^1(x, y) = \frac{2 \cdot I(x, y)}{\max\{I(x, y)\}} - 1, \quad (14)$$

where $I(x, y)$ denotes the pixel value of pixel (x, y) in the input image. The ' $\max\{I(x, y)\}$ ' means the maximum pixel value in the whole image.

In the training process, all weights started from random values between -0.3 and 0.3 . The learning rate η and the momentum term α were 0.03 and 0.9 , respectively. The training set for neural networks learning consisted of five chest radiographs and five hand-drawn target images. Figure 5 shows a pair of the subsampled histogram-equalized input image and its target image. The sizes of subsampled (averaged and subsampled) images in squared format and target images were 255×255 and 231×231 , respectively. In this training set, one pixel on the target image corresponded to one training example, thus, the total number of training connections was $266,805$ ($231 \times 231 \times 5$). The number of free parameters of the neural network was 1049 , which met the requirement of the VC dimension [30].

After 300 training iterations, the neural network converged a small value of mean-square-error defined in

Eq. (4). The trained convolution neural network which possesses fixed weight factors (i.e., kernels) was used for the extraction of the lung structure on the chest radiographs. Figure 6 shows a test input image and its output image. In Fig. 6(b), areas of lungs are successfully enhanced. The binarized image of the output image, Fig. 6(b), obtained by using the adaptive thresholding. The outline image after the Laplacian filter following the noise reduction are shown in Figs. 7(a) and (b), respectively. As seen in Fig. 7(b), the outline image is eroded. The erosion areas were mainly due to the superimposed clavicles and posterior ribs on the lungs. We iteratively applied the smoothing method three times. The smoothed image and the superimposed image by Fig. 6(a) are shown in Figs. 8(a) and (b). As can be seen in Figure 8, the shift-invariant convolution neural network incorporated with the boundary smoothing algorithm can detect lung boundaries of the test chest radiographs.

To show the performance of the smoothing method, a seriously eroded boundary image and its output of smoothing method superimposed by its input image are shown in Figure 9. In fact, the original chest image had bright clavicle bones at the upper areas of both lungs. We found that these clavicle bones which tend to detract from the uniformity of the lung fields. Even though the original image was used as a training set for the convolution neural network, the output image was still greatly eroded as demonstrated in Fig. 9(a). The smoothing process was applied to Fig. 9(a) for three times. The result is shown in Fig. 9(b) which

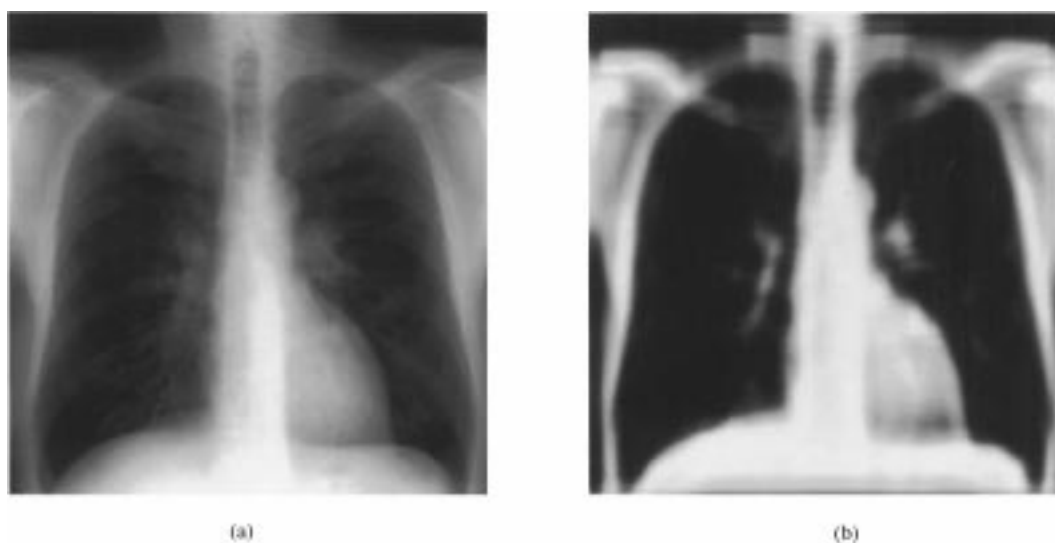


Figure 6. (a) Input image as a test for the trained neural network; (b) its output image.

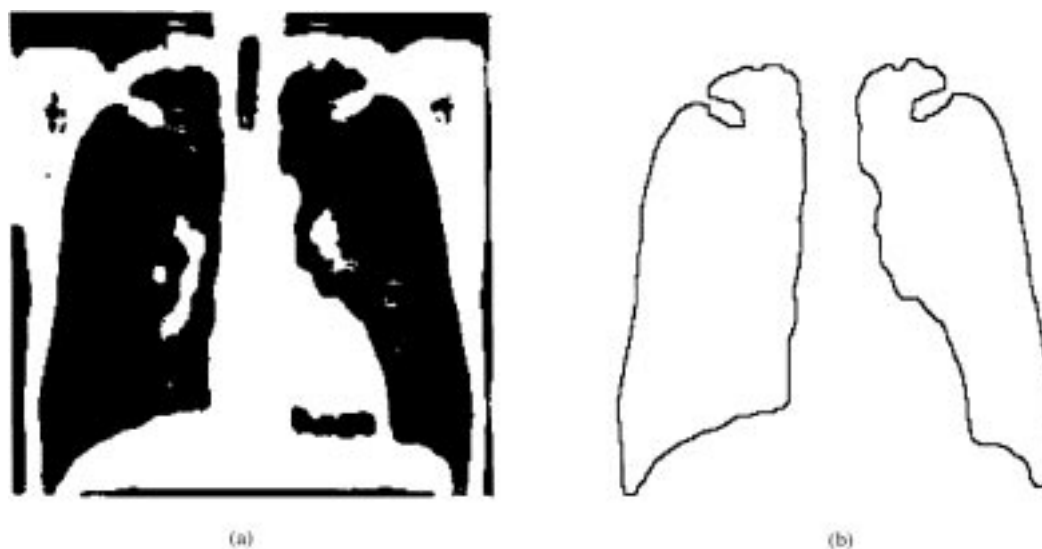


Figure 7. (a) The binarized image of Fig. 6(b) by using the adaptive thresholding method; (b) the boundary image after the Laplacian filter following the noise reduction.

demonstrates that this method was working very well to obtain smoothed boundaries of the lungs.

We applied this method to 21 test chest radiographs to evaluate our approach. It is difficult to validate the correct boundaries of the lungs. Our initial evaluation indicated that the outputs of three chest radiographs (i.e., approximately 14% of the test images) were not completely matched to the lung fields. The other 18 images were matched well with the lung fields of the original chest radiographs. The assessment of match is based on the fourth author's (radiologists) visual judgment. Perfect match and minor mismatch were

considered well match cases in the experiment. The mismatches seemed to be caused by the insufficient training in the neural network. This problem could have been resolved if more training examples were available.

4. Discussion and Conclusions

In this paper, we have described the use of the shift-invariant neural networks to detect the anatomical structures on digital chest radiographs. We have demonstrated that by training the neural network with

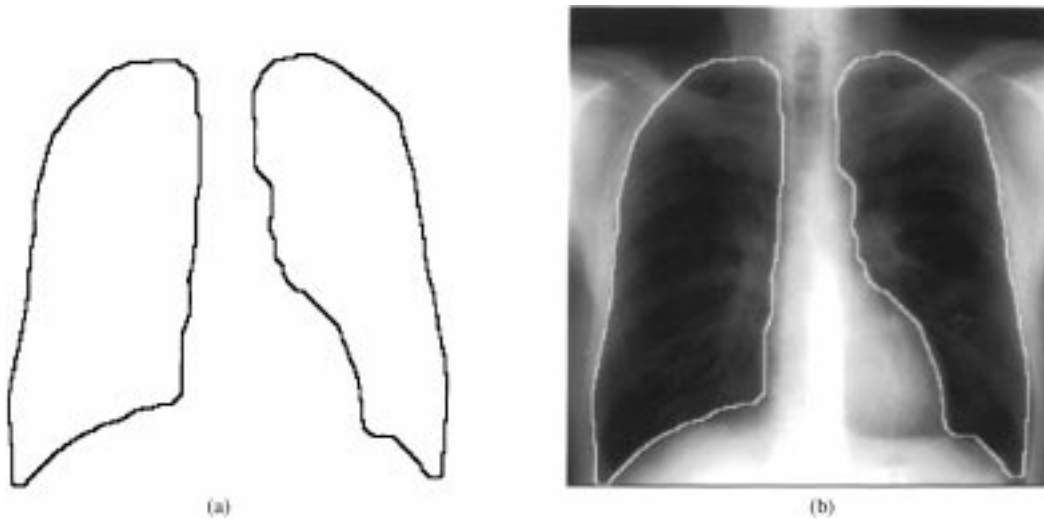


Figure 8. (a) The smoothed boundary image; (b) the overlaid image on Fig. 6(a).

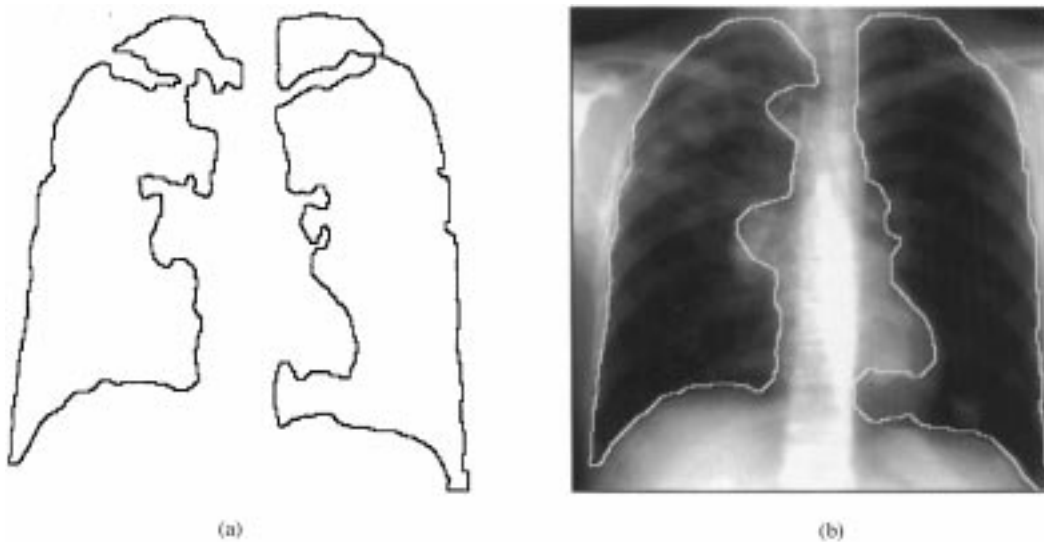


Figure 9. (a) A greatly eroded boundary image, (b) its output image after the smoothing method and the input image is superimposed.

a few images, the network could be generalized for the processing of other chest radiographs. In addition, the novel post-processing followed by the processing of the neural network provided the successful detection of global anatomical structures. The boundary smoothing method did not use any information about the fundamental structures of the lungs. We believe that the method can be improved with a priori knowledge, since the adult lung fields have global similarity embedded in the human chest anatomy. In addition, accurate boundary detection of the lung is not required in this task.

Human eyes coupled with brain neural processes form a very sophisticated perception system. The modified neocognitron neural network structure, which

tries to simulate the human perception system, is a simplified version of an artificial vision system that the authors intend to use in various image perception tasks in lung cancer detection [8–10], breast cancer detection [9, 23, 27, 28], and cellular boundary detection [31, 32]. We will continue to work on our underlying hypothesis that a simulated artificial vision neural system can be used to function as human eyes. The vision system coupled with other neural signals is capable of performing multiple perception tasks with great accuracy. At the end of our neural network research in medical image applications, we shall be able to identify a specific set of convolution kernels for a given task. Therefore, we anticipate that a general

shift invariant neural network (or neocognitron) can be established. By switching a set of kernels, the neural network would be able to perform the corresponding task to assist the physician. This framework design could be appropriate for the further VLSI development of shift-invariant neural network for medical diagnosis applications.

Acknowledgments

This work was supported by Grant #RPG-95-034-03-EDT from American Cancer Society. The authors are grateful to the reviewers' constructive comments for the improvement of this paper and to Ms. Susan Kirby for her editorial assistance.

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