

## COMPUTER AIDED DIAGNOSIS FOR PNEUMOCONIOSIS RADIOGRAPHS' USING NEURAL NETWORK

Hiroshi KONDO, Lifeng ZHANG, and Takaharu KODA  
Kyushu Institute of Technology JAPAN  
[kondou@ele.kyutech.ac.jp](mailto:kondou@ele.kyutech.ac.jp)

**KEY WORDS:** X-ray photo, Pneumoconiosis, Neural Network.

### ABSTRACT

Computer aided diagnosis for pneumoconiosis using neural network is presented. The rounded opacities in the pneumoconiosis X-ray photo are picked up by a back propagation (BP) – neural network with several typical training patterns. The training patterns from 0.6 mm $\phi$  to 30 mm $\phi$  are made by simple circles. The neck problem for an automatic pneumoconiosis diagnosis has been to reject the unnecessary part like ribs and vessel's shades. In this paper such an unnecessary part is rejected well by adding several output neurons for own presenting neural network. These neurons are used only for picking unnecessary parts up. The input for the neural network is 30 $\times$ 30 pixel image which is quarried succeedingly from the bi-level ROI (region of interest) image with the size 500 $\times$ 500 pixel. The new technique called moving normalization is developed here in order to made an appropriate bi-level ROI image. The total evaluation is done from the size and figure categorization and density categorization. many simulation examples show that the proposed method gives much reliable results than traditional ones.

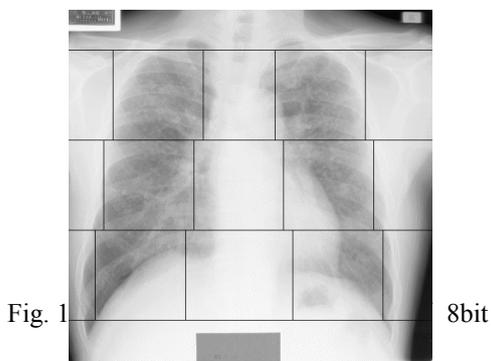
### 1. INTRODUCTION

In recent years computer-aided diagnosis is very popular in a medical field. The aim of computer-aided diagnosis is to alert the radiologist by indicating potential lesions and/or providing quantitative information as a second opinion. Since the middle of 1980, a number of computerized schemes for computer-aided diagnosis have been developed for chest radiography, mammography, angiography, and bone radiography. Especially in chest radiography, many computerized schemes have been applied to the detection and classification of pneumoconiosis, because the quantitative analysis of it has been required from the view point of workmen's accident compensation insurance. Pneumoconiosis is a lung disease caused by, for example, the long term inhalation of coal dust and the local tissue reaction to the accumulated dust particles. The first radiological symptom in the development of simple pneumoconiosis is the appearance of small opacities, either rounded or somewhat irregular, in the chest X-rays. According to the profusion of small opacities, categories 0-3 have been established to indicate the severity of the disease where category 0 means normal case and category 3 means very numerous small opacities. The early studies of computer pneumoconiosis analysis have been done by several groups (Morishita, Yanagisawa, Katsuragauia, Doi, MacMabon, Nakamori, Sasaki, and Fennessy. In their studies the texture analysis for the X-ray photos has been taken. Recently, however, the study trends toward the detection of the small rounded opacity itself because of the extremely development of the computer hard and software. They have utilized a special filtering for dropping off the unnecessary part like rib shade in the X-rays. The performance of the filtering is not satisfied sometimes due to the vagueness of the X-rays. In this paper the neural network is introduced to pick the rounded opacities up from the X-ray photo with no filtering. A neural network is powerful for pattern matching. Here a back propagation neural network with three layers is used.

### 2. PNEUMOCONIOSIS

Pneumoconiosis is one of the serious lung occupational disease. Hence the diagnosis result of a medical doctor gives a big implication for the workmen's accident compensation insurance. Even such doctor's diagnosis results, however, are not often consistent with each other. For this reason it has been required that the quantitative analysis of pneumoconiosis is established. According to the classification scheme of the International Labor Office (ILO), there are two kind of categories : one is number and area density classification and the other is size-figure one. The former one has three ranks from 0 to 3, where 0 means normal case and rank 3 means very serious case. The size-figure classification has also three types as P, Q, and R, where P means the equivalent diameter  $d$  of the opacity is less than or equal to 1.5 mm, Q means 1.5 mm  $< d \leq$  3.0 mm, and R means 3.0  $< d \leq$  10.0 mm. Figure 1 shows a normalized X-ray photo with 3000 $\times$ 3000 $\times$ 8 bit. The normalization is made by setting the minimum gray level 0 (black) and the maximum value 255 (white). The other gray levels are transformed linearly between the above two values. Figure 1 is the photo for (3,P) category. Usually in the analysis of a

pneumoconiosis chest X-ray image the original image like Fig 1 is divided by three blocks from the top to the bottom shown in Fig 1. We call them high lung field, middle lung field, and low lung field respectively. From these fields the region of interest (ROI) is Quarried for the analysis (See Fig.1). The size of the ROI is 512 ~ 512 pixel here. The opacity figures are almost rounded but sometimes irregular as a complex figure. The rounded opacities in the pneumoconiosis chest X-ray image appear so often especially in the high and middle lung fields because of the position near bronchial tubes. Figure 2 shows an example of ROIs. This is the right high lung field from (Q,2) categorized image. From such ROI image the rounded opacities must be detected. The field evaluation for the classification is done by calculating the number density and the area density of the rounded opacities, and by comparing those values of the ILO standard images.



### 3. TRADITIONAL METHOD

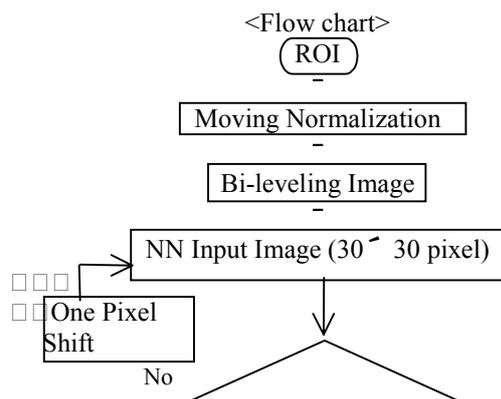
There are two types of approach for pneumoconiosis radiographs analysis. One is in lung texture analysis and the other is in a number and area density approach. The texture approach has done by Sasaki, Katsuragawa, and Yanagisawa in 1992. They use physical texture measures obtained from an analysis of the power spectrum of lung textures in digital chest radiographs. First they select the ROI's for inter-rib spaces from the original image. After correction of non-uniform background trend in ROI's two dimensional Fourier transform is performed for filtering by visual system response. Finally the root mean square variation and the first moment of the power spectrum are calculated for an evaluation of the pneumoconiosis. The final evaluation is made by a graphical manner with a horizontal axis RMS variation and a vertical axis the first moment of power spectrum. This method gives us a relatively easy tractability of categorizing the chest X-ray image. The exactness of the evaluation results, however, is not so reliable because of the dependence on the ROI size and the trend correction. On the other hand as a density approach for pneumoconiosis analysis Chen, Hasegawa, and Toriwaki's paper (1989) is excellent. They use a method to detect each rounded opacity. From the original chest X-ray image, first they extract the opacity candidates by using smoothing filter, 2D circular difference filter, and a threshold value processing. Then dropping the unnecessary parts like blood vessels and/or rib shades, they detect rounded opacities. The number density is calculated from the number of the detected opacities. And the area density is also gotten from the area of the opacities. Finally the evaluation is made from the above results. They have gotten 71% correspondence rate to doctors evaluation results. And the correspondence rate of the detected rounded opacities is 72% (true positive). The others (28%) are false positive or false negative. It looks very hard to detect all true opacities for this method because the 2D circular difference filter is sensitive not only to rounded opacities but also to rib and vessels shades, although the procedure of this method is relatively simple.

property for a pattern matching. Here we utilize a back propagation NN with three layers. The training patterns are circular figures with various radius like the rounded opacities.

Figure 3 shows a flow chart of the proposed method. In this figure ROI means a region of interest which is an input image with 512 ~ 512 pixel for this processing. Next step is moving normalization of the ROI. Chest X-ray image has often a big variance in its gray levels.

### 4. NEW METHOD USING NEURAL NETWORK

The correspondence rate of the evaluation results depends upon the exactness of a rounded opacity detection. It is the most important part of the pneumoconiosis analysis to detect each rounded opacities. In this paper a neural network is utilized for detecting a rounded opacity. A neural network is abbreviated to NN here. An NN has an excellent



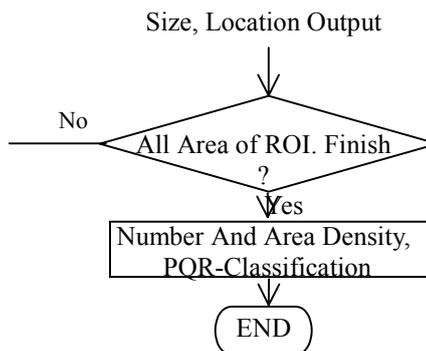
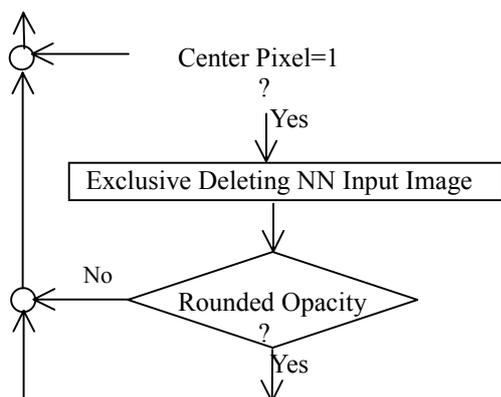


Figure.3 Flow chart of the proposed method

Especially tiny area average value is quite different with that of another area. Hence only a simple normalization of the ROI is not necessarily sufficient for processing. We introduce here a new technique in order to get a high contrast image and we call it a moving normalization that is shown in the following section. From the result of the moving normalization we can make a bi-level image by using a threshold value. The input of NN is taken from the bi-level image and its size is 30 × 30 pixel. If the center pixel of the taken input has 0 (black) then it is not needed to input because only the center image of the input is the object image for NN. If the center pixel of the input has 1 (white) then other isolate whites are deleted i. e., changing from 1 to 0 and take it as an input to NN. This processing is called here an exclusive deleting one. It is important to delete the back ground because NN output reacts also for back ground of the input. The detection of rounded opacities is the next step. This is the main topic of this paper and also shown in the following section. Finally calculating the number density and area density we get a classification result in comparison with these value of the ILO standard X-ray images.

4.1 Moving normalization

In the chest X-ray image usually the contrast is low but the local area gray level is often much different with the other local area one. Hence the full picture normalization in the gray level gives the unsatisfactory results for our processing.

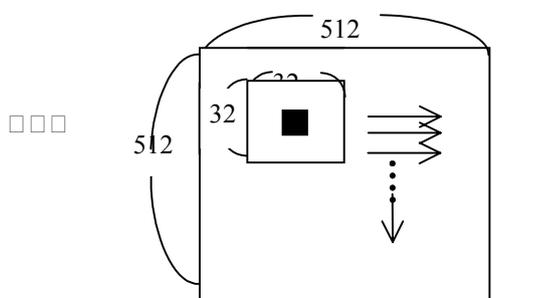


Fig.4 Procedure of moving normalization



Here we employ special technique for the normalization.

First, the tiny area  $R_e$  with 32 × 32 pixel is taken from the ROI at left top corner. Let the minimum and the maximum values of the  $R_e$   $f_{min}$  and  $f_{max}$  respectively the gray level  $f(i, j)$  of  $R_e$  is changed as follows.

$$g(i, j) = (f(i, j) - f_{min}) \times \frac{F_{Max}}{f_{max} - f_{min}} \quad (1)$$

where  $F_{max}$  is the maximum value; if we employ 8bit for the quantization then  $F_{Max} = 255$ . The result  $g(i, j)$  is quantized from zero to 255. After transforming by using Eq.(1), we leave the central pixel and dispose all other pixels. And we repeat this procedure by shifting one pixel to the left. The procedure is done from left to right and from top to bottom. The marginal 15 pixels of the ROI are also disposed. If we need such margins then it is sufficient to take ROI wider by 15 pixels. Figure 5 is one example of the moving normalization. Very high contrast image is gotten in comparison with the original. This image is much suitable for bi-leveling. In a moving normalization we tried to take 8 × 8, 16 × 16, 32 × 32, 64 × 64. And 32 × 32 is the best one of all.

### 4.2 Bi-leveling

As an NN input the simplest figure is favorable for the pattern matching. Here we employ a bi-level image for our NN. The bi-level image is made from the moving normalized image Fig.5. Fig.6 is a histogram of Fig.5. From this figure we see that it is symmetric and so it is very easy to make a bi-level image. The threshold value for making a bi-level image is taken as a mid point i.e., valley between two major modes. Exactly we can determine the threshold value by using the peak score of Fig.6.

Fig.6 Histogram of Fig.5  
( $T_h$  : Threshold value)

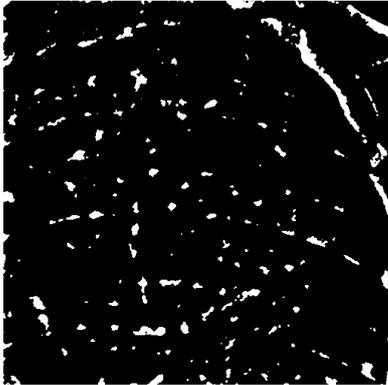


Figure 7 shows a resulting bi-level image. Almost all rounded opacities and rib shades are detected so clearly. It means the moving normalization is effective as the pre-stage of a bi-leveling.

### 4.3 Neural Network Approach

NN has an excellent feature for pattern matching. Furthermore the pattern matching is done in a real time. We employ the back propagation NN with three layers. It requires the training patterns that is shown in the succeeding section.

#### 4.3.1 Back propagation Neural Network

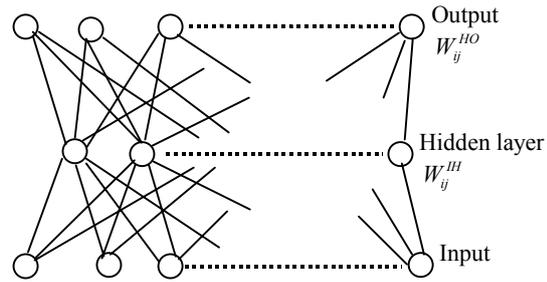


Fig.8 Neural Network Structure

Three layers back propagation first are

gation NN with training patterns are reliable and suitable. The output values are 0 ~ 1 through a logistic function. The outputs are set as 0.6 mm  $\phi$ , 0.8mm  $\phi$ , 1.0mm  $\phi$ , and 3mm  $\phi$  diameters of rounded opacities. The number of outputs are 18. The 13 outputs for rounded opacities. The other 5 outputs for unnecessary parts like vessel and/or rib shades. Hidden layer has 171 neurons that is determined optimally. The input layer has 30 ~ 30 neurons i.e., 30 ~ 30 pixel image picked up from bi-level image.

With the number of input layer  $N_i$  the hidden layer unit  $H_j$  is expressed as

$$H_j = f_j^I \sum_{i=1}^{N_i} W_{ij}^{IH} I_i \quad (2)$$

where  $I_i$  in the  $i$  th input value of the input layer and  $W_{ij}^{IH}$  is the coefficient between the input layer and the hidden layer.  $f_j^I()$  is defined as

$$f_j^I() = \begin{cases} \frac{1}{1 + e^{-x}} & : f_j() \geq T_h \\ 0 & : f_j() < T_h \end{cases} \quad (3)$$

( $T_h$  : Threshold value)

similarly with  $N_h$  the number of hidden layer neurons and  $W_{ij}^{HO}$  the coefficient between a hidden layer and output one, the output  $O_j$  is

$$O_j = f_j^O \sum_{i=1}^{N_h} W_{ij}^{HO} H_i \quad (4)$$

where  $f_j^O()$  is a logistic function shown as

$$f_j^0(x) = \frac{1}{1 + e^{-x}} \tag{5}$$

this gives a value between 0 and 1.

### 4.3.2 New Method

The outputs of NN correspond to 0.6 ~ 3.0mm  $\phi$  rounded opacities by step 0.2mm. As for the opacities bigger than 3mm  $\phi$ , the ROI image is reduced into 1/5 scale by averaging. Hence the size of each output corresponds to 3.0 ~ 15.0mm  $\phi$ . It means that the same NN can be utilized for detection of 3.0 ~ 15.0mm  $\phi$ . It is sufficient to detect a rounded opacities with the size until 15 mm  $\phi$  because the rounded opacities bigger than 15.0 mm  $\phi$  is very rare for the pneumoconiosis X-ray photos. In this paper the most popular opacities in pneumoconiosis I.e., small rounded opacities are only detected.

Output Error

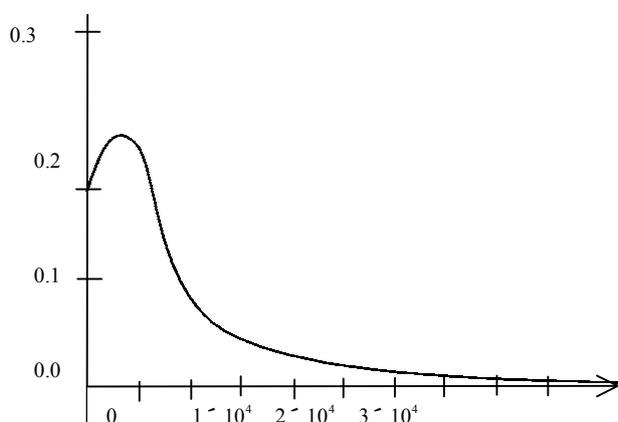


Fig.9 Output error-repeating times Characteristic curve

The convergence of the back propagation NN is made after 17321 repeating times. The repeating is basically done according to a maximum principal. Figure 9 shows the output error-repeating times Characteristic curve. This is one of the typical curve of the back propagation method. The input image to the NN is not of bi-level because of the averaging for the size bigger than 3mm  $\phi$ . Since the figure of the rounded opacities is quite different with a circle for making a bi-level image multi-level image is much better as a neural network input for the bigger size 3mm  $\phi$  ~ 15mm  $\phi$ .

### 5. TRAINING PATTERN

Back propagation NN requires training patterns. Figure 10 shows several training patterns for pneumoconiosis rounded opacities with several sizes. The last five elliptic figures are for unnecessary parts like vessel and rib shade. These are actually not rounded opacities but thin and long ones. Hence such training patterns are effective for reduction the false positive. The big rounded opacities are made by averaging 5\*5 pixel and put it into one pixel.

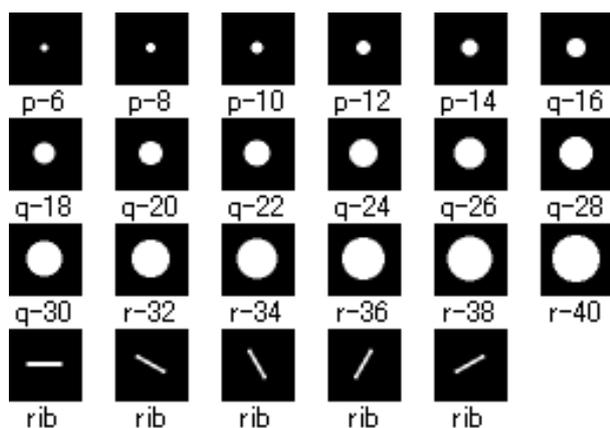


Fig.10 Several training patterns



Fig.12 Simulation example (3, r) type ROI

6.

**SIMULATION**

Figures 11 and 12 are simulation examples. Figure 11 is type 1 (weak) with many p-size rounded opacities. The circle which wraps the rounded opacities is a marking for the detection. It is shown that many opacities are well detected. Of course, Q-size and r-size of the rounded opacities are also there. But the major size is P-size, so we call this ROI (1, P). Figure 12 shows a detecting result with (3, r) type. Many big rounded opacities are detected. But when the figure of the opacity is not rounded our NN may not catch such an opacity. One solving approach of this problem is to average and to reduce the size. After detecting such opacities we calculate the densities;

$$D_N = \frac{N_r}{N_E} \quad (6)$$

$$D_A = \frac{N_a}{N_E} \quad (7)$$

where  $N_r$  and  $N_a$  is the number area of rounded opacities respectively.  $N_E$  is the back ground all area.  $D_N$  is called the number density and  $D_A$  is called the area a density. The classification is done in comparison with the densities of ILO standard pneumoconiosis X-ray photo.

**7. CONCLUSION**

We have presented a new automatic diagnosis for pneumoconiosis radiographs using neural network. Rounded opacities are caught by NN from tiny to big one. The detecting rate is higher than the several traditional methods. As a pre-processing for using NN we have developed a moving normalization method which is very effective for getting a high contrast image of a chest X-ray photo. It is important to modify an input suitably for NN. From upper left side to lower right side of the ROI the input scan is performed successively by one pixel with  $30 \times 30$  pixel size.

Although NN has a merit in real time processing, our proposed system is not a real time one because it takes a little bit much time for pre-processing and so many time repeating of NN processing. Now the processing time is about 5 minutes for our personal computer (500MHzCPU). 5 minute are not so quick but it seems not to be unrealistic.

As a left problem is to check a large amount of the chest X-rays and certify the high consistency with the doctor's opinion.

**REFERENCES**

- Katsuragawa S., Doi K., Macmabon H., Nakamori N., Sasaki Y., and Fennelsy J., Quantitative computer-aided Analysis of lung texture in Chest Radiographs, 1988 RSNA annual meeting of the kurt Rossmann Laboratories for Radiologic Image Research, Dept. of Radiology. Univ. of Chicago Radio Graphics vol 10, PP257-269.
- Savol.M.A., Li.C.C., and Hoy.R.J, computer-Aided Recognition of Small Rounded Pneumoconiosis Opacities in Chest X-rays, 1980 IEEE Trans. on PAMI,VOL.PAMI-2, No.5, PP479-482, Morishita J., DoiK., Katsuragawa S., Monnier-Cholley L., and MacMahon H., Computer-aided diagnosis for Interstitial infiltrates in chest radiographs: Optical-density dependence of texture measures, 1995 Am. Assoc. phys. Med., vol.22, PP1515-1523
- Sasaki Y., Katsuragawa S., and Yanagisawa T., Quantitative Analysis of Pneumoconiosis in Standard Chest Radiographs, 1992 Dept. of Radiology, vol.52 – 10, PP1385-1393
- Chen X., Hasegawa J., and Toriwaki J., Recognition of Small Rounded Opacities for Quantitative Diagnosis of Pneumoconiosis Radiographs, 1989 IEICE Trans. on D-II vol.J72-D-II, No.6, PP944-953