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Automatic Detection of Interstitial Lung Disease using Neural Network

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Abstract

Automatic detection of interstitial lung disease using Neural Network is presented. The rounded opacities in the pneumoconiosis X-ray photo are picked up quickly by a back propagation (BP) neural network with several typical training patterns. The training patterns from 0.6 mmØ to 4.0 mmØ are made by simple circles. The total evaluation is done from the size and figure categorization. Mary simulation examples show that the proposed method gives much reliable result than traditional ones.

Key words : X-ray photo, Pneumoconiosis, Neural Network, Automatic diagnosis

I. Introduction

In the last ten years computer-aided system are extremely 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 options. 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 viewpoint 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 of 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 [1][2][3]. In their studies the texture analysis for the X-ray photo 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 [4]. They have utilized a special filtering for dropping off the unnecessary part like rib shade in the X-ray. The performance of the filtering is not satisfied sometimes due to the vagueness of the X-ray. 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.

II. Classification of 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 kinds 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 1.5mm$<$**d** 3.0mm, and **R** means 3.0$<$**d** 10.0 mm. Figure 1 shows a normalized X-ray photo with $3000\times3000\times8$ 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 value. 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

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(See Fig. 1). The size of the ROI is 512×512 pixel here. The opacity figures are almost rounded. The rounded opacities in the pneumoconiosis chest X-ray image appear so often 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 (2,Q) 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.

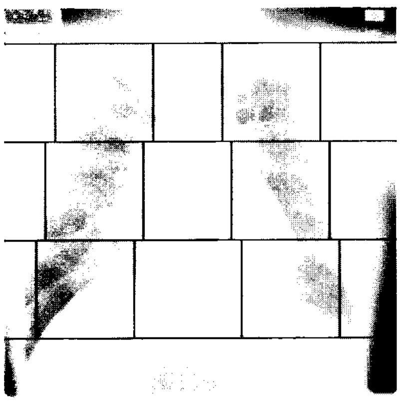

Fig. 1. X-ray photo (3,P) 3000×3000×8bit

Fig. 2. Example of ROI (3,P)

III. Procedure of Pneumoconiosis Analysis

The coincidence rate with a medical doctor in the evaluation results depends upon the exactness of rounded opacity detection. It is the most important part of the pneumoconiosis analysis to detect each rounded opacity. 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 property for a pattern matching. Here we utilized a back propagation NN with three layers. The training patterns are circular figures with various radiuses like the rounded opacities.

Fig. 3 show 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.

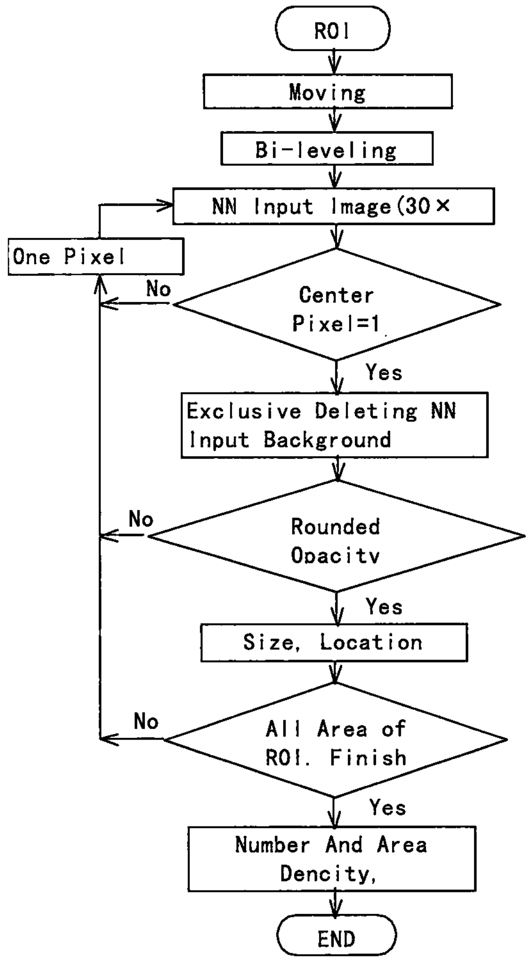

Fig. 3. Flow chart of the proposed method

Especially tiny area average value is quite different with that of another area. Hence only a full-picture 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 background 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.

3.1 Moving Normalization

In a chest X-ray image usually the contrast is low but the local area average 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. Here we employ special technique for the normalization. First, the tiny area R_e with 32×32pixel is taken from the ROI at left top corner. Let the minimum and the maximum values in the area R_e, f_{min} and f_{max} respectively the gray level $f(i, j)$ of R_e is changed as follows.

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

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 0 to 255. After transforming by using Eq. (1), only the central pixel is left and all other pixels are disposed. 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 4 is one example of the moving normalization. Very high contrast image is gotten in comparison with the original. Fig.4 has the same local mean and local variance at any point. Hence taking one threshold value we can make a desired bi-level image. (Fig. 5) In a moving normalization we tried to take 8×8, 16×16, 32×32, and 64×64. And 32×32 is the best one of all.

Fig. 4. Moving normalization

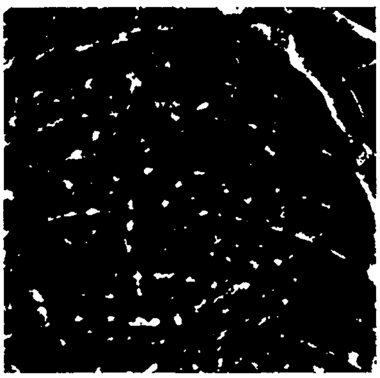

Fig. 5. Bi-level image

IV. Detection of Rounded Opacities

Using a neural network we detect the rounded opacities in the X-ray photo. Here we utilize a back propagation neural network (NN). Back propagation NN requires training patterns. Figure 6 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 but thin and long ones. Hence such training patterns are effective for reducing the false positive. The number of NN output is 23 which includes 18 different rounded opacities and 5 thin and long ones shown in Fig.6, the hidden layer neuron number is 171 determined by heuristic way, and the input layer neuron number is 900 (30×30).

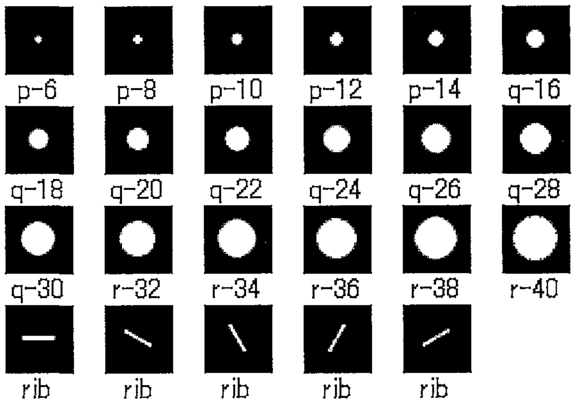

Fig. 6. Several training patterns

Figure 7 shows a status of detecting a rounded opacity by NN. The target equivalent diameters are 1.0 mmØ and 2.0 mmØ. The horizontal axis is the position and the vertical axis is the output value percent.

Table 1 shows the output value at each position and its identification size. The peak value happens at the position 84 (pixel) and its size is p-10 (1.0 mmØ) for the left opacity. Similarly for the right opacity the peak value happens at the position 170 (pixel) and its size is q-20 (2.0 mmØ). Form this figure we can see easily that our NN can detect the position and the opacity size exactly.

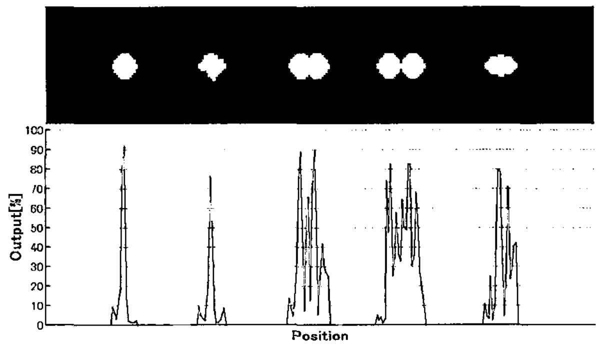

Fig. 7. Neural Network Detection

V. Simulation

Figure 8 and 9 are simulation examples. Figure 8 is type 1 (light) with many P-size rounded opacities. The circle which wraps the rounded opacities is a marking for the 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 9 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 many not catch such opacity. One solving approach of this kind problem is to average and to reduce the size, where we employ it. After detecting the opacities we calculated the densities:

$$D_N = N_r / N_E \quad (2)$$

$$D_A = N_a / N_E \quad (3)$$

where N_r and N_a are the number and the 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 density. The classification is done in comparison with the densities of ILO standard pneumoconiosis X-ray photo.

Table.1 Output Characteristic

Position	Output	Identification	Position	Output	Identification
31	0.0000	NULL	166	0.0000	NULL
32	0.0000	NULL	167	0.0000	NULL
33	0.0000	NULL	168	0.0000	NULL
34	0.0916	rib	169	0.0501	rib
35	0.0697	rib	170	0.0249	rib
36	0.0311	p-14	171	0.0389	rib
37	0.1280	p-14	172	0.0118	p-14
38	0.1800	p-14	173	0.0307	p-14
39	0.7903	p-12	174	0.7403	p-12
40	0.9158	p-12	175	0.4775	p-14
41	0.1357	p-14	176	0.8243	p-14
42	0.0224	p-14	177	0.2504	p-14
43	0.0164	q-18	178	0.3367	q-18
44	0.0119	rib	179	0.5774	q-18
45	0.0132	rib	180	0.3666	q-18
46	0.0216	rib	181	0.3292	q-18
47	0.0000	NULL	182	0.6434	q-18
48	0.0000	NULL	183	0.5067	q-18
49	0.0000	NULL	184	0.4912	p-14
75	0.0000	NULL	185	0.8264	p-14
76	0.0000	NULL	186	0.8243	p-14
77	0.0000	NULL	187	0.3056	p-14
78	0.0970	rib	188	0.3552	rib
79	0.0503	rib	189	0.6810	rib
80	0.0351	rib	190	0.5111	rib
81	0.0222	p-14	191	0.2682	rib
82	0.1188	p-14	192	0.1804	rib
83	0.2188	p-12	193	0.0915	rib
84	0.7641	p-12	194	0.0000	NULL
85	0.4494	p-12	195	0.0000	NULL
86	0.0729	p-14	196	0.0000	NULL
87	0.0128	p-8	221	0.0000	NULL
88	0.0118	rib	222	0.0000	NULL
89	0.0273	rib	223	0.0000	NULL
90	0.0556	rib	224	0.1085	rib
91	0.0862	rib	225	0.0465	rib
92	0.0000	NULL	226	0.0351	p-8
93	0.0000	NULL	227	0.2473	p-8
94	0.0000	NULL	228	0.0260	p-8
121	0.0000	NULL	229	0.1035	p-14
122	0.0000	NULL	230	0.5258	p-14
123	0.0000	NULL	231	0.7985	p-14
124	0.1381	rib	232	0.7859	p-14
125	0.0823	rib	233	0.3146	p-14
126	0.0456	rib	234	0.0489	p-10
127	0.1110	p-14	235	0.2573	p-8
128	0.3140	p-14	236	0.7078	p-8
129	0.7510	p-14	237	0.2364	rib
130	0.8872	p-14	238	0.3001	rib
131	0.5402	p-14	239	0.4021	rib
132	0.0733	p-14	240	0.4214	rib
133	0.5618	q-18	241	0.0000	NULL
134	0.6562	q-18	242	0.0000	NULL
135	0.1297	p-14	243	0.0000	NULL
136	0.6781	p-14			
137	0.8962	p-14			
138	0.5896	p-14			
139	0.0550	p-14			
140	0.2530	rib			
141	0.4178	rib			
142	0.3040	rib			
143	0.2705	rib			
144	0.2515	rib			
145	0.0000	NULL			
146	0.0000	NULL			
147	0.0000	NULL			

Ⅵ. Conclusions

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 method [3][4][5]. 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 lower right side of the ROI the input scan is performed modify an input suitably for NN. From upper left side to successively one pixel by one pixel. Although there are many twin or tripple overlapped rounded opacities in a heavy disease X-ray photo, our NN can catch them so well separately or as one rounded opacity depend upon the overlap rate.

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 60 minutes for our personal computer (700MHz).

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

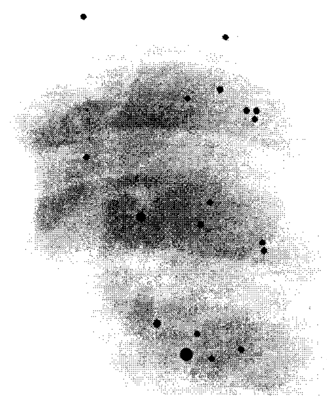

Fig. 8. Simulation example (1,P) type ROI

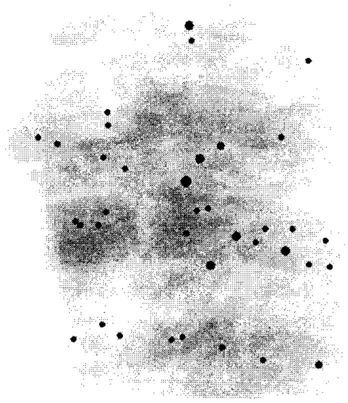

Fig. 9. Simulation example (3,R) type ROI

Reference

[1] 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. Unv. Of Chicago Radio Graphics vol. 10, P. 257-269.

[2] Savol.M.A., Li.C.C,. and Hoy. R. J., "computer-Aided Recognition of Small Rounded Pneumoconiosis Opacities in Chest X-rays", *1980 IEEEE Trans.* on PAMI, vol. PAMI-2, no. 5, P. 470-482

[3] Sasaki Y., Katsuragawa S., and Yanagisawa T., "Quantitative Analysis of Pneumoconiosis in Standard Chest Radiographs", 1992 Dept. of Radiology, vol. 52-10, P. 1385-1393

[4] 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, P. 944-953

[5] H.Kobatake, "Toward synthetic diagnosis of pneumoconiosis by computer", Proc. 3rd Japan-France Joint Conf. On Biomedical Electronics, P.184-188, 1989