A Computerized Analysis System in Chest Radiography: Evaluation of Interstitial Lung Abnormalities

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We evaluated the usefulness of a computerized analysis system in the detection of interstitial lung abnormalities in digitized chest radiography. This system uses the processes of four-directional Laplacian-Gaussian filtering, linear opacity judgment, and linear opacity subtraction. For qualitative analysis, we employed a combined radiographic index, which was calculated from two normalized radiographic indices obtained by linear opacity judgment and subtraction of linear opacities. We selected 50 regions of interest (ROIs) in patients with mild interstitial lung abnormalities, 50 ROIs in patients with severe interstitial lung abnormalities, and 50 ROIs in individuals with normal lung parenchyma. High-resolution computed radiography (HRCT) findings were used as the standard of reference for this study. These ROIs were processed by our computerized analysis system, and radiographic indices were obtained from each ROI. The area under the receiver operating characteristic curve (Az) was used as the measure of performance. The combined radiographic index provided better results in the mild interstitial lung abnormality group ($Az = 0.94 \pm 0.02$), but it also yielded good results in the severe interstitial lung abnormality group ($Az = 0.98 \pm 0.01$). These results indicate that this system of combining radiographic indices has improved the detection performance over that with our previous system.

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KEY WORDS: computer-aided diagnosis, digital chest radiography, image processing, interstitial lung disease, receiver operating characteristic curve (ROC).

CHEST RADIOGRAPHY is the most common imaging procedure for the diagnosis of interstitial lung disease.¹ The interpretation of chest radiographs poses important problems, because the radiographic patterns observed are varied and often subtle.² Furthermore, the terms used by radiologists to describe radiographic patterns are neither objective nor quantifiable. Therefore, a computerized system with which one can quantitatively analyze interstitial lung abnormalities in chest radiographs would improve diagnostic accuracy.

Many investigators have reported computerized methods for evaluating interstitial lung diseases in chest radiography.³⁻⁷ Sutton and Hall³ used physical measures based on the density distribution on chest radiographs to distinguish a normal lung from a lung with pulmonary fibrosis. Revesz and Kundel⁴ used the power spectrum of the lung texture

based on an optical Fourier transform to distinguish normal lungs from lungs with interstitial lung abnormalities. Tully et al⁵ also used an analysis of the optical Fourier spectrum to distinguish among normal lungs, alveolar infiltrates, and interstitial infiltrates. Katsuragawa et al^{6,7} developed a classification method for distinguishing between normal lungs and abnormal lungs with interstitial disease that used power spectrum analysis and the "visual system response" of human observers. They indicated that the results corresponded well with the characteristics recognized visually by radiologists.

We have been investigating a computerized analysis system for detecting and classifying interstitial lung abnormalities.⁸ This method uses the processes of four-directional Laplacian-Gaussian filtering and linear opacity judgment. First, chest radiographs are digitized, and regions of interest (ROIs) are selected from the right upper and lower lung areas. To extract linear opacities selectively, we perform four-directional Laplacian-Gaussian filtering and binarization, as well as linear opacity judgment processing, for each ROI. The Laplacian-Gaussian filter mimics human visual perception.⁹ The four-directional Laplacian-Gaussian filter enhances linear elements of interstitial lung abnormalities in various directions. However, this filter, in the first stage of the method, extracts only very short linear opacities or only candidate pixels of linear opacities. Linear opacities or true linear opacities from these pixels are extracted in the second stage, linear opacity judgment processing, which is a method of detecting straight line segments directly on the image plane by the search line method. Finally, the radiographic index, which is a percent-

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age of the ROI, is calculated from the chest radiographs as a physical measure.

The main feature of our previous algorithm was the extraction of linear opacities, because extracting various other types of radiographic patterns seen in chest radiographs was thought to be difficult. This system could differentiate abnormal lungs from normal lungs, and honeycombing lesions in the interstitial lung abnormalities from other interstitial lung abnormalities (interstitial changes other than honeycombing). In our previous system, other elements in addition to linear opacities were also extracted in the first image processed with four-directional Laplacian-Gaussian filtering and binarization; however, these elements were ignored in the previous system. We therefore made an attempt to use these extracted elements for the improvement of our computerized analysis system.

In this study, we added as a third stage a process that subtracts the second image, which is processed by linear opacity judgment, from the first image, which was processed by four-directional Laplacian-Gaussian filtering and binarization. Moreover, we employed a new radiographic index, which we called the "combined radiographic index," calculated from the radiographic indices obtained from the images of the linear opacity judgment process and its subtraction process.

MATERIALS AND METHODS

Study Group and Digitization of the Chest Radiograph

Conventional posteroanterior chest radiographs (35 cm $\times$ 35 cm) were digitized to a 2,000 $\times$ 2,000 matrix (0.175 mm/pixel) with 1,024 gray levels (10 bits) with a laser scanner (Konica Corp., Tokyo, Japan). To evaluate our computerized analysis system, we used ROIs selected at the level of the right upper and right lower lung on the digitized chest image displayed on a cathode-ray tube. The size of the ROI was 296 $\times$ 296 (51.8 mm $\times$ 51.8 mm) (Fig 1). The presence or absence of interstitial lung abnormalities was evaluated by high-resolution computed tomography (HRCT). HRCT examinations with a GE9800 scanner, General Electric Medical Systems, Milwaukee, WI, or a Quantex scanner, Yokogawa Medical Systems, Tokyo, Japan, consisted of multisections 1.5 or 2.0 mm thick at 10- or 20-mm intervals through the chest. The images were reconstructed with a bone algorithm.

The abnormal ROIs were divided into two groups. One was a mild interstitial lung abnormality group, and the other was a severe interstitial lung abnormality group. This classification was based on the HRCT findings. First, on the scout view, we selected three sections close to the position of the ROI for image processing. Next, we calculated the percentage of interstitial abnormalities in the right lung for each HRCT section. These calculations were based on the radiologists' observations. We defined the average score for the three sections in the severe interstitial lung abnormality group as greater than 50% and that of the mild interstitial lung abnormality group as less than or equal to 50%.

We selected 50 ROIs with mild interstitial lung abnormalities, 50 ROIs with severe interstitial lung abnormalities, and 50 ROIs with normal lung parenchyma from our database of digitized

Fig 1. Chest radiographs were digitized, and regions of interest (ROIs) with 296 $\times$ 296 matrix size (51.8 mm $\times$ 51.8 mm) were selected in the right upper and lower lung areas for filtering by four-directional Laplacian-Gaussian filters. (A) Normal lung; (B) abnormal lung. (Reprinted with permission.⁸⁾)

chest radiographs. In each group, the number of ROIs selected from the upper lung and that of ROIs selected from the lower lung were the same. The average age and gender of the individuals were closely matched among the three groups.

Overall Scheme of a Modified Computerized Analysis System

By using our modified method, we added three processes to our previous system: linear opacity subtraction, normalization of radiographic indices, and calculation of the combined radiographic index. The overall scheme of our new algorithm is shown in Fig 2. From this algorithm, four different radiographic indices were obtained for evaluation of interstitial lung abnormalities on digitized chest radiographs.

Filtering by Four-Directional Laplacian-Gaussian Filters and Binarization

Because the Laplacian-Gaussian filter has band-pass characteristics, it allows adjustment of the spatial frequency to be detected. Moreover, this filter corresponds to a physiological model of human vision.⁹ To enhance linear opacities in the selected ROI, we employed a one-dimensional Laplacian-Gaussian filter, which enhances specific directional elements.

Fig 2. Overall scheme for our modified computerized analysis system for detection of interstitial lung disease on chest radiographs. Normalized radiographic indices: D_{bin} was obtained from ROIs processed by four-directional Laplacian-Gaussian filtering and binarization, D_{lin} was obtained from ROIs processed by linear opacity judgment, and D_{sub} was obtained from the ROIs processed by linear opacity subtraction. The combined radiographic index, D_{com} , was obtained from D_{lin} and D_{sub} .

This filter is described as follows:

$$\nabla^2 G(x) = \frac{1}{\sqrt{2\pi}\sigma^5} (x^2 - \sigma^2) e^{-\frac{x^2}{2\sigma^2}}$$

where $G(x)$ is the Gaussian distribution, and x is the coordinate axis perpendicular to a specific direction α_i , and σ is the spatial spread parameter, which corresponds to the standard deviation. We varied i from 1 to 4 ($\alpha_1 = 0$, $\alpha_2 = \pi/4$, $\alpha_3 = \pi/2$, $\alpha_4 = 3\pi/4$) and obtained four processed images by using these four-directional Laplacian-Gaussian filters. The matrix size of this filter was 15×15 pixels ($2.625 \text{ mm} \times 2.625 \text{ mm}$), and the width of a line at the center of this filter was set to 5 pixels (0.875 mm). The spatial frequency to be detected can be adjusted by selection of a suitable σ . This enables us to detect the opacities that correspond to interstitial lung abnormalities. We set σ at 0.438 mm in this system, because of the relationship $w = 2\sigma$, where w is the width of the line at the center of the filter. Because the likely diameters of peripheral-vessel opacities were thought to be approximately 0.5 to 1.0 mm , w should be set to a lower value. The same Laplacian-Gaussian filter was used for all images.

In the filtering process, some peripheral parts of the ROI cannot be filtered. Therefore, the following processing was performed in a submatrix of 256×256 ($44.8 \text{ mm} \times 44.8 \text{ mm}$).

The process of binarization needs the following steps: Individual binarization was done for each image that had been processed with the four-directional Laplacian-Gaussian filter. Next, the binary summation image was obtained by logical addition of the four binary images. To do the individual binarization, in a preliminary study, we first selected five candidates of the threshold for 20 cases, based on the observations of the radiologists. These were not included in this study population. We next chose one threshold for this system, based on the results of this preliminary study. This same fixed threshold was applied to all images.

Linear Opacity Judgment Processing and Subtraction Processing

For selective extraction of linear opacities in an ROI, linear opacity judgment processing by the search line method¹⁰ was performed on the four binary Laplacian-Gaussian-filtered images separately. The search line method is a method of detecting straight line segments directly on the image plane.

First, a search line of θ and L_s was selected on all pixels within the ROI, where θ was a certain direction and L_s was predetermined fixed the number of pixels corresponding to the length of the search line. Next, the number N of pixels (pixels with values greater than zero) on the search line was counted. If N was greater than the threshold, T_s , these pixels on that search line were determined to be elements of linear opacity. Thus, in this interpolation process, all elements on the search line judged as linear opacity were regarded as elements of linear opacity therefore, when pixels were not distributed continuously, they were interpolated between the pixels that were determined to be elements of linear opacity. For each pixel in the image, this process was repeated for θ at intervals of $\pi/36$ within a range of $\alpha_i - \pi/4$ to $\alpha_i + \pi/4$. For each i ($\alpha_1 = 0$, $\alpha_2 = \pi/4$, $\alpha_3 = \pi/2$, $\alpha_4 = 3\pi/4$), the processed image of linear opacity judgment processing was obtained. Finally, the summation image was

obtained by adding of the four processed images of linear opacity judgment processing. In this study, we determined that L_s was 30 pixels (5.25 mm) and T_s was 24 pixels. The linear opacity judgment processing images in Fig 3, obtained from a normal case and an abnormal case, correspond, respectively, to the normal case and the abnormal case in Fig 1. Figure 3A is the processed image of the normal case, and Figure 3C is the processed image of the abnormal case.

In linear opacity judgment processing, short linear elements below the threshold of the filtered image could not be extracted. For evaluation of the degree of severity of interstitial lung

disease, which included various types of radiographic patterns, another method that used short linear elements was needed. To use the short linear elements that were not extracted by the search line method, we employed the linear opacity subtraction technique. The subtraction image $C(i,j)$ is defined by the following expression:

$$C(i, j) = A(i, j) - B(i, j);$$

$$\text{if } C(i, j) < 0, \text{ then } C(i, j) = 0,$$

where $A(i,j)$ is the image obtained from four-directional Lapla-

Fig 3. Outputs of linear opacity judgment and linear opacity subtraction processing in selected ROIs (256 × 256 matrix size). (A) Image of an ROI for a normal lung, obtained by linear opacity judgment processing. White regions are judged as linear opacities by linear opacity judgment processing. (B) Image of an ROI for a normal lung, obtained by linear opacity subtraction processing. Gray regions indicate subtracted regions by linear opacity subtraction, and white regions indicate opacities obtained by subtraction processing. (C) Image of an ROI for an abnormal lung, obtained by linear opacity judgment processing. (D) Image of an ROI for an abnormal lung, obtained by linear opacity subtraction processing. (Reprinted with permission.¹⁶⁾)

cian-Gaussian filtering and binarization, and $B(i,j)$ is the image obtained from linear opacity judgment. To eliminate the linear opacities of anatomic structures, we used a greater length L_s for the search line and a higher threshold T_s than were used for the previous linear opacity judgment method. The value of L_s was 50 pixels (8.75 mm), and that of T_s was 40 pixels. The linear opacity subtraction images in Fig 3, obtained from a normal case and an abnormal case, correspond, respectively, to the normal case and the abnormal case in Fig 1. Figure 3B is the processed image of the normal case, and Figure 3D is the processed image of the abnormal case.

Normalization of the Radiographic Index

To evaluate interstitial lung opacities quantitatively, we defined a radiographic index, d . This is the percent area of extracted opacities of the ROI. With this method, we were able to obtain three different radiographic indices as physical measures. One was d_{bin} , expressing the percent area of the binary summation image $A(i,j)$ in the ROI obtained by four-directional Laplacian-Gaussian filtering and binarization. The second was d_{lin} , expressing the percent area of the linear opacity judgment summation image $B(i,j)$ in the ROI, and the last was d_{sub} , expressing the percent area of the subtraction image $C(i,j)$ in the ROI. In Fig 3, each d_{bin} was obtained from Figures 3A and 3C, and each d_{sub} was obtained from Fig 3B and 3D. Each d_{bin} was obtained from the images processed by four-directional Laplacian-Gaussian filtering and binarization, which were used in the linear opacity judgment processing and subtraction processing.

In this study, we employed a new index calculated from the radiographic indices obtained from the linear opacity judgment output image and its subtraction image. To define the new index, we normalized these radiographic indices by using the average and standard deviation of the radiographic indices obtained from the normal control group, which was not included in the study population. We used 25 cases for normal control group. We define the normalized radiographic index D by the following expression:

$$D = (d - d'_m) / \sigma'_m$$

where d'_m is the average value of the radiographic indices in the control group and σ'_m is the standard deviation of those. This normalization was performed for the right upper lung area and for the right lower lung area. The normalized radiographic indices D_{bin} , D_{lin} , and D_{sub} were obtained from the ROIs processed by four-directional Laplacian-Gaussian filtering and binarization, linear opacity judgment, and linear opacity subtraction, respectively.

Combined Radiographic Index

To detect interstitial lung abnormalities in both mild and severe cases, we employed a new quantitative physical index, which we called the "combined radiographic index, D_{com} , which was obtained from two different radiographic indices, D_{lin} and D_{sub} . This new combined radiographic index is defined by the following expressions:

$$D_{com} = \text{minimum}(D_{lin}, D_{sub}) \quad \text{for } D_{lin} < 1 \text{ and } D_{sub} < 1$$

$$D_{com} = \text{maximum}(D_{lin}, D_{sub}) \quad \text{for } D_{lin} \geq 1 \text{ and } D_{sub} \geq 1$$

$$D_{com} = (D_{lin} + D_{sub})/2 \quad \text{otherwise}$$

ROC Analysis

The ability to detect interstitial lung abnormalities on chest radiographs with these radiographic indices was evaluated by receiver operating characteristic (ROC) analysis.¹¹⁻¹⁴ To produce ROC curves, we used a five-level scale of confidence that described the presence of abnormalities. The classification of severity for each index was defined as follows:

$$T = 0 \quad \text{for} \quad D < 0.5$$

$$T = \text{int}(D) \quad \text{for} \quad 0.5 \leq D < 3.5$$

$$T = 4 \quad \text{for} \quad D \geq 3.5$$

where T is the number of categories, D is a normalized radiographic index or a combined radiographic index, and "int" is the operator, which makes D into an integer. T represents the degree of severity (0 is minimum and 4 is maximum). To compare the performances of normalized radiographic indices, the areas under the ROC curves (A_z)¹⁵ were compared by use of the CORROC2 computer program (Metz CE, Department of Radiology, University of Chicago, Chicago, IL), which compares ROC curves derived from correlated data sets.

RESULTS

Figure 4A and Table 1 show the results for the normal group and for the entire interstitial lung abnormality group. The combined radiographic index, D_{com} ($A_z = 0.96 \pm 0.16$), was significantly better than the normalized radiographic index, D_{bin} , obtained from the ROIs processed by four-directional Laplacian-Gaussian filtering and binarization ($A_z = 0.94 \pm 0.21$; $P = .027$), the normalized radiographic index, D_{lin} , obtained from the ROIs processed by linear opacity judgment ($A_z = 0.87 \pm 0.35$; $P = .002$), and the normalized radiographic index, D_{sub} , obtained from the ROIs processed by linear opacity subtraction ($A_z = 0.90 \pm 0.04$; $P = .005$).

Figure 4B and Table 1 show the results for the normal group and the mild interstitial lung abnormality group. The combined radiographic index, D_{com} ($A_z = 0.94 \pm 0.02$) was significantly better than the normalized radiographic index, D_{bin} , ($A_z = 0.89 \pm 0.03$; $P = .011$) and the normalized radiographic index, D_{lin} , ($A_z = 0.81 \pm 0.05$; $P = .0004$). However, there were no significant differences between D_{com} and the normalized radiographic index, D_{sub} , ($A_z = 0.90 \pm 0.04$; $P = .26$).

Figure 4C and Table 1 show the results for the normal group and the severe interstitial lung abnormality group. There were no significant differences between D_{com} ($A_z = 0.98 \pm 0.01$) and D_{bin} ($A_z = 0.99 \pm 0.01$; $P = .71$), and D_{com} and D_{lin} ($A_z = 0.99 \pm 0.01$; $P = .27$). However, D_{com} was

Fig 4. Results of evaluation by our computerized analysis system. (A) ROC curves for distinction between ROIs of normal lungs and ROIs with entire interstitial lung abnormalities. Dcom is better than other indices. (B) ROC curves for distinction between ROIs of normal lungs and ROIs with mild interstitial lung abnormalities. Dcom is better than Dbin and Dlin. ROC curve for Dcom is above that for Dsub. However, there are no significant differences between Dcom and Dsub. (C) ROC curves for distinction between ROIs of normal lungs and ROIs with severe interstitial lung abnormalities. There are no significant differences among Dcom, Dbin, and Dlin. However, these indices are better than Dsub.

significantly better than Dsub ($Az = 0.83 \pm 0.06$; $P = .0072$).

For Dcom, Dbin, and Dlin, the detection of interstitial lung abnormalities in the severe group was better than that in the mild interstitial lung

abnormality group (Dcom: $P = .022$, Dbin: $P = .0009$, Dlin: $P = .0001$; respectively). For Dsub, however, there were no significant differences between the normal group and the severe interstitial lung abnormality group ($P = .30$).

Table 1. Areas Under ROC Curves for Interstitial Lung Abnormalities

	Total	Mild	Severe
Dbin	0.94 ± 0.21	0.89 ± 0.03	0.99 ± 0.01
Dlin	0.87 ± 0.35	0.81 ± 0.05	0.99 ± 0.01
Dsub	0.90 ± 0.04	0.90 ± 0.04	0.83 ± 0.06
Dcom	0.96 ± 0.16	0.94 ± 0.02	0.98 ± 0.01

NOTE. Each value is the mean $\pm$ 1 standard deviation.

Abbreviations: Dbin, four-directional Laplacian-Gaussian filtering; Dlin, linear opacity judgment; Dsub, linear opacity subtraction; Dcom, combined radiographic index.

DISCUSSION

To improve the performance of our computerized analysis system, we attempted to use short extracted linear opacity elements that were ignored in our previous computerized analysis system. For this reason, we added a third-stage process that subtracted the second image, processed by linear opacity judgment, from the first image, processed by four-directional Laplacian-Gaussian filtering and binarization. Furthermore, to evaluate interstitial

lung opacities quantitatively, we defined normalized radiographic indices.

In the mild interstitial lung abnormality group, Dsub performed better than did Dlin. Conversely, in the severe interstitial lung abnormality group, Dlin performed better than did Dsub. The reason for these results can be explained as follows:

Fewer extracted opacities were processed by linear opacity judgment in the mild interstitial lung abnormality group than in the severe interstitial lung abnormality group. However, in both groups, similar numbers of extracted opacities were normal anatomic structures, such as ribs and vessels. Therefore, in cases involving mild interstitial lung abnormalities, a higher proportion of extracted opacities that were normal anatomic structures than in cases involving severe interstitial lung abnormalities. These results suggest that Dlin was less quantitative in the mild interstitial lung abnormality group than in the severe interstitial lung abnormality group, because the effect of normal anatomic structures was relatively greater in the former group. Conversely, Dsub performed better in the mild interstitial lung abnormality group. Because the proportion of elements not judged to be linear opacities was relatively greater, and as a result of the subtraction process, the effect of normal anatomic structures could be ignored.

With four-directional Laplacian-Gaussian filtering and binarization, extracted elements were more densely distributed in severe than in mild interstitial lung abnormalities. With the search line method in the linear opacity judgment process, the more densely the extracted elements are distributed, the more easily they are judged as elements of linear opacities, and the greater is the number of pixels interpolated as elements of linear opacity. Therefore, the extracted elements in severe interstitial lung abnormalities tended to be more easily judged as elements of linear opacities than were the more sparsely distributed elements in mild interstitial lung abnormalities. After the linear opacity subtraction process, more opacities were obtained in the severe interstitial lung abnormality group than in the mild interstitial lung abnormality group; however, fewer opacities were obtained than were expected when compared with cases involving mild interstitial lung abnormalities. This difference degraded the performance of Dsub compared with that of Dlin in the severe interstitial lung abnormality group.

Our results suggest that, in the mild interstitial lung abnormality group, it would be better to use Dsub, obtained from the linear opacity subtraction process; however, in the severe interstitial lung abnormality group, it would be better to use Dlin, obtained from the linear opacity judgment process. A physical measure that is useful in cases with both mild and severe interstitial lung abnormalities would be desirable. We thought that we could get better performance by combining the two indices. The new single combined radiographic index, Dcom, provided better results in the mild than in the severe interstitial lung abnormality group, but also showed good results in the severe interstitial lung abnormality group. This index was superior to either Dlin or Dsub alone.

Our previous computerized analysis system uses the process of four-directional Laplacian-Gaussian filtering and linear opacity judgment. From this system, we could obtain Dbin and Dlin. As a result of adding a linear opacity subtraction process to our previous computerized system, we could employ Dcom. The performance of Dcom is significantly superior compared with each performance of Dbin and Dlin in the mild interstitial lung abnormality group, and the performance of Dcom is equivalent to each performance of Dbin and Dlin in the severe interstitial lung abnormality group. So, we could improve the performance of our computerized analysis system compared with our previous system, especially in the mild interstitial lung abnormality group.

In daily clinical practice, the diagnosis of interstitial lung abnormalities in the chest radiography is important. However, this is a difficult problem for radiologists, especially in the case of mild interstitial lung abnormality. In such a case, our computerized analysis system could provide the quantitative data about the degree of interstitial lung abnormalities to the radiologist, and the images themselves to confirm the results. So, our system might help radiologists diagnosis interstitial lung abnormalities in chest radiography.

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