Image Recognition and Its Application to Radiograph

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화상인식과 X선 영상에의 응용에 관한 연구

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ABSTRACT

In this study, we propose a method for quantifying the degree of advance of pulmonary emphysema by using chest X-ray images. With this method, we devise two schemes for this purpose. One is for detecting blood vessels by using a deformable model with the tree-like structure and using an evaluation function specialized by knowledge about blood vessels appeared in chest X-ray images, and the other is for quantifying the degree of advance by using several features, which were extracted from blood vessels, and the equation of quantitative evaluation. In order to evaluate the performance, we applied the proposed method to 189 ROIs(Regions of Interest) of ten chest X-ray images and compared the values by the proposed method with those by a medical doctor.

요 약

본 연구는 디지털 화상처리기술의 대표적인 응용분야로서 주목받고 있는 X선 사진을 대상으로 한 계산기 지원진단에 관한 연구의 일종으로서, 폐의 중요한 질환중 하나인 폐기종의 진단을 지원하는 계산기 시스템에 관한 연구이다. 구체적인 내용으로서는 흉부X선 사진으로부터 말초혈관을 자동추출하고, 추출된 혈관을 토대로 여러가지의 특징량을 구하여, 최종적으로 폐기종의 병세진행도를 정량평가하는 시스템에 관한 연구이다. 혈관도형을 추출하여 병의 진행 정도를 정량적으로 평가하기 위해 본 연구에서 제안한 평가방법을 10장의 X선 사진에 설정된 189개의 관심영역에 적용하여, 의사의 평가치와 본 연구의 제안방법에 의한 평가치를 비교·검토함으로써 그 유효성을 검증하였다.

키워드: image recognition, chest X-ray image, computer-aided diagnosis, deformable model

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Ⅰ. Introduction

Pulmonary emphysema is one of the diseases of lung, which may be mainly due to smoking, infection of respiratory organ, aging and so on. Since there is no way to restore the damaged lung to its original state, it is very important to check the degree of its advance for making appropriate decision on prescription and rehabilitation.

Its diagnosis is mainly carried out with chest X-ray image, CT image, ECG(Electrocardiogram), test of bronchi. With chest X-ray images, a medical doctor diagnose its advance as normal or severe with several clues such as widths of blood vessels, flatness of diaphragm, transparency in lung area, and so on.

Since, under its progress, the blood vessels are damaged due to disorganization of alveoli around them, they look like thin and clear, and finally come to be not seen on the images if the progress is severe. Therefore, it is said usually to be strong correlation between the status of blood vessels and the advance of pulmonary emphysema.

However, since chest X-ray images have low signal-to-noise(S/N) ratio and complex underlying background, it is very difficult task to find blood vessels, and to extract some features which have relation to the status of them.

In this study, we propose a method for quantifying the degree of advance of pulmonary emphysema by using chest X-ray images. With this method, we devise two schemes for this purpose. One is for detecting blood vessels on chest X-ray images, and the other is for quantifying the degree of its advance by using several features extracted from blood vessels.

In order to detect blood vessels on the images, the devised scheme uses a deformable model. Recently, ACM(Active Contour Model) has been applied to wide research fields for extracting contours of shapes[1]-[6]. And it was shown that those models work well even though the input image has low S/N ratio and is lacking in information about the density around the boundaries of shapes[3]-[4]. However, since those models have been described as an open or a close curve, they are supposed to be not suitable for extracting the boundaries of shapes which have complicated and tree-like structure such as blood vessels in lung area on chest X-ray images. Also, several researches for detecting blood vessels from X-ray images have been reported[7]-[9]. However, since all of those researches have used the images in which coronary artery shadows were enhanced by barium and shown high S/N ratio, they also seem to be not appropriate to detect blood vessels in conventional chest X-ray images.

Therefore, we propose, in this paper, a deformable model with tree-like structure and its evaluation function which is specialized by knowledge about blood vessels appeared in chest X-ray images. Also, in order to quantify the degree of advance of pulmonary emphysema, we devise a scheme in which information about detected blood vessels is used. As explained previously, a medical doctor diagnoses the degree of its advance mainly with information about the status of blood vessels. Therefore, in this scheme, the quantitative evaluation is carried out by using several features which are expected to be in variation with the degree of its advance.

The outline of this method is described briefly in section 2, and the details of structure and evaluation function of the proposed deformable model are defined in section 3. In section 4, we present a scheme for detecting blood vessels and its experimental results. And the details of a scheme for quantifying the degree of advance of pulmonary emphysema and its experimental results will be shown in sections 5 and 6, and finally the conclusion will appears in section 7.

Ⅱ. Outline of the proposed method

The outline of this method is described briefly below and in Fig.1. Firstly, regions of interest(ROI) are set between ribs on a digitalized chest X-ray image. And then, blood vessels in each ROI are detected by means of the devised deformable model, and finally, by using several features measured from those blood vessels, quantitative evaluation of the degree of its advance is carried out.

Ⅲ. Structure and evaluation function of the devised deformable model

3.1 Structure of the deformable model

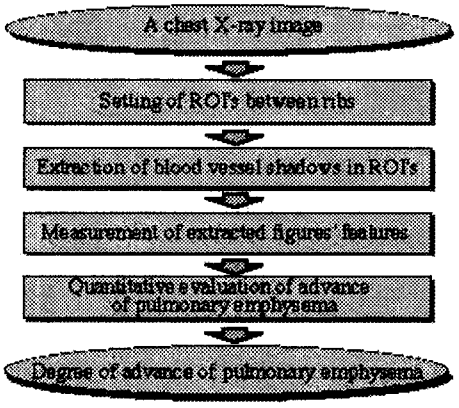


Fig. 1 Outline of the proposed method

The devised deformable model is motivated from the characteristics of blood vessels such as tree-like structure and stick-like shape. Fig.2 shows its structure. This model is composed of one or more branches, and each branch consists of a center line and two boundaries on both sides of the line. The center line means a medial axis, and two boundaries represent both side outlines of blood vessel. Since, contrary to the previous models, this model consists of a center line and two boundaries, it is expected to be suitable for describing the shape of blood vessels properly.

Center control points are placed on the center line, and have their own widths of blood vessels. And by using the positions and the widths of them, boundary control points are decided as shown in Fig.3. Actually, detection of blood vessels is done by moving these control points according to the maximization of evaluation function.

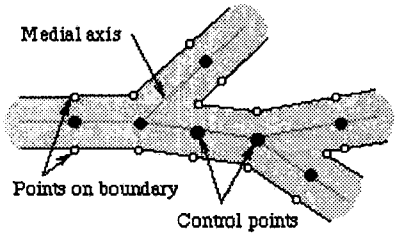


Fig. 2 Structure of the proposed deformable model

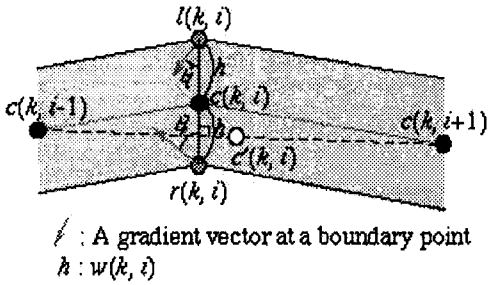


Fig. 3 Control points on a center line and two boundaries

3.2 Definition of evaluation function

As shown in Fig.3, $c(k,i)$ is the ith control point of the kth branch on center line, and $w(k,i)$ is the width at $c(k,i)$. Control points $r(k,i)$ and $l(k,i)$ on both boundaries are placed on the positions where $w(k,i)$ apart from $c(k,i)$ along the normal to the direction of the line connecting the locations $c(k,i-1)$ and $c(k,i+1)$, respectively.

The evaluation function of the model is defined as

$$E_{total} = \sum_{k=1}^{M} \sum_{i=1}^{N} \{ E_{inn}(k,i) + E_{ext}(k,i) \} \quad (1)$$

where M is the number of branches belonging to

the model, and N_k is that of control points on the kth branch. $E_{inn}(k,i)$ and $E_{ext}(k,i)$ represent the internal and the external evaluation function at $c(k,i)$, respectively, and they are defined as

$$E_{inn}(k,i) = \omega_1 E^{c}_{inn}(k,i) + \omega_2 E^{w}_{inn}(k,i) \quad (2)$$

$$E_{ext}(k,i) = \omega_3 E^{c}_{ext}(k,i) + \omega_4 E^{r}_{ext}(k,i) + \omega_5 E^{l}_{ext}(k,i) \quad (3)$$

where $\omega_1 \sim \omega_5$ are the weights of each evaluation function.

3.2.1 Internal evaluation function of center line (E^{c}_{inn})

The internal evaluation function at control point $c(k,i)$ is defined as

$$E^{c}_{inn}(k,i) = 1.0 - \left(\frac{\left| \vec{v}(c'(k,i)) - \vec{v}(c(k,i)) \right|}{\bar{L}(k)} \right) \quad (4)$$

where $c'(k,i)$, as shown in Fig.3, is the point set on the mid-position between $c(k,i-1)$ and $c(k,i+1)$, $\vec{v}(a)$ means the position vector of point a, and $\bar{L}(k)$ represents the mean distance between two adjacent points belonging to the kth branch. E^{c}_{inn} comes to be maximum when every control points are on a straight line and with same interval.

3.2.2 Internal evaluation function of width (E^{w}_{inn})

This function is for making the widths of shape almost same at each control point on center line, and is given as below

$$E^{w}_{inn}(k,i) = 1.0 - \left(\frac{\left| w(k,i) - \bar{w}(k) \right|}{\bar{w}(k)} \right) \quad (5)$$

where $w(k,i)$ is the width at $c(k,i)$, $\bar{w}(k)$ is the average width of the kth branch. This definition is basing on the assumption that the widths at every control points of any branch are not varied severely and almost same if the branch is enough short.

3.2.3 External evaluation function of center line (E^{c}_{ext})

Since, along cross-sectional line of blood vessel, the density of its center is higher than those of other places, this function works each control point of center line for being moved to the center of shape. Actually, E^{c}_{ext} represents, with this scheme, the average of the densities calculated on two line segments connecting $c(k,i-1)$ and $c(k,i)$, $c(k,i)$ and $c(k,i+1)$, respectively. The density means gray value of the image after the process of scale space explained afterward.

3.2.4 External evaluation functions of both boundaries (E^{r}_{ext} and E^{l}_{ext})

Based on the fact that the magnitudes of gradient vectors in the region of boundary are greater than those of other places, these functions are defined as

$$\begin{cases} E^{r}_{ext}(k,i) = g(r(k,i)) \cos\theta_r \\ E^{l}_{ext}(k,i) = g(l(k,i)) \cos\theta_l \end{cases} \quad (6)$$

where $g(r(k,i))$ is the magnitude of gradient vector at control points $r(k,i)$, and θ_r is the angular differences between the direction of gradient vector at $r(k,i)$ and that of the line connecting $r(k,i)$ and $l(k,i)$.

These functions are for moving control points on both boundaries to the positions where the magnitudes of gradient vectors are high and the

angular differences are small. The magnitude of gradient vector will be discussed in next section.

3.3 Definition of density and magnitude of gradient vector

Since the regions of lung on chest X-ray images have not only complex background, but also several widths of blood vessels, it is not so easy to detect blood vessels by using a fixed-size filter. With this scheme, in order to detect correctly several widths of blood vessels, scale space which is made by convoluting the input image with several sizes of filters is used when calculating the density and the magnitude of gradient vector.

When the density at (x, y) of input image is $f(x, y)$, the density $F(x, y)$ is defined newly as below and used in calculating the external evaluation value of center line.

$$F(x,y) = \max_{\sigma_L \le \sigma \le \sigma_H} \left\{ \frac{f(x,y) * G(x,y,\sigma)}{\sigma_{f*G}} \right\} \quad (7)$$

Where $G(x, y, \sigma)$ is the gaussian filter with standard deviation(S.D.) σ which varies from the lowest scale σ_L to the highest scale σ_H, " $*$" means convolution, and " σ_{f*G} " is the S.D. of density after convoluting $f(x, y)$ with $G(x, y, \sigma)$. And the largest value of $||(g_x^{(\sigma)}, g_y^{(\sigma)})||$ from σ_L to σ_H is taken as the magnitude of gradient vector at (x, y).

Ⅳ. Scheme for detecting blood vessels

This scheme detects blood vessels in lung region on chest X-ray image by using both the deformable model and the evaluation function described previously. The overall procedure of this scheme is shown in Fig.4.

With this scheme, when a initial model is placed on the input image, it deforms its shape by moving the control points to the place on which the evaluation value becomes maximum, until the number of unmoved control points reaches the threshold T. Also during deforming, the model elongates and cuts its branches, and integrates with other branches too. Details of each operation are explained as follows.

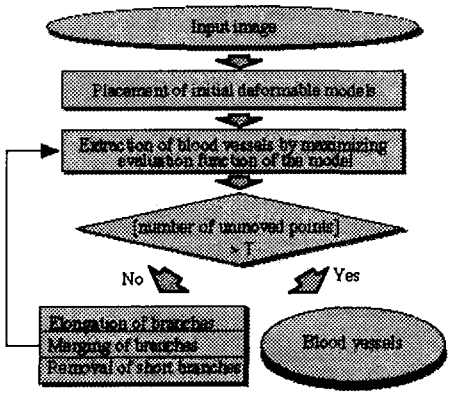


Fig. 4 Overall procedure of the scheme for detecting blood vessels

4.1 Initialization of the model

The input image is convoluted with Laplacian Gaussian filter, then the convoluted image is binarized with the threshold 0. And the binarized image is thinned resulting in a image which has the value 1 on the thinned line segments and 0 on the background.

The above operations are iterated from σ_H to σ_L with interval 1(pixel), and then the results with each scale are filed up on an image. With reverse Euclidean distance transform[10], the filed-up image changed to the binarized image where the region of blood vessel is valued as 1 and that of background is 0. The region of blood vessels is thinned to line segments, and then the initial model is created by putting the control points on this line segments with the widths of 5 pixels.

4.2 Deforming the model by maximization of evaluation function

As explained previously, detection of blood vessels is carried out by deforming the model under the rule of maximization of evaluation value. Actually, the initial model deforms its shape by moving the positions of control points and by changing the widths at those points until it reaches maximum evaluation value.

In this operation, we employed Greedy algorithm[11] as a rule of maximization of evaluation value. This algorithm finds new positions and widths of all control points, so as that those points have maximum evaluation value, by computing sequentially their evaluation values at current locations and 8-neighbors while changing current widths (+1,0,-1) simultaneously.

4.3 Elongation and integration of the model during deformation

Since the center lines, used in making the initial model, are not guaranteed in the fact that there is nothing wrong or insufficient among its branches, the model, while deforming, elongates and cuts its branches, or integrates with other branches.

The model decides the length D, as described in Eq.8, for elongating its branches.

$$D=2.5\times\left[F(c_e)+\frac{\{g(r_e)+g(l_e)\}}{2}\right]\times(1-\cos\theta_{rl}) \quad (8)$$

Where $F(c_e)$ is the density at the end control point of a branch, $g(r_e)$ and $g(l_e)$ are the magnitudes of gradient vectors at r_e and l_e on both boundaries, respectively, and $\cos(\theta_{rl})$ is the angular difference between the gradient directions at r_e and l_e. Actually the greater the magnitudes of gradient at both boundaries are and the smaller the difference between their directions is, the longer D is. As shown in Fig.5, the model elongates its branch with the length D to the direction parallel to the line connecting the end and its adjacent control point.

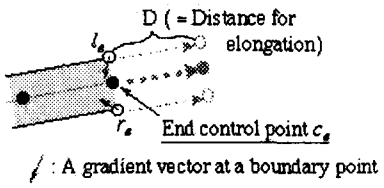


Fig. 5 Elongation of a branch

Also, the model searches an area in order to check whether its branches collide or not with other ones. That search area is defined as shown in Fig.6.

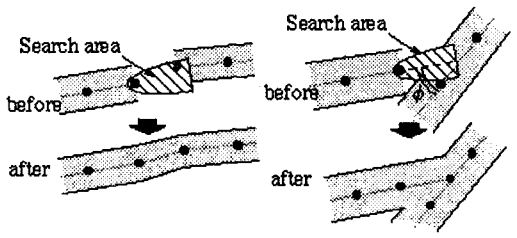
If its branch collides with the end parts (type I) or middle parts (type II) of other one, two branches are integrated to one. Fig.6(a) and (b) show the search areas and the results of integration progress of type I and II, respectively. In case of type II, if the angle ϕ is within 68 and 112 degree, two branches are considered to be in cross situation and not integrated.

Moreover, the model checks the length of each branch, and cuts short branch among them if its length is below 1mm. That is the reason why a short branch is supposed to be either detected wrongly in the process of thinning or due to the noise in background.

V. Scheme for quantifying the degree of advance

In order to quantify the degree of advance, we extract three features from blood vessels detected in chapter 4. One of them is the feature about the widths, another is about the number, and the other is about the clearness of blood vessels. These features are based on the characteristics of the status of blood vessels under the progress of pulmonary emphysema. With its progress, blood vessels look like thin and clear, and finally become unvisible on chest X-ray images when the progress

come to be severe.



(a) Type I (b) Type II

Fig. 6 Integration of two branches

With this scheme, since we intend to quantify the degree of advance of a person by comparing three features from current image with those from the image taken when he was in normal status, we need essentially such normal images. However, because it is difficult to get those images, we should make typical three features of normal case by several images diagnosed as normal by a medical doctor.

Usually, due to variances of personality, condition of taking picture and digitalization, each chest image has its own characteristics of density. Therefore, in order to make these features reasonable in spite of such variances, we should correct them according to the characteristics of density.

The variance due to personality come to be appeared mainly as the discrepancy of widths of blood vessels. This variance is corrected by measuring the width of a blood vessel which is supposed to be in the same position and not affected by any other diseases except pulmonary emphysema, and then by normalizing their widths measured from each image such like Eq.9.

$$\bar{w}_t = \frac{H_t}{H_s} w_t \tag{9}$$

Where H_t and H_s are the width of the blood vessel measured by densitometric method[12] from a test and a standard images, respectively. w_t and $\bar{w}_t$ are the widths of blood vessel before and after correction, respectively. In this study, we call the evaluated image a test image and the image made by averaging several normal images a standard image.

The variance due to condition of taking picture and digitalization appears as difference of the distribution of density. In order to correct this difference, we extract the region of lung, and measure the mean density in that region, and then normalize the density of each image by using this measurement.

5.1 Definition of three features

5.1.1 Feature about the widths of blood vessels

This feature is for measuring how thin blood vessels are in comparison with those of normal status. As explained previously, blood vessels damaged with the organization of alveoli around them by pulmonary emphysema become thinner than those of normal status.

We define this feature as below by using two distributions of widths of blood vessels in ROIs of both a test image and a standard image.

$$F_W = \frac{(E\{w_s\} - E\{w_t\})}{(\sqrt{V\{w_s\}} + \sqrt{V\{w_t\}})/2} \tag{10}$$

where $E\{w\}$ and $V\{w\}$ represent the mean and the variance of w, respectively. The thinner blood vessels are, the greater the feature F_W becomes.

5.1.2 Feature about the number of blood vessels

This feature is based on the fact that, under severe progress of pulmonary emphysema, blood vessels come to be disappeared on chest images. On the assumption that the number of blood vessels has relation to their cross-sectional densities, it is defined as below by using the ratio of the sum of densities belonging to the region of blood vessels.

$$F_A = 1.0 - (D_t / D_s) \tag{11}$$

where D_t and D_s are the sum of densities of blood vessels' region in a test and a standard

image.

5.1.3 Feature about the clearness of blood vessels' boundaries

As shown in Fig.7 and explained previously, blood vessels look like thinner and clearer than those in normal status with the progress of pulmonary emphysema. Usually, the magnitude of gradient vector is used to represent the clearness of boundary. However, as shown in Fig.8, since each chest image has its own characteristics on the density, the gradient is not suitable for representing this feature. Therefore, we define this feature as follows.

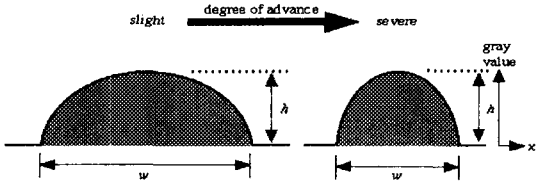


Fig. 7 Variation of the value d in Eq. 12 due to the degree of advance

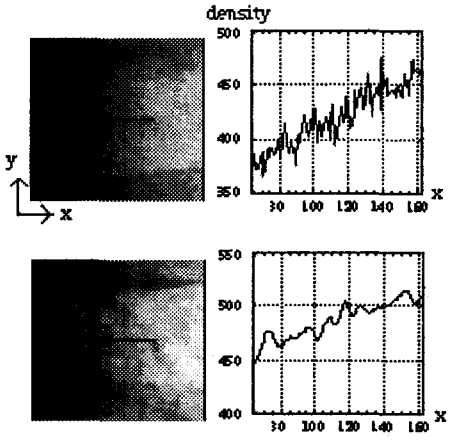


Fig. 8 Comparison of density profiles of two images

$$F_G = \frac{(E\{d_s\} - E\{d_t\})}{(\sqrt{V\{d_s\}} + \sqrt{V\{d_t\}})/2} \quad (12)$$

where d_s and d_t are the values obtained by dividing the width w of blood vessel by the difference h between density of center and that of background in standard and test image, respectively. In this study, the difference is calculated by background substruction after surface fitting with the density of background.

5.2 Definition of quantitative evaluation

With three features, the equation for calculating the value concerning the degree of advance is defined as follows.

$$\tilde{E}_V = \alpha_1 F^2_W + \alpha_2 F^2_A + \alpha_3 F^2_G + \alpha_4 F_W + \alpha_5 F_A + \alpha_6 F_G + \alpha_7 \quad (13)$$

Where $\alpha_1 \sim \alpha_7$ are weights of each term.

Ⅳ. Experimental results and discussion

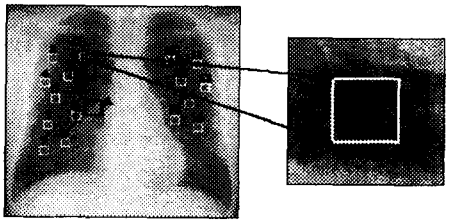
We have applied the proposed method for quantifying the degree of advance, outlined above, to ten chest X-ray images. These images were digitalized in 3520×3520 or 3556×3556 pixel with sampling interval 0.1(mm/pixel) by ten bits. The ROIs were set on inter-ribs of these images in 70 to 100 square pixels with care of not crossing rib shadows. In order to take account of the processing for image's edge, we actually used the images in 230×230 pixels which including ROIs amid.

In this experiments, there were about nineteen ROIs placed in a chest image, and parameter values used for scale space and evaluation functions were σ_L=5, σ_H=15 (pixel), w_1= w_3= w_4=1.3 and w_2= w_5=1.0.

6.1 Experimental results of detecting blood vessels

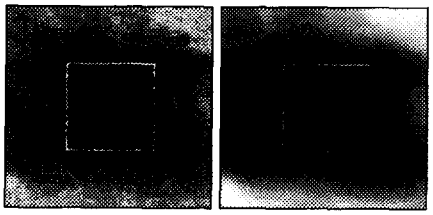
Fig.9(a) shows a digitalized chest image including sixteen ROIs, and Fig.9(b) shows a partial image including ROI No.1 of (a) with white frame. With the input image of Fig.9(b), its initial models(a),

density(b) and magnitude of gradient images(c) used in model's deformation, and finally detected blood vessels(d) which are superimposed on the input image, were shown in Fig.10. This detection of blood vessels took 150 seconds with 191 control points.

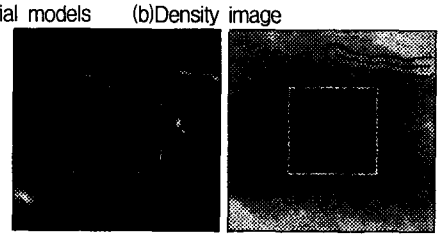


(a) (b)

Fig. 9 A chest image(a) and a partial image(b) including No.1 ROI of (a)



(a)Initial models (b)Density image

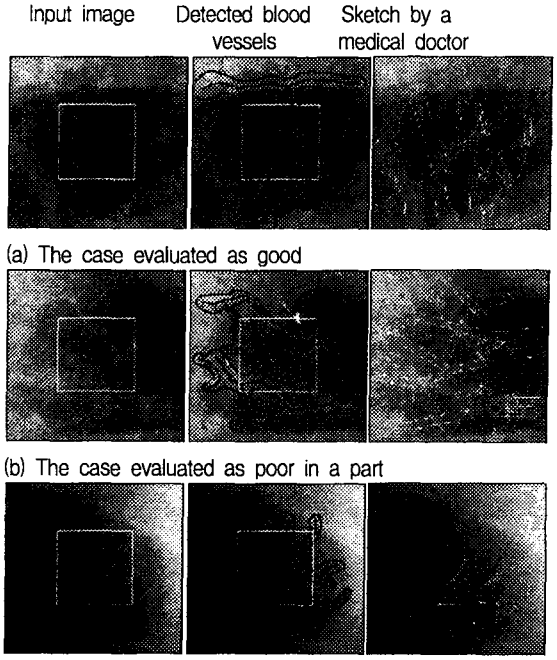


(c)Gradient image (d)Detected blood vessels

Fig. 10 Experimental result of Fig.9(b)

We have detected blood vessels from 189 ROIs of ten chest images, and evaluated the performance of the proposed scheme by comparing detected blood vessels with their sketches by a medical doctor. The performance was evaluated with two viewpoints : 1)whether there is any blood vessel wrongly or not detected, 2)how similar the shapes of detected blood vessels are to those of real ones. Fig.11(a) represents a sample evaluated as good in both viewpoints, (b) is one in which a blood vessel was not detected at the position of white arrow, and (c) as poor in both viewpoints because there are too many vessels detected wrongly.

With evaluation of this scheme's performance, we found the fact that blood vessels were detected well in above 90 percentage among all ROIs.



(c) The case evaluated as poor

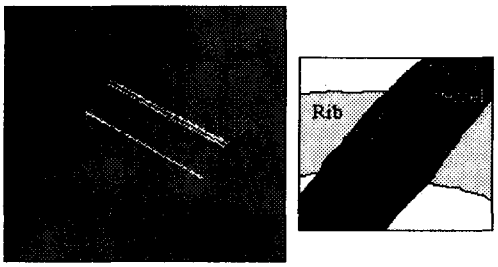
Fig. 11 Other experimental results

6.2 Experimental results of Quantitative evaluation

We have measured three features from detected blood vessels of 189 ROIs. The width of blood vessel for correcting the variance due to personality is measured around the region of hilum of lung, such like the region A of Fig.9(a). Fig.12 shows that region A in which the width of blood vessel is described as the length of white line for correction.

Fig.13 shows the comparisons of each feature between the values obtained by this scheme and the ones evaluated by a medical doctor. A medical doctor evaluates every ROI with each feature in

three steps. The criterion of each step is shown in Table 1. The remark $p<0.05$ on the graph represents that, by Mann-Whitney's Test, there is significant difference between two distributions with 5% of level of significance. These graphs show that three features are useful for quantifying the degree of advance with this scheme. Correlation coefficients among three features were : 0.422 between F_W and F_A, 0.170 between F_W and F_G, 0.350 between F_A and F_G, and these coefficients also show the fact that three features were reasonable.



(a) (b)

Fig. 12 A blood vessel for correction(a) and its width described as three white lines(b)

Quantitative evaluation is carried out by inserting these features to Eq.13. The reason why this kind of equation is used is that, as shown in Table 2, the differences of mean between the groups of ROIs divided by a medical doctor are not varied linearly. And each weight is decided in order that the square-root-error between $\tilde{E}_V$ and E_V, the values of advance evaluated by this method and by a doctor, come to be minimum. Those coefficients actually obtained with this method were : α_1=0.133, α_2=0.603, α_3=0.300, α_4=0.887, α_5=-0.674, α_6=-0.180, α_7=2.58.

Fig.14 shows the comparison between the values resulted from quantitative evaluation by this method and those by a medical doctor. Correlation coefficient between both values is 0.73. Fig.14 and its coefficient clearly show that, by this method using three features and the equation of quantitative evaluation, it is possible to quantify the degree of advance of pulmonary emphysema with conventional chest X-ray images.

Table 1 Creteria for evaluation of each ROI with three features by a doctor

Evaluation value / Items to be evaluated	1	2	3
Width of blood vessels	the same as normal	slightly thin	thin
Number of blood vessels	the same as normal	comparatively few	few
Clearness of boundaries of blood vessels	the same as normal	slightly clear	clear

Table 2 Differences of the mean between each group

	Difference of mean between	
	group 1 and 2	group 2 and 3
F_W	0.3355	0.4454
F_A	0.1670	0.2104
F_G	0.2668	0.6602

Ⅵ. Conclusion

In this study, we proposed a method for quantifying the degree of advance of pulmonary emphysema by using conventional chest X-ray images. With this method, we devised a scheme for detecting blood vessels by using a deformable model with the tree-like structure and using an evaluation function specialized by knowledge about blood vessels appeared in chest X-ray images. And also we contrived another scheme for quantifying the degree of advance by using three features which were extracted from blood vessels.

In order to evaluate the performance, we applied

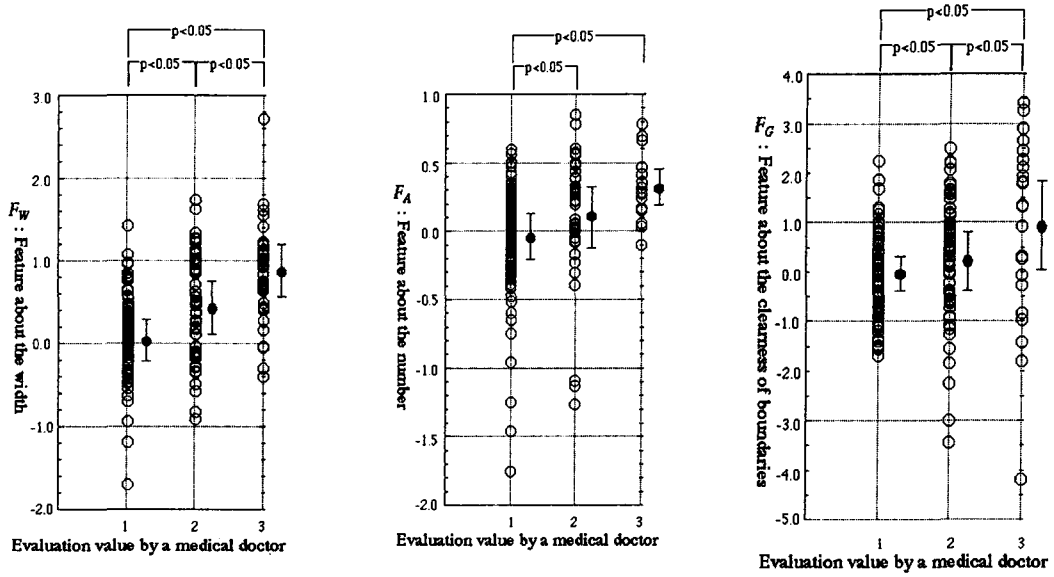


Fig. 13 the comparisons of each feature between the values obtained by this scheme and the ones evaluated by a medical doctor.

this method to 189 ROIs of ten chest X-ray images. The reault was that the correlation coefficient between the values resulted from quantitative evaluation by this method and those by a medical doctor is 0.73, and it is confirmed that the proposed method using three features and the equation of quantitative evaluation enable to quantify the degree of advance of pulmonary emphysema with conventional chest X-ray images.

In future, we are intending to develop other features in order to improve the performance of this method, and also to devise a tool for setting ROIs automatically.

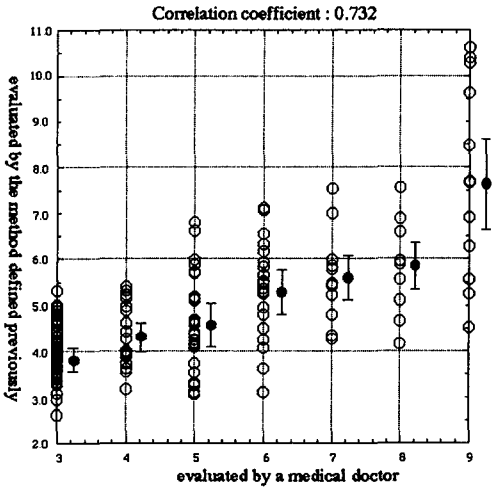


Fig. 14 Relationship between $\tilde{E}_V$ and E_V

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