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Computer-aided Diagnosis for Improved Detection of Lung Nodules by Use of PA and Lateral Chest Radiographs

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Abstract

Rationale and Objectives—We developed a computerized scheme for detection of lung nodules in the lateral views of chest radiographs, in order to improve the overall performance in combination with the computer-aided diagnostic (CAD) scheme for posterior-anterior (PA) views.

Materials and Methods—We used 106 pairs of PA and lateral views of chest radiographs (122 lung nodules) for development of the CAD scheme. In the CAD scheme for lateral views, initial candidates of lung nodules were identified by use of a nodule enhancement filter based on the edge gradients. Thirty four image features extracted from the original and the nodule-enhanced images were employed for the rule-based scheme and for artificial neural networks (ANNs) for removal of some false-positive candidates. The computer performance was evaluated with a leave-one-case-out test method for ANNs. For PA views, we used the existing CAD scheme, which was trained with one half of 924 chest images and then tested with the remaining images.

Results—When the CAD scheme was applied only to PA views, the sensitivity in the detection of lung nodules was 70.5%, with 4.9 false positives per image. Although the performance of the computerized scheme for lateral views was relatively low (60.7% sensitivity with 1.7 false positives per image), the overall sensitivity (86.9%) was improved (6.6 false positives per two views), because 20 (16.4%) of the 122 nodules were detected only on lateral views.

Conclusions—The CAD scheme by use of lateral-view images has the potential to improve the overall performance for detection of lung nodules on chest radiographs when combined with a conventional CAD scheme for standard PA views.

INTRODUCTION

Lung cancer is the most common cause of cancer death in the United States (1). Treatment for advanced lung cancer is unsatisfactory at present; however, treatment for early-stage lung cancer would be much more effective for improving the 5-year-survival rate (2). Chest radiography and computed tomography (CT) have been employed for the early detection of lung nodules. Currently, the effectiveness of lung cancer screening methods by use of chest radiography and CT is being examined in the National Lung Screening Trial (NLST) (3). Despite differences in opinion about the effectiveness of screening by use of chest radiography (4-7), chest radiography has been the most common radiologic examination in the world.

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Therefore, when chest radiographs are available, it would be useful to apply them for the early detection of lung nodules.

Computer-aided diagnosis (CAD) for the detection of lung nodules on chest images has been developed (8,9) and has become available for clinical practice (10-12). However, CAD methods employed only posterior-anterior (PA) views of chest images, even if both PA and lateral views for the same patient were available. In fact, lateral views of chest images were commonly obtained together with PA views in many medical centers and clinical institutions. Even though different opinions have been expressed about the necessity of obtaining PA and lateral views in the past (13-18), it is reasonable to use a lateral view in supporting the performance of a CAD scheme for the detection of lung nodules, and thus in assisting radiologists' decision-making, if a lateral view together with a PA view has already been obtained.

In this study, we developed a computerized scheme for detection of lung nodules in the lateral views of chest radiographs in order to improve the overall performance in combination with the CAD scheme for PA views.

MATERIALS AND METHODS

Our institutional review board approved the use of the image database in this study. Informed consent for each case was waived because this was a retrospective study.

Image database

We used 106 pairs of PA and lateral views of digital chest radiographs (122 lung nodules) in this study. This database was selected from 426 lung nodule cases (collected in our institution from January 1999 to July 2004) with the following inclusion criteria: (i) nodule location confirmed by CT, (ii) a maximum number of three nodules for each case, (iii) the patient in the upright position, (iv) the largest nodule size 30 mm on either view, (v) one image pair per patient, and (vi) nodule(s) visible in the lateral view. Note that the number of lung nodule cases selected with the inclusion criteria from (i) to (v) was 228. Therefore, only 122 lung nodules included in 106 (46.5%) of the 228 cases were visible in lateral views, whereas all lung nodules could be identified in PA views. In other words, the database selected for this study was enriched for lateral nodules and does not represent clinical frequency. Note also that this database did not include any cases with lung nodules which were visible only in lateral views, because the 426 lung nodule cases were selected initially based on PA views.

The 106 patient radiographs were obtained from 58 women and 48 men (age range, 18-94 years; mean age, 64 years). The 122 lung nodules included 73 lung cancers, 26 benign nodules, and 23 unknown nodules. The final diagnoses for 69 among the 73 lung cancers, including 28 adenocarcinomas, 16 non-small cell carcinomas, 13 squamous cell carcinomas, 4 small cell carcinomas, 5 carcinomas, 1 large cell cancer, 1 clean cell cancer, and 1 carcinoid tumor, were determined by pathologic examination, and the remaining four lung cancers were classified as being of unknown subtype. In addition, 45 of the 106 patients had diffuse lung diseases, including 14 emphysemas, 13 interstitial changes, 9 pleural changes, 5 cases of bronchitis, and 4 of edema; in which all diagnoses were determined by one chest radiologist based on the findings in CT images.

All of the images were converted from the original image format, such as 1760×1760 or 1760×2140 matrix size and 10-bit gray scale to 500×500 matrix size (0.700 mm pixel size) and 10-bit gray scale by use of an averaging method. We believe that the pixel size of 0.700 mm would be sufficiently small to analyze relatively large objects (lung nodules), the size of which is usually ranged from 5.0 mm to 30.0 mm. In addition, the computation time can be reduced

by use of a small matrix size. We used 106 lateral-view images for development of a CAD scheme for the detection of lung nodules on lateral views, whereas 106 PA view images were used only for testing by use of our existing CAD scheme (9) for the detection of lung nodules on standard chest radiographs. In this way, we obtain the overall performance of the CAD scheme for PA and lateral views.

The size of a lung nodule was determined by the diameter of the circle that had the same area as that of the outline of the nodule which was drawn by consensus of two chest radiologists. In addition, the degree of subtlety for radiologists' visual detection of the lung nodules was determined by the consensus of three radiologists by use of five-degree subjective ratings. The five degrees of subtlety in the detection of a lung nodule were defined as extremely subtle, very subtle, subtle, relatively obvious, and obvious.

Table 1 shows the number of cases in each subtlety group and each size group of lung nodules for 121 lung nodules in PA views and 118 in lateral views. It should be noted that one and four lung nodules were not included in Table 1 for PA and lateral views, respectively, because these lung nodules overlapped with other lung nodules in the same image, and thus, were not specified to be present in PA or lateral views. The mean size of the lung nodules was 21.5 mm (size range, 8.4-36.9 mm) for PA views and 22.2 mm (size range, 9.5-41.5 mm) for lateral views.

CAD scheme for detection of lung nodules on PA views

In order to obtain the baseline computer performance for the detection of lung nodules on PA views, we used an existing CAD scheme, which was trained with one half of 924 chest images and then tested with the remaining images (9). There were 38 cases (39 lung nodules) that overlapped with cases in the database used for the development of a CAD scheme for lateral views.

Our existing CAD scheme (9) for the PA view consisted of three major steps, i.e., (i) segmentation of lung fields and anatomical classification by use of 7×7 regions of interest (ROIs), (ii) identification of initial nodule candidates and extraction of a total of 71 image features in four different images, and (iii) elimination of false positives by use of sequential application of three artificial neural networks (ANNs) for the distinction between true positive and false-positive candidates.

The computer performance obtained from four different data sets, which were derived from the 924-image database, indicated that the average sensitivity in detecting lung nodules was 70.1% with 5.0 false positives per image for test cases and 70.4% sensitivity with 4.2 false positives per image for training cases (9).

CAD scheme for detection of lung nodules on lateral views

Figure 1 illustrates an overall computerized scheme for the detection of lung nodules on lateral views. Details of our computerized scheme are described below.

1. Segmentation of lung fields—In the initial step of lung segmentation on lateral views, the matrix size of the input image (500×500) was reduced to 128×128 initially, and then the gray scale of the input image was adjusted by use of the pixel values in the upper 5% and 95% of the area under the histogram of the input image, which were linearly mapped to 1023 and 0, respectively, in the density-adjusted image.

In the next step, a binary image of the chest region in the lateral view was roughly segmented by use of the pixel value range between the upper 20% and 90% of the area under the histogram of the density-adjusted image for determining the centroid of the chest region. Figure 2 shows

(a) a density adjusted-image, (b) a binary image of the chest region, (c) a segmented lung region on a density adjusted-image, and a histogram of pixel values (d) for the density-adjusted image. The segmented area in Fig. 2 (b) corresponds to an approximate chest region surrounded by anterior and posterior skin lines, and opaque regions caused by shoulders and diaphragm, but not to the lung region. We used this segmented region only for determining the centroid of the chest region, which was employed in the next step of the lung segmentation.

In order to determine the anterior, posterior, apex, and diaphragm boundaries of the lung field, we obtained four rectangular search areas by use of the location of the centroid (X_c , Y_c) in Fig. 2 (b). The shape of the anterior boundary of a lung field was determined by use of an anterior skin line of the chest region, which was obtained by use of a threshold pixel value of 80 for the density-adjusted image. The shift distance of the anterior boundary between the skin line and the frontal edge of the lung field was determined by use of the minimum thickness of the front chest wall, which was automatically estimated with a maximum density change in the horizontal direction where the frontal lung field was generally exposed clearly in the lateral view.

In the same way, the shape of the posterior boundary of the lung field was determined by use of a posterior skin line of the chest region, and the shift distance was determined by use of a maximum density change in the horizontal direction. If an anterior or a posterior skin line was not included entirely within an image, we simply used a vertical straight line instead of a missing skin line.

The apex and diaphragm boundaries of the lung field were determined by use of threshold pixel values corresponding to 15% and 25%, respectively, of the area under the histogram of the density-adjusted image. Percentages of the area under the histogram used in this study were determined empirically. Finally, an un-smoothed lung region which was enclosed by four estimated boundaries was smoothed by use of morphological filtering combined from erosion and dilation operations as shown in Fig. 2 (c). Figure 3 shows 16 images of chest lateral views with a contour of an automatically segmented lung field which were selected randomly from the 106 cases.

2. Lung nodule detection and image feature extraction—Nodule-enhanced images were produced by sequential application of the ARG filter and the Gaussian filter for identifying initial candidates of lung nodules (9).

Initial nodule candidates were identified among a large number of islands derived by use of six levels of multiple-gray-level thresholding (8), if the three image features of an island, i.e., the effective diameter, circularity, and irregularity met the following requirements: an effective diameter of 6.0 mm or greater, circularity of 0.50 or greater, and irregularity of 0.40 or lower. Threshold values used in the initial identification were determined empirically.

Once an initial lung nodule candidate was identified, we obtained 10 image features based on the contour of an isolated island on the nodule-enhanced image, such as the (i) threshold value [%] at the initial identification level, (ii) effective diameter, (iii) circularity, (iv) irregularity, (v) average pixel value within the island, (vi) standard deviation of the pixel value within the island, (vii) contrast value obtained by the difference between the maximum and minimum pixel values within the island, (viii) difference in pixel values between inside and outside regions, (ix) horizontal distance from the midline, and (x) sequential order of a candidate among all of the candidates detected initially.

In addition to the 10 image features obtained initially from the nodule-enhanced image, twenty-four image features were extracted from the original and nodule-enhanced images at the

location of the initial detection of a nodule candidate. Furthermore, in order to avoid an effect of background density trend in the original image, we applied a two-dimensional density trend correction technique (19) together with a Gaussian smoothing filter to create a density-trend-corrected ROI (64×64 matrix size) for the original image.

Finally, a total of 34 image features were extracted based on geometric features (8), gray-level features, edge-gradient features (8), and background features which were determined with image features related to the characteristics of the background structure of a nodule candidate obtained from the background region, which was determined by the area between the nodule outline and the outer frame of an ROI (64×64 matrix size) of the original image (9).

3. Rule-based test and artificial neural networks (ANNs)—We employed a rule-based test based on a two-dimensional linear discriminant analysis method with pairs of image features (8) in order to remove obvious false-positive candidates. A total of 30 image feature pairs which consisted of 31 different image features were selected automatically from the total number of 561 pairs based on the number of false positives eliminated without any reduction of true positives. In this rule-based test, linear threshold boundaries for distinguishing obvious false positives were determined manually and tested with the same image database by use of a two-dimensional plot of image feature pairs.

After the reduction of obvious false positives by use of a rule-based test, we employed ANNs with 12 image features as the input data. These 12 image features included (i) the effective diameter, (ii) average pixel value, (iii) average and (iv) standard deviation of edge gradient for the nodule-enhanced image, (v) effective diameter, (vi) irregularity, (vii) average and (viii) standard deviation of pixel values, (ix) contrast, (x) difference in pixel value between inside and outside, (xi) background edge gradient peak area ratio, and (xii) standard deviation of background pixel value for the original image. All parameters for ANNs were determined empirically, i.e., one hidden layer with six hidden units, 1.0 for the slope of the sigmoid function, 500 for the number of iterations, and 0.02 for the learning rate.

The performance of the computerized scheme for the detection of lung nodules on lateral views was evaluated by use of a leave-one case-out method. In this method, one of the 106 lung nodule cases was tested with the ANN which was trained with the remaining 105 cases, and then we repeated the same procedure until all 106 cases were tested. We also employed free-response receiver operating characteristic (FROC) curves (20) which indicated the relationship between the sensitivity [%] of lung nodule detection and the number of false positives per image.

RESULTS

The performance of our existing CAD scheme for PA views indicated that the sensitivity in detecting lung nodules was 70.5%, with 4.9 false positives (FPs) per image, for 122 lung nodules in the 106 cases. This performance level is almost the same as the average sensitivity obtained from four different testing data sets randomly extracted from 924 lung nodule cases (9).

Although 38 cases overlapped in the two studies, the sensitivity in detecting lung nodules for these overlapped 38 cases was 69.2% (27/39), which was slightly lower than that for the remaining “new” 68 test cases.

The performance of the CAD scheme for the 106 lateral views evaluated with a leave-one-case-out method for ANNs was 60.7% sensitivity with 1.7 FPs/image. Figure 5 illustrates FROC curves for CAD schemes for PA and lateral views, and also for the combination of two CAD schemes. Because of the small numbers of false positives, the FROC curve of the CAD

scheme for lateral views was better than those for PA views and for the combination of two CAD schemes. We empirically determined one fixed performance as shown above for each of the two CAD schemes for PA and lateral views in order to combine the two performances.

Table 2 shows the numbers of correctly identified lung nodules, sensitivities, and the numbers of false positives obtained with two CADs for PA and lateral views. The overall sensitivity (86.9% with 6.6 FPs/image) was improved from that of the CAD for the PA view only when we combined it with the CAD result obtained with lateral views. There were 32 (26.2%) and 20 (16.4%) lung nodules correctly identified only by use of the individual CAD scheme for PA and lateral views, respectively.

Figure 6 illustrates three sets of PA and lateral views with truth marks (dashed circles) and arrowhead marks of the CAD output. As shown in Table 3, 44.3% of lung nodules were identified correctly by both CAD schemes (Fig. 6 (a)). Because there were overlaps of the right and left diaphragm boundaries on the lateral view, some lung nodules located just above the diaphragm were not identified by the CAD scheme on the lateral view (Fig. 6 (b)). When lung nodules were located close to the mediastinum region and on a relatively posterior side of the lung, such lung nodules were likely to be identified by the CAD scheme for lateral views rather than that for PA views (Fig. 6 (c)).

DISCUSSION AND CONCLUSION

The prevalence of lung nodules visible on lateral views was relatively small, partly because it was very difficult generally to identify lung nodules on lateral views, and because these nodules were frequently located in the upper lobes. However, a certain number of lung nodules on lateral views could be identified easily by radiologists, and also by the CAD scheme, compared with those on PA views. For example, Tala (18) stated that a lateral view was decisive in 20% of patients with lung carcinoma, and also 13% of missed lung nodules were seen well on the lateral views in a study by Austin, et al. (13).

Because of the low percentage of chest radiographs with lung nodules that can be seen on lateral view, a gain in the sensitivity for detection of lung nodules obtained in this study by use of lateral views should be evaluated carefully. For example, if only 46.5% of lung nodules as shown in this study, can be seen on both PA and lateral views, and if 16.4% of these visible lung nodules can be identified only by use of the CAD scheme for lateral views, the actual gain in sensitivity would be 7.6% for the original 228 lung nodule cases, which appears to be comparable to the results reported by Tala (18), Stitik and Tockman (17), and Austin et al. (13).

The FROC curve obtained with the CAD scheme for lateral views was superior to that for PA views and also for the combination of PA and lateral views. These results should be interpreted carefully, as discussed below. We believe that the lateral view would not be the primary one for the detection of lung nodules on chest radiographs. Instead, we should use the CAD scheme for lateral views as a supporting tool in addition to the results obtained with the CAD scheme for PA views.

The performance of our CAD system for the PA view (70.5% sensitivity with 4.9 FPs/image) was not as good as at in previous reports obtained by use of a commercially available CAD system (21,22). For example, the sensitivities and the numbers of FPs/image for lung nodule cases reported by Kakeda et al. (11) and Sakai et al. (12) were 73.0 % with 4.0 FPs/image and 74.0 % with 2.0 FPs/image, respectively. However, we believe that the CAD performance strongly depends on the database used in each study. In general, the CAD performance could be high when the number of cases in the database is relatively small, and if the lung nodules included in the database are relatively easily detectable by radiologists (18,19). In the study by

Kakeda et al. (11) with 323 lung nodules and that of Sakai et al. (12) with 50 lung cancers, the areas under the ROC curve for radiologists' performance in the detection of lung nodules without CAD were 0.92 and 0.90, respectively, which are very high, thus indicating that a small number of cases and relatively easy cases were used. On the other hand, in our previous study (9), we used 924 lung nodule cases for training and testing the CAD scheme for the lung nodule detection on PA views. Therefore, it is very difficult to determine whether our CAD system was superior or inferior to the CAD schemes used in the previous two studies. However, we believe that the performance obtained in this study would be comparable to that in clinical situations, because our computerized scheme was trained for various types of lung nodules which would be considered closely comparable to those in the general population.

The number of FPs in the performance of CAD for lateral views was relatively small, which may be due to several reasons. For example, the ARG filter was relatively large, and the anatomic structures in chest lateral views are relatively small. Strong crossings of anterior ribs which are almost perpendicular to posterior ribs in PA views were one of the main causes of false positives produced in CAD for PA views; however, there were no similar strong crossings of ribs on the lateral views. In addition, an effective lung field in a lateral view was smaller than that in a PA view. Therefore, the number of false positives obtained from CAD for lateral views would be generally small compared with that for PA views.

Although our lung segmentation technique for lateral views sometimes missed a part of the lung apex as well as the right anterior inferior lung, and the left lung projected below the right hemidiaphragm as shown in Fig. 3, this technique seemed simple, but useful compared with those for the previously developed technique in our institution (23). Because our lung segmentation technique was developed only for detection of lung nodules on lateral views, we believe that a robust and simple technique is more important than a complex technique for accurate segmentation on the boundaries of a lung field. In fact, all lung nodules projected on lateral views were included in the segmented lung region in this study.

We did not use the vertical locations of lung nodule candidates on both PA and lateral views for identifying lung nodules, because the changes in positioning and respiration between the two views were not consistent and thus not useful for the computerized scheme to identify lung nodules.

One limitation in this study was the small number of cases used for the development of the CAD scheme for lateral views. Although we used a leave-one-case-out method for evaluating the performance level of the CAD scheme, some parameters in rule-based tests were determined by use of the same image database for training and testing of the CAD scheme. Therefore, further improvement in the computerized scheme would be required if these CAD schemes are applied to clinical situations. In addition, an observer performance study for the detection of lung nodules on lateral views without and with the CAD output, which was not done in this study, would be necessary for evaluation of the usefulness of this CAD scheme in terms of improvement of the accuracy in radiologists' performance.

In conclusion, we believe that the new CAD scheme by use of lateral-view images has the potential to improve the overall performance for detection of lung nodules on chest radiographs when combined with a conventional CAD scheme for standard PA views.

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REFERENCES

1. Jemal A, Murray T, Ward E, et al. Cancer statistics, 2005. *CA Cancer J Clin* 2005;55:10–30. [PubMed: 15661684]
2. Ginsberg RJ, Rubinstein LV. Randomized trial of lobectomy versus limited resection for T1 N0 non-small cell lung cancer. Lung Cancer Study Group. *Ann Thorac Surg* 1995;60:615–622. [PubMed: 7677489]discussion 622–613
3. National Lung Screening Trial. Available at <http://www.cancer.gov/nlst>. Accessed September 6, 2006
4. Fontana RS, Sanderson DR, Woolner LB, et al. Screening for lung cancer. A critique of the Mayo Lung Project. *Cancer* 1991;67:1155–1164. [PubMed: 1991274]
5. Warner EE, Mulshine JL. Lung cancer screening with spiral CT: toward a working strategy. *Oncology (Williston Park)* 2004;18:564–575. [PubMed: 15209187]discussion 578, 583–564, 587
6. Oken MM, Marcus PM, Hu P, et al. Baseline chest radiograph for lung cancer detection in the randomized Prostate, Lung, Colorectal and Ovarian Cancer Screening Trial. *J Natl Cancer Inst* 2005;97:1832–1839. [PubMed: 16368945]
7. Byers T, Barrera E, Fontham ET, et al. A midpoint assessment of the American Cancer Society challenge goal to halve the U.S. cancer mortality rates between the years 1990 and 2015. *Cancer* 2006;107:396–405. [PubMed: 16770789]
8. Xu XW, Doi K, Kobayashi T, MacMahon H, Giger ML. Development of an improved CAD scheme for automated detection of lung nodules in digital chest images. *Med Phys* 1997;24:1395–1403. [PubMed: 9304567]
9. Shiraishi J, Li Q, Suzuki K, Engelmann R, Doi K. Computer-aided diagnostic scheme for the detection of lung nodules on chest radiographs: localized search method based on anatomical classification. *Med Phys* 2006;33:2642–2653. [PubMed: 16898468]
10. Freedman M, Lo S, Osicka T, et al. Computer-aided detection of lung cancer on chest radiographs: effect of machine CAD false-positive locations on radiologists' behavior. *Proc SPIE Medical Imaging: Image Processing* 2002;4684:1311–1319.
11. Kakeda S, Moriya J, Sato H, et al. Improved detection of lung nodules on chest radiographs using a commercial computer-aided diagnosis system. *AJR Am J Roentgenol* 2004;182:505–510. [PubMed: 14736690]
12. Sakai S, Soeda H, Takahashi N, et al. Computer-Aided Nodule Detection on Digital Chest Radiography: Validation Test on Consecutive T1 Cases of Resectable Lung Cancer. *J Digit Imaging*. 2006
13. Austin JH, Romney BM, Goldsmith LS. Missed bronchogenic carcinoma: radiographic findings in 27 patients with a potentially resectable lesion evident in retrospect. *Radiology* 1992;182:115–122. [PubMed: 1727272]
14. Forrest JV, Sagel SS. The lateral radiograph for early diagnosis of lung cancer. *Radiology* 1979;131:309–310. [PubMed: 441309]
15. Muhm JR, Miller WE, Fontana RS, Sanderson DR, Uhlenhopp MA. Lung cancer detected during a screening program using four-month chest radiographs. *Radiology* 1983;148:609–615. [PubMed: 6308709]
16. Quekel LG, Kessels AG, Goei R, van Engelshoven JM. Miss rate of lung cancer on the chest radiograph in clinical practice. *Chest* 1999;115:720–724. [PubMed: 10084482]
17. Stitik FP, Tockman MS. Radiographic screening in the early detection of lung cancer. *Radiol Clin North Am* 1978;16:347–366. [PubMed: 746141]
18. Tala E. Carcinoma of the lung. A retrospective study with special reference to pre-diagnosis period and roentgenographic signs. *Acta Radiol Diagn (Stockh)* 1967;268(Suppl):261–16.

19. Katsuragawa S, Doi K, MacMahon H. Image feature analysis and computer-aided diagnosis in digital radiography: detection and characterization of interstitial lung disease in digital chest radiographs. *Med Phys* 1988;15:311–319. [PubMed: 3405134]
20. Chakraborty DP. Maximum likelihood analysis of free-response receiver operating characteristic (FROC) data. *Med Phys* 1989;16:561–568. [PubMed: 2770630]
21. Chan HP, Sahiner B, Wagner RF, Petrick N. Classifier design for computer-aided diagnosis: effects of finite sample size on the mean performance of classical and neural network classifiers. *Med Phys* 1999;26:2654–2668. [PubMed: 10619251]
22. Shiraishi J, Abe H, Engelmann R, Doi K. Effect of the number of cases in image database on the performance of computer-aided diagnosis (CAD) for the detection of pulmonary nodules in chest radiographs. *Proc SPIE Medical Imaging: Image Processing* 2003;5032:177–182.
23. Armato SG 3rd, Giger ML, Ashizawa K, MacMahon H. Automated lung segmentation in digital lateral chest radiographs. *Med Phys* 1998;25:1507–1520. [PubMed: 9725142]

Figure 1.
Overall computerized scheme for the detection of lung nodules on chest lateral views.

Figure 2.

Example of density-adjusted chest lateral views without and with a contour of segmented lung field, a binary image of a roughly segmented chest region, and a histogram of pixel values on density-adjusted image of which the pixel value range between the upper 20% and 90% of the area under the histogram was used for segmenting the chest region.

Figure 3.
Examples of chest lateral views with contours of automatically estimated segmented lung field.

Figure 4.
Example of original chest lateral image including one lung nodule (arrow), and nodule-enhanced image obtained by use of the ARG filtering technique.

Figure 5.
FROC curves for the detection of 122 lung nodules (106 cases) obtained with CAD schemes for PA and lateral views, and also for the combination of two CAD schemes.

Figure 6.

Examples of PA and lateral views with a lung nodule, true location of lung nodules (dashed circles), and the computer output for lung nodule candidates (arrowheads) obtained with each CAD scheme for PA and lateral views.

(a) A subtle lung nodule in the right middle lobe was identified correctly by both CAD schemes. One false-positive mark on the PA view which cued a large vessel in the hilum and another false-positive mark in the center of the lateral view seemed to be paired.

(b) A small and very subtle lung nodule located just above the right diaphragm was correctly identified by CAD on the PA view, but not on the lateral view, because the nodule was hidden by the overlap of the right and left diaphragm.

(c) Relatively large, but very subtle lung nodules located in the right mediastinum region were not identified by CAD on PA views, but could be recognized by radiologists and were correctly identified by CAD on lateral views, with one false positive for each lateral view.

Table 1

The number of lung nodules in each subtlety group and in each nodule size group for 121 and 118 lung nodules on PA and lateral views, respectively.

Degree of subtlety	Effective diameter of Lung nodules (mm)							Total
		5-10	10-15	15-20	20-25	25-30	30-40	
Extremely subtle	PA	0	0	0	0	0	0	0(0.0%)
	Lat	0	1	0	0	0	0	1(0.8%)
Very subtle	PA	0	2	6	2	5	1	16(13.2%)
	Lat	0	8	8	9	1	0	26(22.0%)
Subtle	PA	2	14	12	12	7	6	53(43.8%)
	Lat	1	6	13	12	7	2	41(34.7%)
Relatively obvious	PA	0	6	9	9	8	4	36(29.8%)
	Lat	1	0	5	14	16	7	43(36.4%)
Obvious	PA	0	0	2	5	6	3	16 (13.2%)
	Lat	0	0	1	1	4	1	7 (5.9%)
Total	PA	2 (1.7%)	22 (18.2%)	29 (24.0%)	28 (23.1%)	26 (21.5%)	14 (11.6%)	121
	Lat	2 (1.7%)	15(12.7%)	27 (22.9%)	36 (30.5%)	28 (23.7%)	10 (8.5%)	118

Table 2

Number of identified lung nodules and sensitivities for 122 lung nodules, the number of false positives (FPs) per image for each of 106 PA and lateral views, and the number of FPs per case for 106 pairs

	PA only	PA and Lateral	Lateral only	Overall
No. of nodules correctly identified by CAD	32	54	20	106
Sensitivity	26.2%	44.3%	16.4%	86.9%
No.of false positives	4.9/image		1.7/image	6.6/case