RIB SUPPRESSION IN FRONTAL CHEST RADIOGRAPHS: A BLIND SOURCE SEPARATION APPROACH

[1]*Tahir Rasheed,*[1]*Bilal Ahmed,*[1]*M.A.U. Khan,*[3]*Maamar Bettayeb,*[1]*Sungyoung Lee,*[2]*Tae-Seong Kim**

[1] Department of Computer Engineering, Kyung Hee University, South Korea.
{*tahir,bilal,khan,sylee*}*@oslab.khu.ac.kr*
[2] Department of Biomedical Engineering, Kyung Hee University, South Korea.
tskim@khu.ac.kr
[3]Department of Electrical/Electronics Engineering, University of Sharjah,United Arab Emirates
maamar@sharjah.ac.ae

ABSTRACT

Chest radiographs play an important role in the diagnosis of lung cancer. Detection of pulmonary nodules in chest radiographs forms the basis of early detection. Due to its sparse bone structure and overlapping of the nodule with ribs and clavicles the nodule is difficult to detect in conventional chest radiographs. We present a technique based on Independent Component Analysis (ICA) for the suppression of posterior ribs and clavicles which will enhance the visibility of the nodules and aid the radiologist in diagnosis.

1. INTRODUCTION

Lung cancer is responsible for causing the bulk of cancer related deaths in both men and women. An estimated 162,460 deaths, accounting for about 29% of all cancer related deaths, are expected to occur in 2006.Lung cancer is the most common form of cancer, according to the latest statistics provided by the American Cancer Society: lung cancer is estimated to produce 174,470 new cases in 2006, accounting for about 12% of all cancer diagnoses. Early detection of lung nodules is the most promising strategy for increasing the chances of survival for a patient. Early detection can be achieved in a population screening; the most common screenings for lung cancer make use of Chest Radiography, or low radiation dose Computer Tomography (CT) scans. Despite the development of advanced radiological exams such as Computer Tomography the conventional Chest X-ray remains the most common tool for the diagnosis of lung cancer. The main reason behind this is the fact that CT and helical CT exams expose the patient to a higher dose of radiation, estimated to be about 100 times higher than that for a conventional chest X-ray. Another reason for the widespread use of conventional chest radiographs is its economic feasibility.

From a diagnostic point of view lung cancer appears in the form of spherical nodules in a conventional radiograph. Owing to the presence of a sparse bony structure composed mostly of ribs and clavicles; the nodule may be partially obscured. Similarly the shadows casted by the heart and other organs cause the nodule to lose its visibility. Thus, the detectability of the nodule is largely dependent on its location in the chest. The problematic cases for nodule detection can be categorized as follows: 1) Overlapping of the ribs: both anterior and posterior, 2) Located in the high-illumination area, 3) Overlapping of the clavicles, 4) Overlapping of blood vessels; as illustrated in Fig.1 and the suppression of ribs and clavicles in chest radiographs would be potentially useful for improving the detection accuracy of a given Computer Aided Diagnostic(CAD) system.

As an image, the chest radiograph can be regarded as a linear combination of a number of sources. Noise introduced during the acquisition process can be regarded as a single complete source. Similarly we assume that the ribs also constitute a separate source which can be eliminated for enhancing the radiograph. We propose a novel technique based on ICA for suppressing the rib structure in a chest radiograph. ICA performs a blind source separation based on the probability distribution of individual components. Therefore, ICA can be used to separate the rib structure from the soft-tissue component as it can be assumed that they constitute independent sources which have been linearly mixed.

2. RELATED WORK

Earlier work on CAD systems for automated nodule detection in chest radiographs was reported in [11]. The process for nodule detection employed multiple gray-level thresholding of the difference image (which corresponds to the subtraction of a nodule-enhanced image and a nodule-suppressed image) and then classified. The system resulted in a large number of false positives which were eliminated by adaptive rule-based tests and an artificial neural network (ANN). The authors in [4] evaluated the usefulness of CAD that incorporated temporal subtraction

*This research was supported by the MIC(Ministry of Information and Communicaton), Korea, under the ITRC(Information Technology Research Center) support program supervised by the IITA(Institute of Information Technology Advancement)(IITA-2006-(C1090-0602-0002))

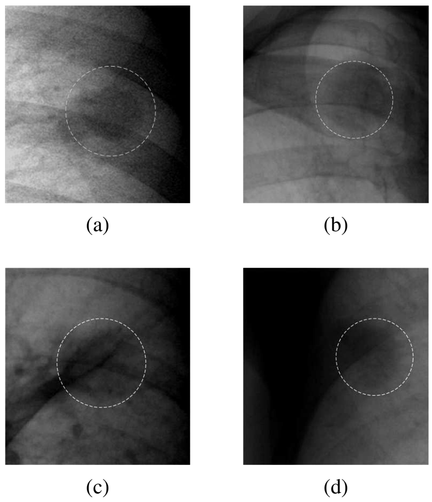


Fig. 1: Effect of location on nodule detection: (a) Nodule with overlapping posterior and anterior ribs. (b) Overlapping clavicle. (c) Overlapping rib and blood vessels. (d) Nodule lying in the high illumination area of the radiograph. (Contrast enhanced images)

for the detection of solitary pulmonary nodules on chest radiographs. The authors in [8] concluded that the accuracy of radiologists in the detection of some extremely subtle solitary pulmonary nodules can be improved significantly when the sensitivity of a computer-aided diagnosis scheme can be made to be at an extremely high level. The authors noted however, that all of the six radiologists failed to identify some nodules (about 10%), even with the corrected computer output. An attempt was made in [10] where the rib cage was suppressed by the means of Massive Training Artificial Neural Network (MTANN). A drawback of the system was the need of a dual-energy bone image in which the ribs are separated from the soft-tissue at the initial training phase. The technique was found to be sensitive to the noise levels owing to the subtraction process.

ICA has been used quite recently for enhancing EEG signals [5]. It has been shown that ICA can remove undesired artifacts from the EEG signal without causing any substantial damage to the original source signal. The main motivation behind such applications of ICA is the reasonable assumption that noise unrelated to the source is independent from the event-related signals, and hence can be separated.

3. INDEPENDENT COMPONENT ANALYSIS

ICA performs a blind source separation (BSS), assuming linear mixing of the sources. ICA generally uses techniques involving higher-order statistics. Several different implementations of ICA can be found in the literature [3]. We will not discuss those implementations in this literature and restrict ourselves to the topic. Let us denote the time varying observed signal or image by

$$\mathbf{x} = (x_1 x_2 .... x_n)^T$$

and the source signal or image consisting of independent components by

$$\mathbf{s} = (s_1 s_2 .... s_m)^T$$

The linear ICA assumes that the signal x is a linear mixture of the independent components,

$$\mathbf{x} = \mathbf{A} \cdot \mathbf{s} \tag{1}$$

Where the matrix A of size $m \times n$ represents linear memory less mixing channels. It is often assumed that $n = m$ (complete ICA) for simplicity, which can be relaxed without any loss of generality. The time index is normally omitted for simplicity. A common preprocessing step is to zero the mean of the data and then apply a linear whitening transform to the image so that it has unit variance and the pixels are uncorrelated. The algorithms must find a set of basis images such that

$$\mathbf{s} = \mathbf{W} \cdot \mathbf{x} \tag{2}$$

where ***W*** is the basis matrix.

3.1. Application to Digital Chest Radiographs

Chest radiographs can be viewed as a mixture of multiple sources; one of which are the ribs. From an image processing point of view the ribs are mostly composed of edges (due to the sparse bony structure). Suppressing these edges, without affecting the other information in the radiograph would enhance the remaining information pertaining to the remaining sources. Assuming that these sources have been linearly mixed, independent component analysis can be used for efficient separation. Fig.2 shows the distribution for the segmented ribs and the whole lung-field. The distribution of the lung-field is more Gaussian as compared to the distribution of the ribs (which is super-gaussian). It is concerned that the radiograph is a mixture of more than one independent components and through blind-source separation these components can be effectively isolated using the optimization of non-Gaussianity criterion for ICA. In our approach we initially segment the ribs from a single radiograph and treat this as *a priori* information for the blind source separation process.

4. EXPERIMENTS AND RESULTS

4.1. Data Description

The chest radiographs were taken from the JSRT database [9]. The images are digitized to 12 bits posterior-anterior chest radiographs, scanned at a resolution of 2048 x 2048 pixels; the size of one pixel is 0.175 x 0.175 mm ^{2}. The database contains 93 normal cases and 154 cases of proven lung nodule. Diameters and the positions of the nodules are provided along with the images. The nodule diameters range from 5-60 mm, and are located throughout the lung field, and their intensities vary from nearly invisible to very bright. The nodules present in the database are representatives of the problems we delineated in the introduction.

4.2. Segmentation of Lung-Fields and Ribs

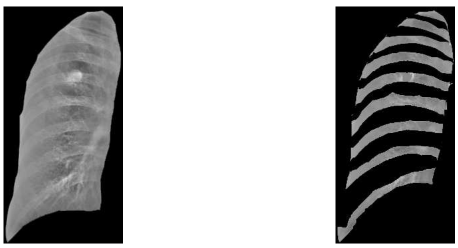
Active Shape Models (ASM)[1] were trained on fifty images to segment the right and left lung-fields using an approach similar to [2]. After lung-field segmentation two separate sets of images were constructed pertaining to the left and right lung-fields. Active Shape Models (ASM)[1] were trained for the delineation and subsequent segmentation of ribs using fifty images from each of the two sets.

4.3. Non-Uniform Illumination Correction

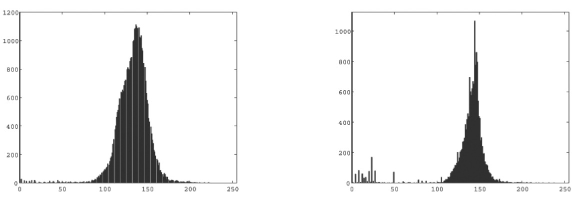
Chest radiographs contain non-uniform illumination due to the acquisition apparatus and their complex structure. Non-uniform illumination can distort edges of ribs and suppress the detail of the texture. Due to this non-uniform illumination pattern the nodule might get partially obscured and loose it basic characteristics. The ribs and the blood vessels can be viewed as potential edges, and in order to clearly demarcate them it is desirable that they have high detail in the image. Removing the non-uniform illumination pattern and making the image homogeneous would enhance the texture detail and the rib edges. Conventional methods of homogenizing image such as homomorphic filtering assume an illumination and reflectance model which considers the illumination as a multiplicative component. We have adopted the technique of [7] for normalizing the image's intensities locally. The technique for normalization achieves results which enhance the overall image contrast and strengthen the edges.

$$I_N = \frac{I - I_{LP}}{\sqrt{(I^2)_{LP} - (I_{LP})^2}} \tag{3}$$

where I refers to the image and 'LP' simply denotes Gaussian blurring of appropriate scale. This local normalization can be considered as making the image zero mean and unit variance. Fig.3 shows the result of this local normalization on a conventional chest radiograph.

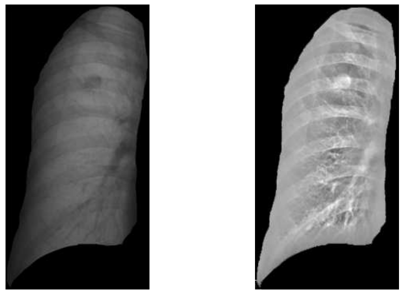


(a) (b)



(c) (d)

Fig. 2: The original enhanced image (a), the segmented ribs (b), and their distributions (c),(d).



(a) Original Image (b) Enhanced

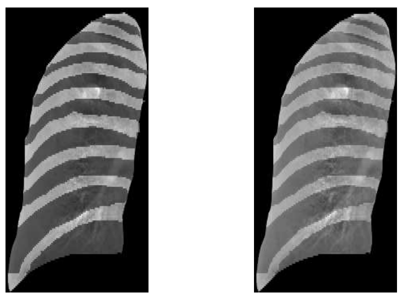
Fig. 3: Enhancing the extracted lung-field image

4.4. Application of ICA

The application of ICA requires at least two observations (mixtures) to separate two independent components. In our case we only have one image of the lung-field. In order to overcome this problem we artificially created two observations by linearly combining the segmented lung-field and the ribs. The linear combination was done using a randomly generated matrix with weight values between 0 and 1. This process of linear combination has been previously defined in (1); where the sources ($\boldsymbol{s}$) are replaced by the lung-field and the ribs. Fig.4 shows the two mixtures so created. These mixtures were then given as input to the FastICA [3] algorithm, using the hyperbolic-tangent non-linearity relating to the super-Gaussian source distributions. Note that we did not apply PCA (principal component analysis) reduction at any stage so as to preserve the texture of the overall chest radiograph. Fig.5 shows the results for a single case. It is evident from the resultant images that the ribs have been suppressed to a greater degree and the nodule is more prominent.

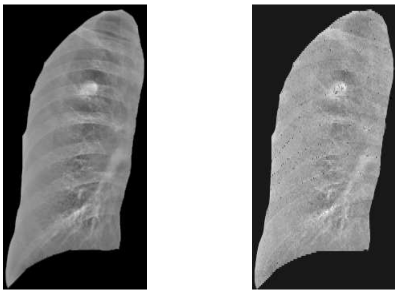
4.5. Evaluation

Visual inspection of the resultant images clearly show that the ribs have been suppressed. Some information has been subtracted from the image, and the main concern for evaluation is the effect of this subtraction on the nodule itself. Firstly, we need to characterize nodules, and then evaluate the effect of this blind-source separation on them. In



(a) (b)

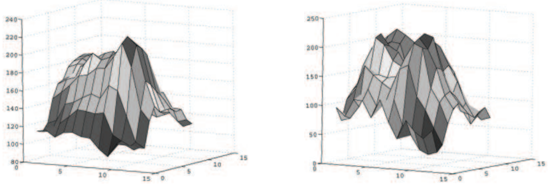
Fig. 4: Artificially created mixtures for blind source separation.



(a) (b)

Fig. 5: Results of the FastICA algoirhtm: (a) Original Image (b) Rib-Suppressed Image

previous works on nodule detection; nodules have been characterized as Gaussian shaped objects or blobs [7]. In Fig.6 we show the Gaussianity of a single nodule before and after rib-suppression. There is a substantial increase in the Gaussianity of the nodule as is evident from the kurtosis values. This increase in Gaussianity constitutes the major contribution of this work. Multiscale blob detection [6] has been employed successfully for blob detection in [7]; the results showed that the application of multiscale blob detector with simple image enhancement resulted in a large number of false positives. This high number of false positive can be attributed to the sparse bony structure present in the image. The removal of this bony component; as has been shown in this work will increase the efficiency of the multiscale blob-detector.



(a) $kurtosis = -1.02$ (b) $kurtosis = -0.83$

Fig. 6: Gaussianity of the nodule before (a) and after rib-suppression (b)(*Excess Kurtosis is shown*).

5. CONCLUSION

We have demonstrated that the suppression of ribs and clavicles can be efficiently achieved through the use of ICA. The removal of these artifacts results in the enhancement of the nodule. Previously multiscale blob detectors have been employed for nodule detection [7] and this enhancement would enable a standard blob-detector to detect a nodule with better accuracy.

6. REFERENCES

[1] T. Cootes, C. Taylor, D. Cooper, and J. Graham. Active shape models– their training and applications. *Comput. Vis. Image Understanding*, 61, 1995.

[2] B. V. Ginneken, A. F. Frangi, J. J. Staal, B. M. ter Haar Romeny, and M. A. Viergever. Active shape model segmentation with optimal features. *IEEE transactions on Medical Imaging*, 21, 2002.

[3] A. Hyvarinen, J. Karhunen, and E. Oja. *Independent Component Analysis*. Wiley Interscience, 2001.

[4] T. Johkoh, T. Kozuka, N. Tomiyama, S. Hamada, O. Honda, N. Mihara, and M. Koyama. Temporal subtraction for detection of solitary pulmonary nodules on chest radiographs: evaluation of a commercially available computer-aided diagnosis system. *Radiology*, 223:806–811, June 2002.

[5] D. Lange, H. Pratt, and G. Inbar. Modeling and estimation of single evoked brain potential components. *IEEE transactions on BioMedical Engineering*, 44, 1997.

[6] T. Lindeberg. Feature detection with automatic scale selection. *International Journal of Computer Vision*, 30:79–116, 1998.

[7] A. M. Schilham, B. V. Ginneken, and M. Loog. A computer-aided diagnosis system for detection of lung nodules in chest radiographs with an evaluation on a public database. *Medical Image Analysis*, 10:247–258, January 2006.

[8] J. Shiraishi, H. Abe, R. Engelmann, and K. Doi. Effect of high sensitivity in a computerized scheme for detecting extremely subtle solitary pulmonary nodules in chest radiographs: observer performance study. *Acad Radiology*, 10:1302–1311, Novemeber 2003.

[9] J. Shiraishi, S. Katsuragawa, J. Ikezoe, T. Matsumoto, K. T., K. Komatsu, M. Matsui, H. Fujita, Y. Kodera, and K. Doi. Development of a digital image database for chest radiographs with and without a lung nodule: receiver operating characteristic analysis of radiologists' detection of pulmonary nodules. *American Journal of Roentgenology*, 174, 2000.

[10] K. Suzuki, H. Abe, H. MacMahon, and K. Doi. Image-processing technique for suppressing ribs in chest radiographs by means of massive training artificial neural network (mtann). *IEEE transactions on Medical Imaging*, 25(4), April 2006.

[11] X. XU, K. Doi, T. Kobayashi, H. MacMahon, and G. M.L. Development of an improved cad scheme for automated detection of lung nodules in digital chest images. *Med Phys.*, 24:1395–1403, September 1997.