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Rib Suppression in Chest Radiographs Using ICA Algorithm

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Abstract: Chest radiographs play an important role in early diagnosis of lung cancer. Due to overlapping of the nodule with ribs and clavicles, the nodule is hard to detect in conventional chest radiographs. In this study A technique is presented based on Independent Component Analysis (ICA) for the suppression of posterior ribs and clavicles which will enhance the visibility of the nodule and will reduces the stress on automatic nodule detection module.

Key words: Lung cancer, radiograph, nodule, independent component

INTRODUCTION

Lung Cancer is responsible for causing the bulk of cancer related deaths in both men and women. About 29% of all cancer related deaths, are expected to occur in 2006. Lung cancer is the most common form of cancer, according to American Cancer Society; it is estimated to produce about 12% of all cancer diagnoses. 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 being the fact that advanced x-ray techniques like 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. Moreover, the widespread use of conventional chest radiographs is due to 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 sometimes be partially obscured. Similarly the shadows casted by the heart and other organs may cause the nodule to lose its visibility.

The problematic cases for nodule detection can be categorized as follows:

- Overlapping of the ribs: Both anterior and posterior.
- Located in the hilum (high-illumination) area.
- Overlapping of the clavicles.

- Overlapping of blood vessels; Therefore, the suppression of ribs and clavicles in chest radiographs would be potentially useful for improving the detection accuracy of a given Computer Aided Diagnosis (CAD) system.

As an image, the chest radiograph can be regarded as a linear combination of three major components namely the bone structure, the soft tissue portion and the noise introduced due to the acquisition process. Bulk of this noise can be removed through conventional image enhancement methods, but to separate the bone structure from the soft tissue component we need specialized techniques. We propose a novel technique based on Independent Component Analysis (ICA) for suppressing the rib structure in a chest radiograph. ICA performs blind source separation based on the probability distribution of the individual components. Therefore, ICA can be used for separating the rib structure from the soft-tissue component as they can be viewed as independent sources which have been linearly mixed.

RELATED WORK

Earlier work on CAD systems for automated nodule detection in chest radiographs was reported in (Xu *et al.*, 1997). The process for nodule detection employed multiple gray-level thresh holding 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 (Johkoh *et al.*, 2002) evaluated the usefulness of CAD that incorporated temporal subtraction for the detection of solitary pulmonary nodules on chest radiographs. The authors in (Shiraishi *et al.*, 2003) 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 correct computer output. An attempt was made in (Suzuki *et al.*, 2006) where the rib cage was suppressed by means of Massive Training Artificial Neural Network (MTANN). A drawback of the system is 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, due to the subtraction process.

Independent Component Analysis (ICA) has been used quite recently for enhancing EEG signals (Lange *et al.*, 1997). 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.

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 (Hyvarinen *et al.*, 2001). We will not discuss those implementations in this literature and restrict ourselves to the topic. Let us denote the time varying observed signal by:

$$x(t) = (x_1(t) \ x_2(t) \dots x_n(t))^T$$

and the source signal consisting of independent components by:

$$s(t) = (s_1(t) \ s_2(t) \dots s_m(t))^T$$

The linear ICA assumes that the signal $x(t)$ is a linear mixture of the independent components,

$$x(t) = A \cdot s(t) \tag{1}$$

Where the matrix A of size mn 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 time series so that they have unit variance and are uncorrelated. The algorithms must find a separating or de-mixing matrix such that:

$$s(t) = W \cdot x(t) \tag{2}$$

Where (W) is the de-mixing matrix.

Application to digital chest radiographs: Chest radiographs can be viewed as a mixture of two components the bone-structure and the soft-tissue. From an image processing point of view the first component is 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 second component. Assuming that these sources have been linearly mixed, independent component analysis can be used for efficient separation. Figure 1 shows the distribution for the segmented ribs and the whole lung-

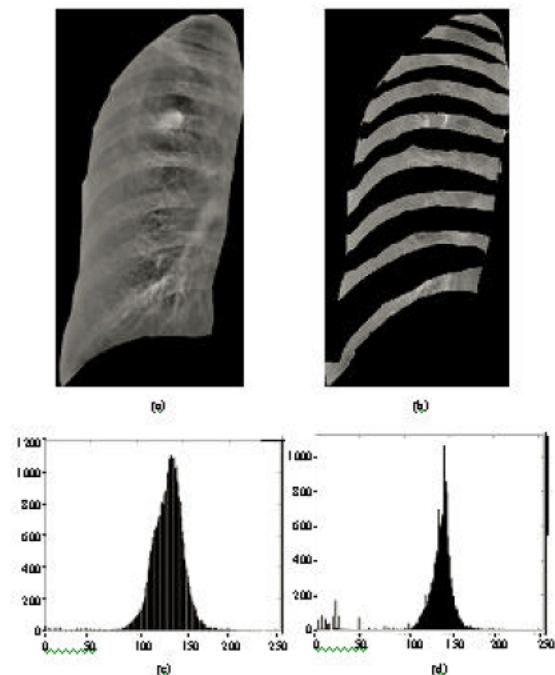


Fig. 1: The original enhanced image (a), the segmented ribs (b) and their distributions (c) and (d)

field. The distribution of the lung-field is more gaussian as compared to the distribution of the ribs (which is super-gaussian). Using the central-limit theorem it can be concluded 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.

EXPERIMENTS AND RESULTS

Data description: The chest radiographs were taken from the JSRT database (Shiraishi *et al.*, 2000). The images are digitized to 12 bits posterior-anterior chest radiographs, scanned at a resolution of 2048×2048 pixels; the size of one pixel is 0.175×0.175 mm². 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.

Segmentation of lung-fields and ribs: Active Shape Models (ASM) (Cootes *et al.*, 1995) were trained on fifty images to segment the right and left lung-fields using an approach similar to (Ginneken *et al.*, 2002). After lung-field segmentation two separate sets of images were constructed pertaining to the left and right lung-fields. Active Shape Models (ASM) (Cootes *et al.*, 1995) were trained for the delineation and subsequent segmentation of ribs using fifty images from each of the two sets.

Image enhancement: 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 lose its 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 (Schilham *et al.*, 2006) for normalizing the image's intensities locally. The

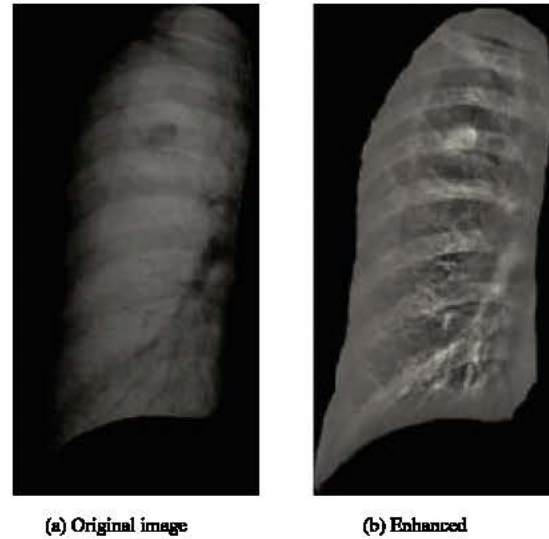


Fig. 2: Enhancing the extracted lung-field image

technique for normalization achieves results which enhance the overall image contrast and strengthen the edges.

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

where LP simply denotes gaussian blurring of appropriate scale. This local normalization can be considered as making the image zero mean and unit variance. Figure 2 shows the result of this local normalization on a conventional chest radiograph.

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 Eq. 1; where the sources (s) are replaced by the lung-field and the ribs. Figure 3 shows the two mixtures so created. These mixtures were then given as input to the FastICA (Hyvarinen *et al.*, 2001) algorithm, using the *tanh* (hyperbolic-tangent) non-linearity relating to the supergaussian 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. Figure 4 shows the results for a single case.

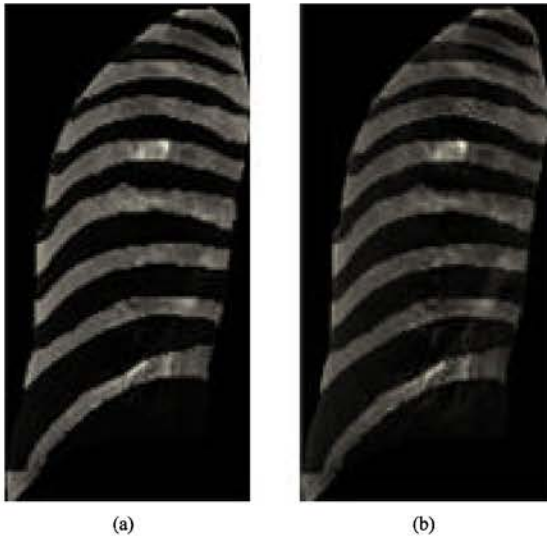


Fig. 3: Artificially created mixtures for blind source separation

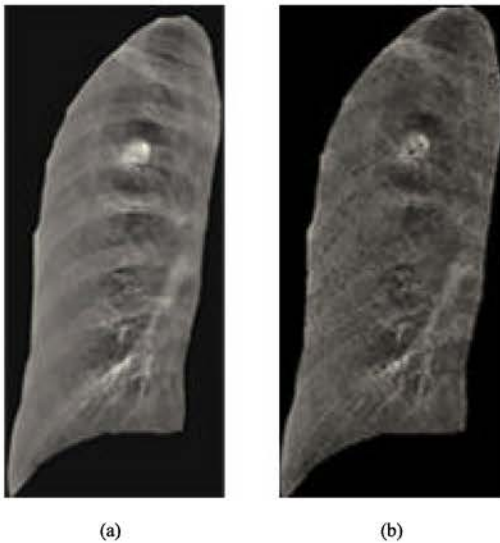


Fig. 4: Results of the FastICA algorithm: (a) Original Image (b) Rib-Suppressed Image

It is evident from the resultant images that the ribs have been suppressed to a greater degree and the nodule is more prominent.

Evaluation: Visual inspection of the resultant images clearly shows 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

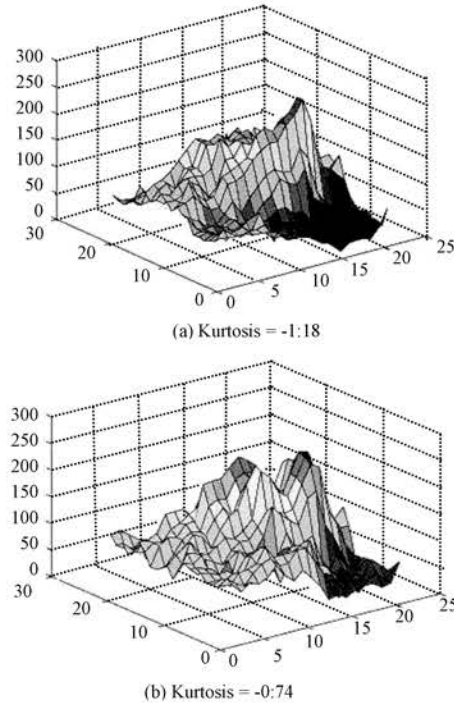


Fig. 5: Gaussianity of the nodule before (a) and after rib-suppression (b)

blind-source separation on them. In previous works on nodule detection; nodules have been characterized as Gaussian shaped objects or blobs (Schilham *et al.*, 2006). In Fig. 5 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 (Lindeberg, 1998) has been employed successfully for blob detection in (Schilham *et al.*, 2006); the results showed that the application image (b) Rib-Suppressed image of multi-scale 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 study will increase the efficiency of the multiscale blob-detector.

CONCLUSIONS AND FUTURE WORK

We have demonstrated that the suppression of ribs and clavicles can be efficiently achieved through the use of Independent Component analysis. The removal of these artifacts results in the enhancement of the nodule.

Previously multiscale blob detectors have been employed for nodule detection (Schilham *et al.*, 2006) and this enhancement would enable a standard blob-detector to detect a nodule with more accuracy. As our future research direction we would like to assess the performance of a classifier for nodule detection in order to assess the impact of this image enhancement on the detection and classification of lung nodules.

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