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Rib Suppression Using Blind Source Property of Independent Component Analysis

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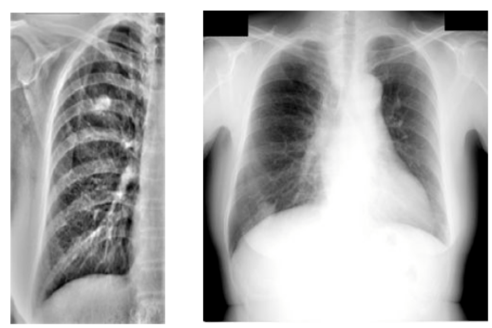
Abstract: Detection of pulmonary nodules in chest X-rays play an important role in early detection of lung cancer. In this research, we developed an image-processing technique for suppressing the contrast of ribs and clavicles in chest X-rays. We present a technique based on Independent Component Analysis (ICA) for the suppression of posterior ribs and clavicles which will enhance the visibility of the nodule and aid the radiologist in the diagnosis process.

Key words: Independent component analysis, chest X-ray, Computer-Aided Diagnosis (CAD), lung nodule, rib suppression

INTRODUCTION

Chest X-rays play an important role in identifying diseases like lung cancer. According to American Cancer Society, lung cancer remains the top cancer killer among both men and women. Early detection of lung nodules is the most promising technique for increasing the chances of survival for a patient. Radiologists may fail to detect lung cancers that have low visibility on chest radiographs (Austin *et al.*, 1992) and the detection of small nodules is subtle (Kundel and Revesz, 1976). Popular screening techniques make use of Chest Radiography, or low radiation dose Computer Tomography (CT) scans for early lung cancer detection. Despite the development of advanced radiological exams such as CT, the conventional Chest X-ray (CXR) remains the most common tool for the diagnosis of lung cancer. The main reason behind this fact is that CT and helical CT exams expose the patient to a much higher dose of radiation, estimated to be about 100 times higher than that for a conventional chest X-ray.

In CXR, posterior view and the anterior view are independent of each other. Thus, both could be treated as different entities. A tool is needed to separate the rib cage from the rest of data. Independent Component Analysis (ICA) is one such approach which decomposes observed signals into mutually independent components (Masayuki *et al.*, 2004). It exploits higher order statistical structures in data. In Lee and Michael (2002), they have used ICA mixture model for image denoising looking at their work we also used ICA to separate Ribs cages from other useful data in CXR images. The Fig. 1 shows an original X-ray image enhanced using the image processing techniques.



(a) (b)

Fig. 1: (a) Original X-ray image and (b) Nodule detected after enhancement

MATERIALS AND METHODS

Conventional methods: Earlier research on CAD systems for automated nodule detection in chest radiographs is mentioned in Kobayashi *et al.* (1996). The process for nodule detection examined a new method of Receiver Operating Characteristic (ROC) analysis in an observational study. The analysis of existing CAD systems revealed that the delectability of the nodule is largely dependent on its location in the chest radiograph. A notable research in this field was done which employed Massive Training Artificial Neural Networks (MTANN) to solve the problem of false-positives and while maintaining the sensitivity of image. But the problem was that the process required a dual energy image and was found sensitive to noise levels (Kenji *et al.*, 2006). Further Gaussian scale-space was used as a CAD technique, improving delectability of nodules but also increasing the

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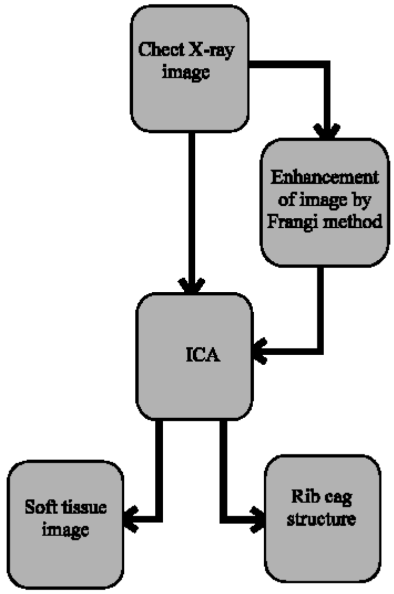


Fig. 2: Proposed method

number of false-positives. Late attempts were made but with little improvement. The problem is still being faced by researchers is the number of false-positives and loss of information in case of noise, due to temporal subtraction.

Proposed method: From image point of view, the CXR can be divided into two parts the posterior view and the anterior view. Both could be treated as different entities. For this we need some special tool which treats the ribcage as a different class and the rest of the data remain unchanged.

ICA finds a linear non orthogonal and coordinate system in multivariate data determined by second and third order statistics. The goal of ICA is to linearly transform the data such that the transformed variables are as statistically independent of each other as possible (Lee and Michael, 2002). For image data ICA basis works as localized edge filters. ICA has also been used to separate images which were mixed as a result of process (Kasprzak and Cichocki, 1996). Our proposed method includes enhancing the image as a filtering process on the basis of geometrical structure used by Frangi *et al.* (1998). After filtering we train the program with the original image and the rib enhanced image. This will prepare the program to differentiate between the ribcage and the soft tissue image. Figure 2 shows the working of our proposed model.

Image enhancement: Since the ribs in the CXR differ from other features in size and geometry, so we can extract our

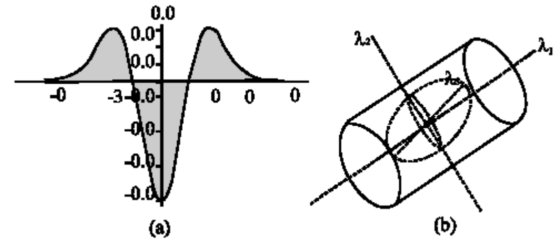
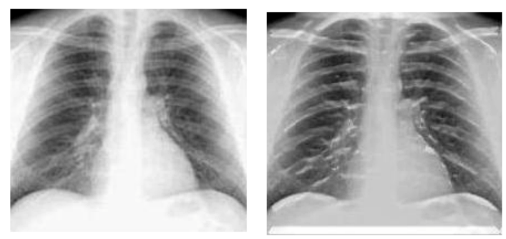


Fig. 3: (a) The second order derivative of a Gaussian kernel of the ranges between (-s, s) and (b) The local principal directions of curvature are described by ellipsoid



(a) (b)

Fig. 4: Enhancing the original chest radiograph

region of interest from the image which is further used in ICA. Local behavior of an image I can be analyzed, by its Taylor expansion:

$$I(x_0 + \delta x_0, s) \approx I(x_0, s) + \delta x_0^T \nabla_{0,s} + \delta x_0^T H_{0,s}\, \delta x_0$$

Second order structural analysis of the image is done by this expansion. $\nabla_{0,s}$ and $H_{0,s}$ are the gradient vector and Hessian matrix of the image computed at scale's' Fig. 3. By analyzing the second order information, we can say Hessian justifies the perspective of vessel detection. The second derivative of scale's' measures the length and the width in the region (-s, s). This enhances the rib cage structure only.

$$\delta x_0^T H_{0,s}\, \delta_{x0} = \left(\frac{\delta}{\partial \delta_{x0}}\right)\left(\frac{\partial}{\partial \delta_{x0}}\right) I(x_0, s)$$

The principle directions are extracted by Eigen-value analysis obtained from the local second order structure of the image (Frangi *et al.*, 1998). By using the Eigen vectors corresponding to the Eigen values we enhance the features which lie in the direction of ribs only as shown in Fig. 4. The ribs are enhanced on the basis of the following formula.

$$V_0(s) = \begin{cases} 0 & \text{if } \lambda_2 > 0, \\ e^{\frac{R_B^1}{2\beta^1}}(1 - e^{-\frac{s^1}{2c^1}}) \end{cases}$$

Where:

$$R_B = \frac{\lambda_1}{\lambda_2}$$

Independent component analysis: ICA a Blind Source Separation (BSS) technique takes the image as a mixture of constituent images. Let us take a time varying signal:

$$x = (x_1, x_2, \ldots, x_n)T$$

And the source signal consisting of independent components

$$s = (s_1, s_2, \ldots, s_m)T$$

The ICA assumes that the signal is the linear mixture of independent sources.

$$x = A.s$$

Where:
A = The mixing matrix.

The algorithm is to find a de-mixing matrix W, hence the sources.

$$s = W.x$$

ICA on chest radiographs: Chest radiographs can be taken as a mixture of two components the rib cage and the soft-tissue. The algorithm will suppress the rib cage leaving behind the soft tissue image.

$$x_i = A_i.s_i; \quad i = 1, 2, 3, \ldots n$$

The algorithm will treat rib cage structure as s_1 and soft tissue image as s_2. Two different samples x_1 being the original image and x_2 being the enhanced image will be feed to the algorithm. The program will find the mixing matrix A, thus, the de-mixing matrix W.

RESULTS

ICA technique FastICA (Hyvarinen *et al*., 2001) algorithm was used with tan h (hyperbolic tangent) non linearity because we are dealing with the Super Gaussian source distributions. PCA reduction was not applied so to that no information is damaged. The rib suppressed image Fig. 5 along with the original image is shown.

Fig. 5: In comparison with the original image, that the ribs are finally suppressed and all hidden information can be extracted easily now

CONCLUSION

In this study, we basically enhanced the rib cage structure on the basis of size as well as geometrical structure. Hence, we obtained an image which is ready for ICA for further processing. The ICA algorithm takes two images, original one and second the enhanced image as two different observations. So we get two different images as a result one is the rib cage structure and other the soft tissue image. We have shown the excellent rib suppression in a clinical image. Further we will increase our data base to make our algorithm more general.

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