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Pyramid-Transform Based Lung-Tissue MRI Image Segmentation

Liyun Yu*, *Member*, Jannick P. Rolland*①, *Member*
*Center for Research and Education in Optics and Lasers (CREOL)
①Department of Electrical Engineering and Computer Science
University of Central Florida Orlando, FL, 32816-2700
E-mail: yu@creol.ucf.edu , rolland@creol.ucf.edu

Abstract---This paper presents a framework based on a pyramid-transform for the segmentation of lung tissue in MRI images. We show that a multi-scale framework is beneficial to the segmentation of tissues; specifically, we show that removal of a large-scale anatomical structure within the lung can be accomplished without the need to provide interactive manipulation of objects within the image. Moreover, we show that higher performance in boundary detection can be achieved using an edge detector operator in combination to a steerable filter bank compared to using the edge detector directly on the image. Currently, early stages of the segmentation are based on the assumption that the lungs are embedded in a high intensity background, as is the case in MRI upper abdomen images. Generalization of the proposed methods to other types of images will require further development of the algorithms but, based on the results of large-scale structure removal presented here, we postulate that further use of a pyramid structure can further benefit the process of auto-segmentation.

1 Introduction

Lung-tissue MRI-image segmentation may benefit anatomy research and clinical diagnosis. Most MRI chest cross-section images show lung tissue embedded on a dark background which is itself embedded in fairly high intensity structures such as the chest surrounding tissue, the heart, and various bones. A typical image is shown in Figure 3a.

Typical medical imaging tasks for such MRI images consists in searching for tumors within the lung tissue and evaluating the structure of the lung texture itself. Under observation of the acquired MRI images with a conventional grayscale, physicians cannot perceive both tumors within large anatomical structures and those within the lung tissue. Therefore, diagnosis of such images is conducted using *grayscale windowing* of the images to observe sequentially the lung tissue and surrounding structures under different grayscales. When looking at the lung tissue, other structures are still present but at a saturated intensity. If such a setting cannot be automated it can be fairly tedious; Moreover, bright structures can be distracting to the search task. If, on the other hand, the same setting is applied blindly to all images it may not be optimal. To optimize the viewing conditions, we propose an algorithm for automatic segmentation of the lung images from their surrounding that can be displayed automatically to the physicians with no need for constant and subjective manipulation of the images.

Moreover, in an effort to provide computerized image-analysis feedback to the physicians, such as various texture measures of the lung tissue, we propose a technique to automatically remove large-scale anatomical structures foreign to the lung texture per se. It is assumed here that those measures are correlated with diagnosis as has been shown, for example, in medical ultrasound liver-images [1].

In recent years, the pyramid transform[2-6] has been essentially used in vision research [3, 7, 8], texture analysis and synthesis[4] and subband coding[9, 10]. The pyramid structure is a method of image analysis based on multiple resolutions in zoom-scale space. Steerable filters are an effective means to capture objects' orientation information from an image. The combination of the two, known as the pyramid transform, has proven to benefit various image processing method.

This paper presents the overall algorithm for automatic segmentation of lung tissues including the removal of an anatomical large-scale structure within the lung tissue. Boundaries of the lung are shown to be more clearly delineated using a steerable filter bank based on the Sobel filter when compared to a Sobel boundary detector alone.

2 Method

We use a pyramid transform for the purpose of both object recognition and boundary detection. A dark object embedded within the lung tissue is recognized and estimated by using a multi-scale pyramid structure. The multiple orientation boundary detection is conducted by using the steerable filters. The lung tissue segmentation task is divided into three steps.

<u>Step 1</u> is the preprocessing of the original image. In this step, the original image is initially segmented by two threshold values computed from equation (1).

$$threshold_i(\alpha) = \min I_i(x,y) + \frac{[\max(I_i(x,y) - \min(I_i(x,y)]}{\alpha} \qquad (1)$$

where $I_i(x,y)$ denotes the image, and α denotes a parameter for thresholding .

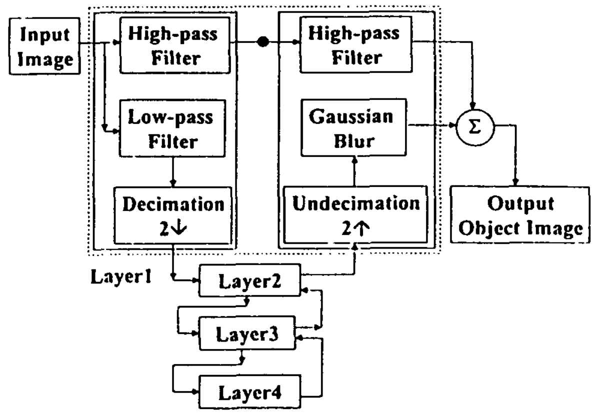


Figure 1. *Pyramid algorithm for the embedded object extraction. It is a four-layer structure (from 256x256 to 16x16). All filters used in the pyramid are designed as quadrature mirror filters.*

It is difficult to estimate the optimal threshold α for the best segmentation without *a priori* knowledge of the objects. The first threshold value $\alpha_1=2$ is used approximately to separate the lung tissue image from the input image. The second threshold value $\alpha_2=3$ is used to roughly estimate the embedded large-scale structure's location and size from the input image. The two thresholds combine together to form the equivalence of a threshold window

$$\min I_i(x,y) + \frac{A}{3} < I_{lung-tissue}(x,y) < \min I_i(x,y) + \frac{A}{2} \qquad (2)$$

where A denotes *max* $I_i(x,y)$ - *min* $I_i(x,y)$.

Step 2 is performing the embedded object removal from the lung tissue. A pyramid structure shown in Figure 1 is used in this step to estimate the embedded object's size and location from the original image and remove it automatically. The advantage of this method is that the approximately estimated object image $I_{lung-tissue}(x,y)$ is processed through spatial muti-scale filters and is then reconstructed by a Gaussian blur quadrature mirror filter bank to capture its size and location[12]. The pyramid structure allows processing of the embedded object at a large scale separately from the scale of the features. Therefore, because the scale of the lung-tissue texture is relatively small compared to the embedded structure, it is preserved by reconstruction of the embedded object. The recognized embedded object is then subtracted from $I_{lung-tissue}(x,y)$. No landmark or other interactive operation is needed for conducting this removal operation.

Step 3 is the boundary detection stage based on the lung tissue image where the embedded large-scale object was removed. A steerable filter bank is used to enhance the performance of the boundary detection. The algorithm of this step is illustrated in Figure 2.

The steerable filter means that the oriented filter is synthesized exactly from a linear combination of a fixed set of basis filters. Directional derivatives of Gaussian are used as the bases to construct such filters and to compute local orientation maps. As noted by Simoncelli, "the steerable filters are asymmetric and designed to produce an optimally localized oriented energy map"[11,12]. It is tuned at four orientations: 0°, 45°, 90°, and 135°. A Sobel boundary detector is used after each of the steerable filter to detect the oriented boundary information then captured. The final boundary information is generated by a linear combination of the outputs of each filter bank.

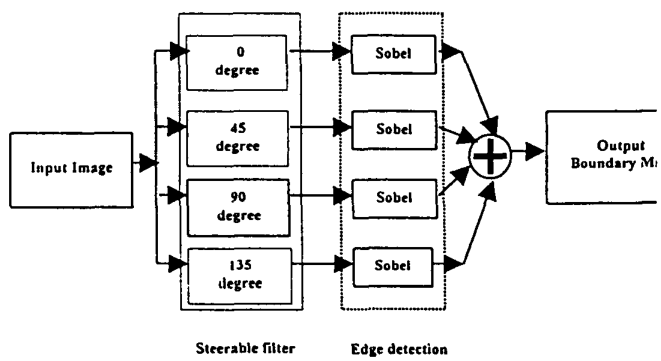


Figure 2. *Boundary detection algorithm using a steerable filter bank and a Sobel boundary detector. The steerable filters are directional derivatives of Gaussian and designed based on quadrature mirror filters.*

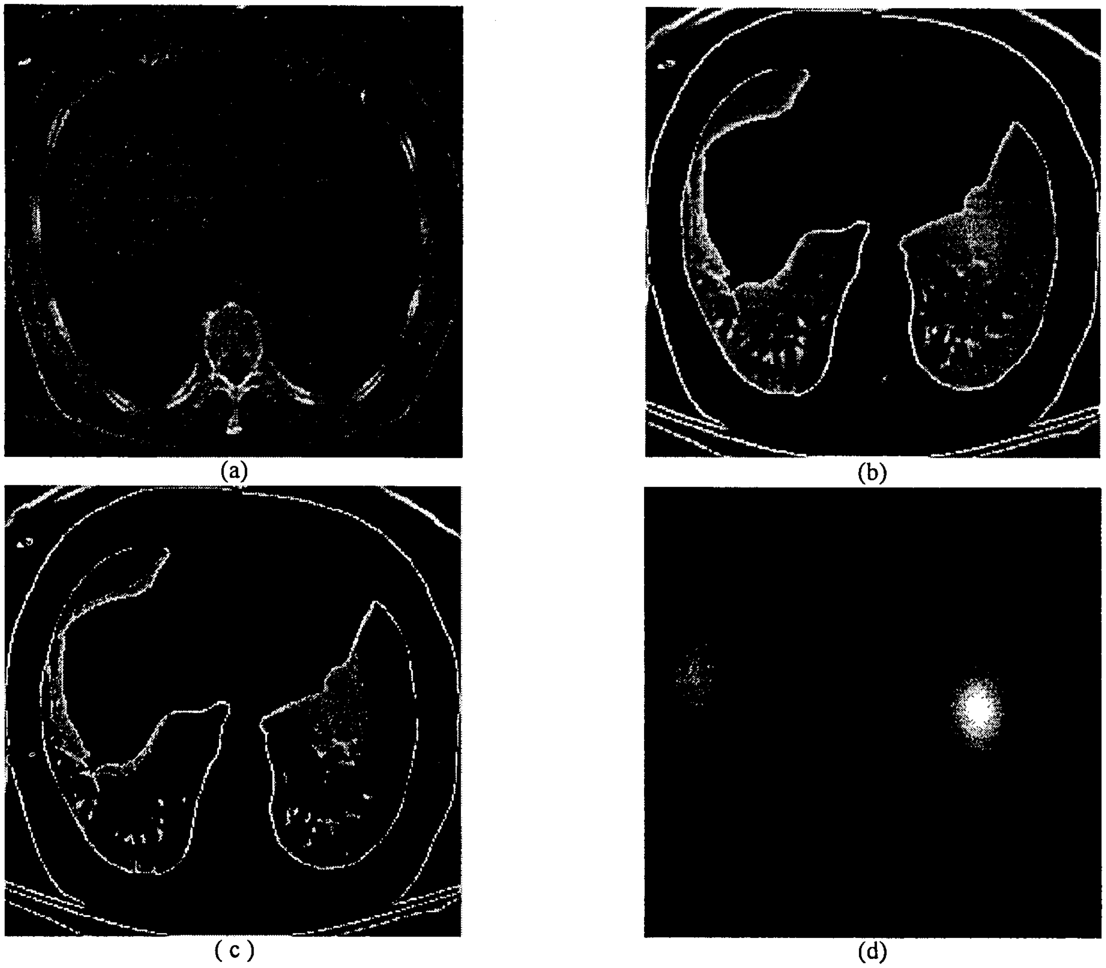


Figure 3. Preprocessing Results. *(a) is the input test image: lung tissue MRI image with 256 x 256 pixels. (Courtesy of Dr. E. Chaney and S. M. Pizer at UNC). (b) is the result of the first threshold preprocess. (c) is the second threshold result. (d) is the estimated and reconstructed large-scale object based on processing image (c) through the pyramid algorithm shown in Figure 1. The thresholds and grayscale range of the images are shown in Table 1.*

3. RESULTS AND DISCUSSION

The test input image, a chest cross-section of lung tissue MRI image, is 256x256 pixels and is shown in Figure 3*a*.

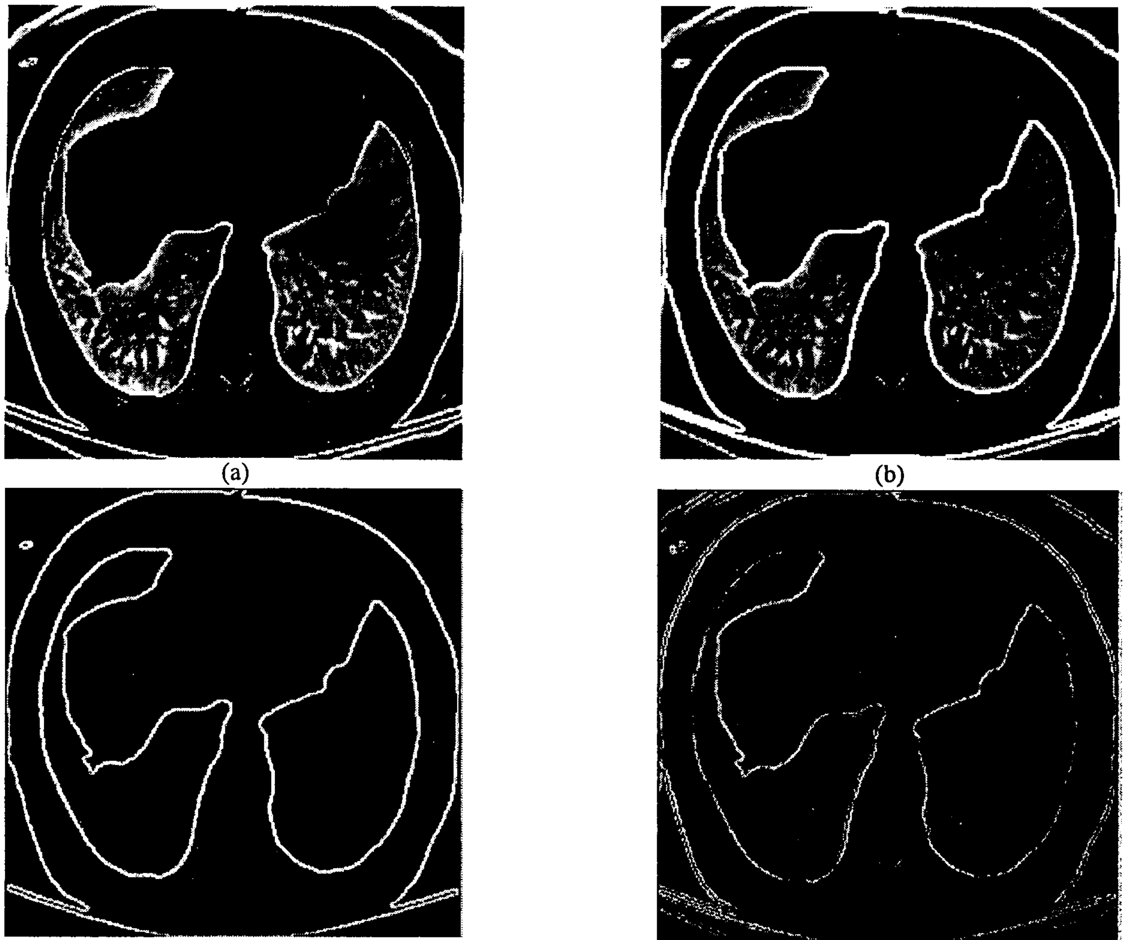
The threshold window preprocessing results by threshold-1 and threshold-2 are shown in Figure 4*b* and 4*c*, respectively. Table 1 shows the threshold values used. We must point out that, while thresholding is sufficient in the first steps of processing for the images at hand, other types of images may require more evolved processing. It works in this specific case because the intensity of the lung tissue of the input image is much lower than that of surrounding structures. Future work will involve separation of the lungs from surrounding structures based on a multi-scale pyramid processing as well.

The pyramid transform is used on the embedded large-scale structure shown in Figure 3*c*. Results of the pyramid processing are shown in Figure 3d. The image of the lung after removal of the large-scale structure is shown Figure 4a.

The steerable filter bank based boundary detection result is showed in Figure 4*c*. Figure 4b shows the overlap of the detected boundary with the image of the segmented lung. For comparison purpose, Figure 4d shows a Sobel detection directly on the segmented image (i.e. without passing through the pyramid).

Table 1 Threshold values computed for preprocess

Sequence Number	Working image Grayscale range (A)	Threshold Computed
(a) to (b)	99.2541	49.6271
(b) to (c)	114.443	8.70486



(a) (b) (c) (d)

Figure 4. *Embedded large-scale object removal and boundary detection results. (a) the large-scale object embedded within the lung tissue was removed (please compare it with Figure 4(b). (b) is the segmentation result. (c) is the boundary detection result based on the steerable filter bank. (d) is the result of Sobel boundary detector applied on image (a).*

4. CONCLUSION

This paper presents the overall algorithm for automatic segmentation of lung tissues as well as removal of anatomical large-scale structures within the lung tissue. Moreover, the lung's boundaries are shown to be more clearly delineated using the steerable filter bank when compared to a Sobel boundary detector.

5 REFERENCES

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