Texture-based image enhancement for segmentation performance

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ABSTRACT

This paper describes a hierarchical algorithm for multi-resolution texture-based image enhancement for segmentation performance. The proposed algorithm is a modification of the steerable pyramid algorithm that has been successfully implemented for research in texture synthesis. [1] We investigate in this paper the application of such a multiscale approach for image analysis to the problem of image enhancement for segmentation. We present the application of the proposed algorithm to two medical images as a first exploration of the potential benefits of the approach. While some quantitative measure of assessment needs ultimately to be developed for performance assessment, some subjective evaluation at this early stage of the research can provide early feedback on the magnitude of a potential benefit. While the early results presented in this paper are encouraging, it is yet to be demonstrated that the proposed algorithm or an optimized version of the algorithm yields increased performance compared to other techniques.

Keywords: texture, multiscale, enhancement, segmentation, pyramid, steerable

1. INTRODUCTION

This work was inspired by a challenging problem in image analysis: How to perform segmentation of images that can be described with texture characteristics in addition to objects' shape-boundary characteristics. Medical images are especially suited to this problem and it is perhaps non coincidental that auto-segmentation of such images is still at its infancy given that most algorithms for medical image segmentation are based on object's shape-boundary characteristics. Texture-based medical images include mammograms, [2-3] ultrasonic liver images, [4-6] and X-Ray lung images. [7-8] Moreover, shape-boundary-based image analysis usually implies assumption that the local intensities are uniform in pixel belonging to the same object which is typically not the case in grayscale medical images. [9] Texture-based image analysis is not limited by this assumption.

While the word texture is commonly used in computer vision, it has no precise scientific definition that is widely accepted.[10-11] However, it has been proposed that texture can be characterized by relatively small scale structures which are distributed uncertainly relative to the object. [24] It is apparent that these characteristics are typical of variances in medical images. The question is whether the texture-based handling of images can be conducted more effectively than shape-boundary-based handling when they appear simultaneously.

Texture-based image segmentation is a fundamental task for computer vision and is especially challenging for medical image processing due to following characteristics: 1) complexity of medical images; 2) absence of models of the anatomy that fully capture the possible deformations in each structure; 3) individual differences between patients and image sources; 4) differences in image quality from different sites, etc. The existing methods for texture-based segmentation are model-based methods [12-18] and multiresolution-multichannel methods. [19-23] Applications of these techniques to medical imaging are fairly recent [e.g. Chan(1995)]. [3]

In this paper, we present a texture-based image enhancement method for segmentation performance. The method proposed uses a combination of a model of human vision,[10,24] a pyramid steerable filter bank [25] and boundary detection methods. We present the application of the proposed algorithm to two medical images as a first exploration of the potential benefits of the approach. While some quantitative measure of assessment needs ultimately to be developed for performance assessment, some subjective evaluation at this early stage of the research can provide early feedback on the magnitude of a potential benefit. While the early results presented in this paper are encouraging, it is yet to be demonstrated that the proposed algorithm or an optimized version of the algorithm yields increased performance compared to other techniques.

2. METHOD

As stated earlier, the proposed algorithm for the research presented in this paper is based on the steerable pyramid filter bank algorithm. Processed images were 256 x 256 pixels and a three layer decomposition was applied as shown Figure 1.

In order to perform the texture-based boundary information enhancement, four Laplacian operators were applied at each layer of the pyramid either directly on the histogram equilized image or after decomposition of the histogram equalized images according to the steerable pyramid filter algorithm. The latter approach is illustrated in Figure 2. The output from each layer is a linear combination of outputs from the reconstruction filter banks. A Sobel boundary detector is applied as the final step to detect the boundary information from the pyramid reconstruction output at the top layer.

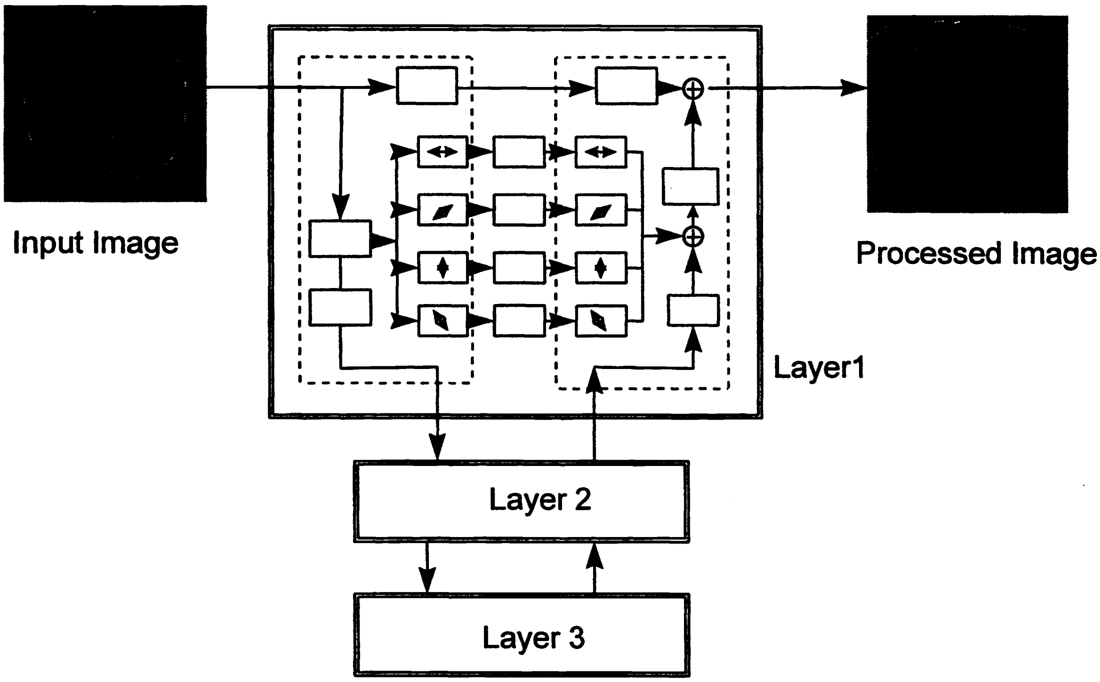


Figure 1. *Pyramid architecture of the algorithm*

The benefit of a pyramid structure for image analysis is to process multiple scale features in the image individually. The multi-scale pyramid used in this paper is based on a model of human vision. [10,24] A quadrature mirror steerable filter bank is used in each layer of this model for capturing orientation information from decomposed resolution in the pyramid structure, and for image reconstruction. Figure 2 also shows the orientation decomposition within one layer of the pyramid algorithm. Decimation and undecimation with a factor 2 is the linking step between each layer.

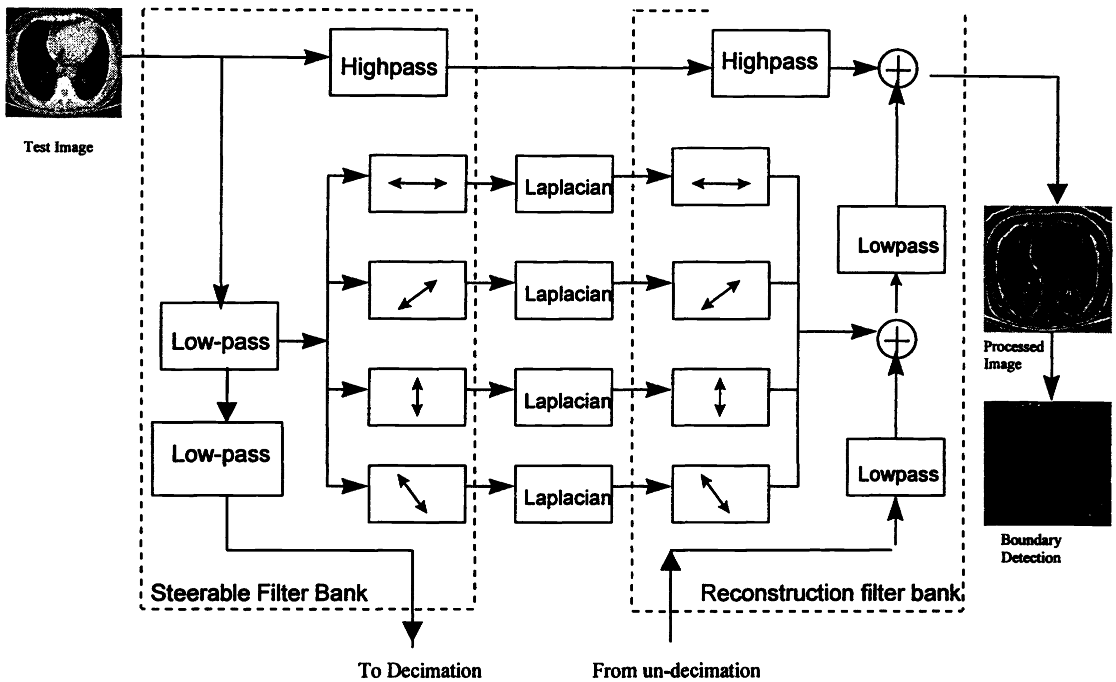


Figure 2. *Algorithm detail within one layer*

Based on the pyramid structure introduced by Simoncelli et al (1992),[25-26] the input image I(x, y) is partitioned into a low-pass and a high-pass sub-images. The low-pass sub-image is used as an input to the steerable filter banks, as well as to the decimation operation that is done recursively. The high-pass sub-image is kept at full density as needed for the reconstruction phase.

The steerable filter kernel is designed based on steering theorems. [26-27] If $G_0(x,y)$ is denoted as a Gaussian function, the steerable filter kernel is represented as

$$G^{\theta}(x,y) = \cos(\theta)G^{0^\circ}(x,y) + \sin(\theta)G^{90^\circ}(x,y), \tag{1}$$

where

$$G^{0^\circ}(x,y) = \frac{\partial}{\partial x}G_0(x,y)$$

$$G^{90^\circ}(x,y) = \frac{\partial}{\partial y}G_0(x,y).$$

Therefore, the orientation information is captured by

$$R^{\theta}(x,y) = G^{\theta}(x,y) * I(x,y). \tag{2}$$

All filters used in this paper are known as quadrature mirror filter banks.[26] The algorithm is coded and implemented with IDL (Interactive Data Language).

3. EXPERIMENTAL RESULTS

Two abdominal cross sections of MRI (256 x 256 pixels) images were prepared (Courtesy of Dr. Stephen Pizer and Dr. Edward Chaney, University of North Carolina at Chapel Hill) as shown in Figures 3 (a) and (c). Histogram equalization is applied on the original images as a first step for contrast enhancement because of the extremely low contrast of the original images. The enhanced images are shown in Figures 3(b) and (d). The images are then used as input to the pyramid structure.

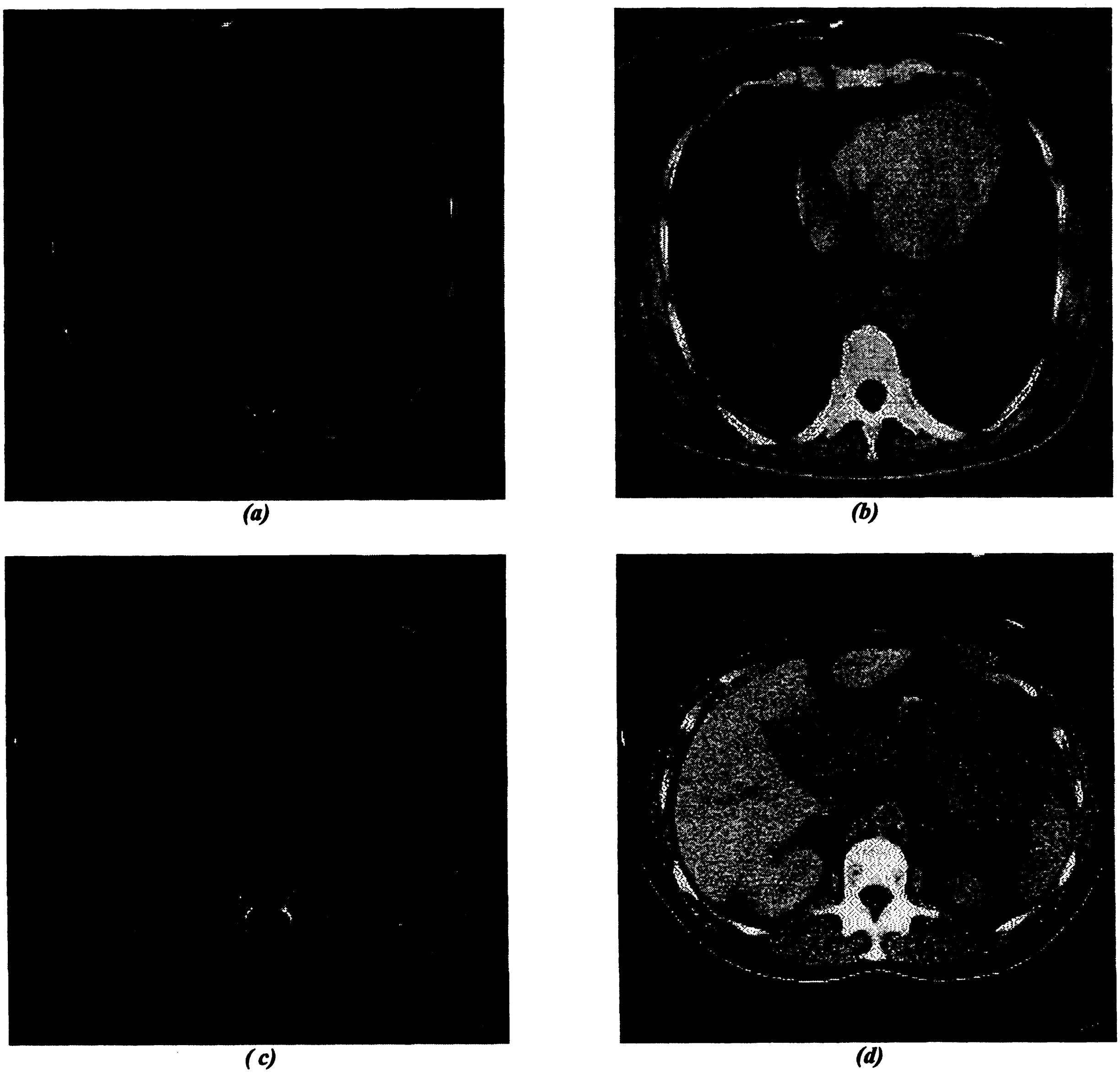
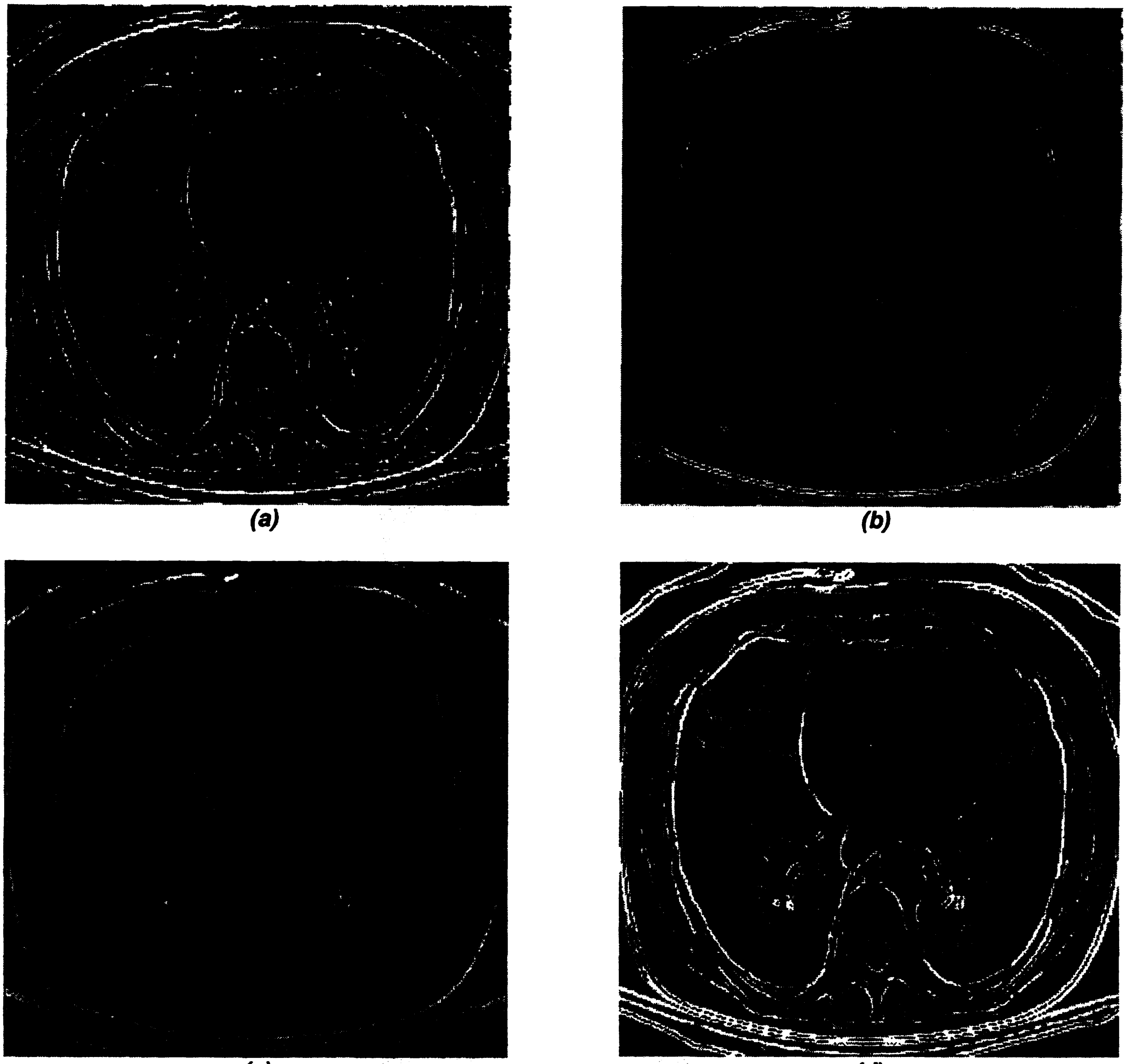


Figure 3. *Two medical images used for this paper for testing the proposed algorithm: They are 256 x 256 pixels. (a) MRI chest cross-section* original image. (b) Histogram equalization of the image shown in (a). (c) MRI abdominal cross-section with liver and kidneys. (d) Histogram equalization of the image shown in (c).



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

Figure 4. *Processing results using Figure 3 (b) as an input image. (a) is the output from the Laplacian operator. (b) is the output of Sobel operator applied on (a). (c) is the output image from the pyramid structure, referred as the processed image. (d) is the output from Sobel operator applied on (c.)*

Figure 4 (a)-(d) shows the results for the first MRI image which is a MRI chest cross section image with lung tissues. The lung vessels from this image are considered as a lung texture that is different from the texture of other organs in the same image. An output from the Laplacian operator followed by the Sobel boundary detector applied directly on the histogram equalized image are shown in Figure 4(a) and 4 (b), respectively. The output of the pyramid filter, referred to as the processed image, applied on the histogram equalized image is shown in Figure 4 (c). The application of the Sobel operator on the processed image is shown in Figure 4 (d).

A similar comparison is shown Figures 5 (a)-(d) for a different cross section of the abdomen that includes the liver and the kidneys. Various organs have typical textures.

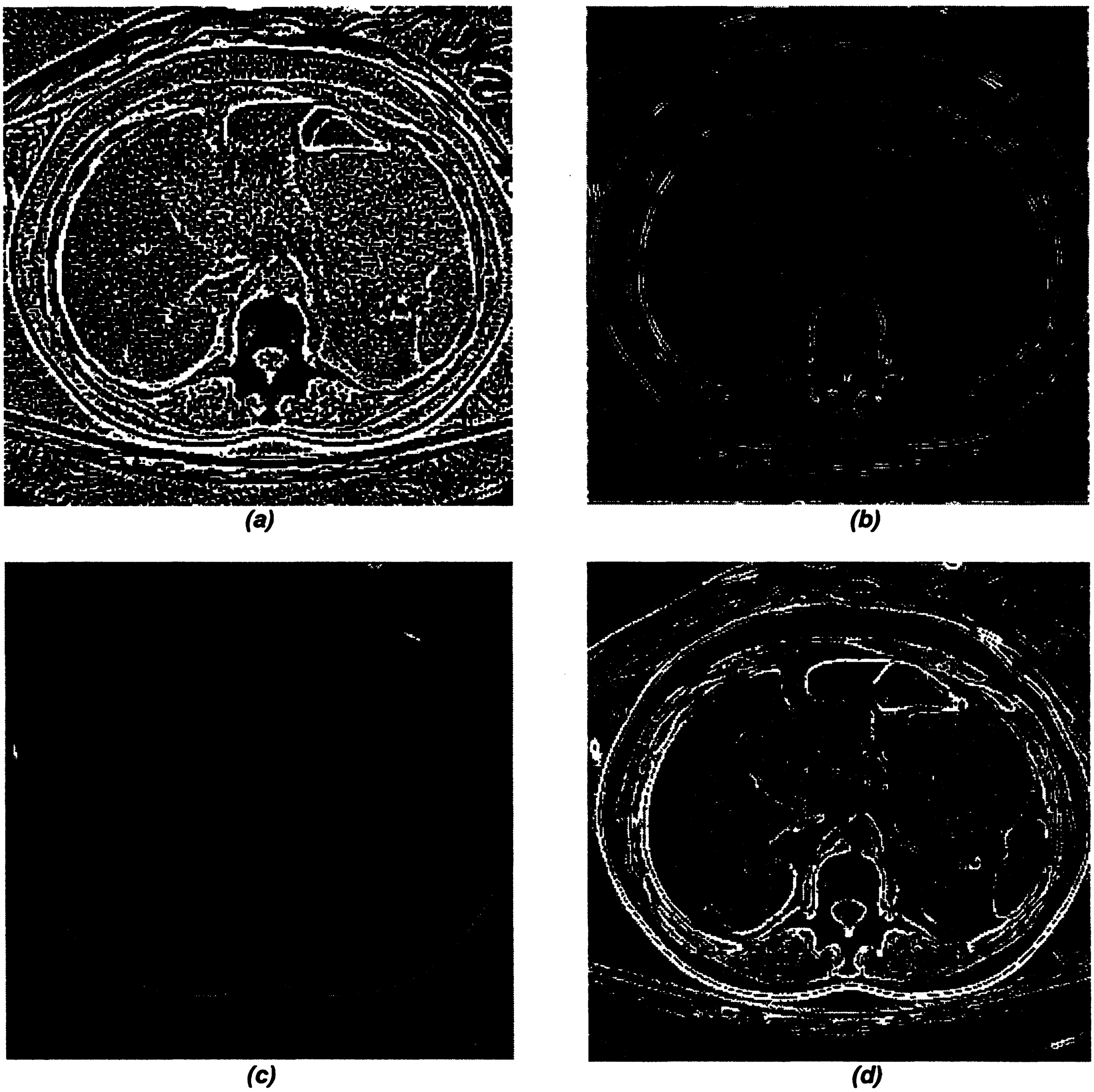


Figure 5. *Processing results based on an abdominal input image. (a) is the output of the Laplacian operator. (b) is the output of Sobel operator applied on (a). (c) is the processed image from the pyramid structure. (d) is the output of Sobel operator applied on (c).*

4. DISCUSSIONS AND FUTURE WORK

This comparison demonstrates that the output of the Sobel operator yields, at least subjectively, higher and finer definition of the boundaries of various organs when applied after processing through the pyramid structure. Also, it is noted that the lung vessels are enhanced after processing through the pyramid. In this sense, we postulate that processing the image at multiple scales and orientation in parallel instead of simultaneously helped enhancement of the image for segmentation performance.

However, while these results are encouraging, the application of the Laplacian operator before the Sobel operator on the histogram equalized image is somewhat artificial and perhaps non optimal because it was included to parallel the processing through the pyramid structure. Perhaps it could be argued that a fairer comparison would be that of the pyramid structure as presented here to a direct Sobel on the histogram equalized image. Before proceeding with further comparison, however, further work is being conducted in our laboratory to 1. Optimize the pyramid-based algorithm for texture-based boundary detection; 2. Evaluate comparison quantitatively.

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