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# Segmentation from Images Using Adaptive Threshold

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**Abstract:** Liver segmentation is an important prerequisite for planning of surgical interventions like liver tumor resections. In this paper we propose a method for automated liver segmentation from images that is invariant in provisions of size, shape and intensity values. The system consists of three stages. In the first stage of the computerized system, Preprocessing of an image is done to reduce the noise and to enhance the image for further processing. In the second stage, liver region is segmented from the liver image. The liver is segmented from images using adaptive threshold finding and morphological processing. In the third stage, post processing enhancement is done on the segmented liver region to increase the contrast of liver region. Experimental results show that our propose technique segments the liver region with accuracy.

**Key words:** Liver · Adaptive threshold · Post processing · Morphological processing

## INTRODUCTION

As a medical imaging technique, computed tomography is quite useful for doctors to analyze the pathological changes of the biological organs. Segmentation of human organs in the medicalimages is of benefit in many areas of medicine, including measurement of tissue volume, computer-guided surgery, diagnosis, treatment planning and research and teaching. The main problem of liver segmentation from images is related to low contrast between liver and near by organs intensities. Liver sometimes presents in different dimensions and makes the detection and segmentation even more difficult.

The liver is a vital organ with vascular, metabolic, secretory and excretory functions. It is extensively perfused and during liver surgery, special care has to be taken in order to avoid bleedings. Imaging techniques such as computed tomography (CT), magnetic resonance imaging (MRI), or positron emission to mography (PET) are nowadays standard instruments for the diagnosis of liver pathologies such as cirrhosis, liver cancer, fulminant hepatic failure. Among these techniques, images are often preferred by diagnosticians since they provide more accurate anatomical information about the visualized structures, thanks to their higher signal to noise ratio and better spatial resolution [1].

The liver cancer is one of the most common internal malignancies also one of the leading death causes. Currently, the confirmed diagnosis used widely for the liver cancer is needle biopsy. The needle biopsy, however, is an invasive technique and generally not recommended [2]. Therefore, computed tomography (CT) has been identified as accurate non-invasive imaging modalities in the diagnosis of the liver cancer. Many clinical applications for computer aided diagnosis require medicalimages to be segmented [5].

For example, planning of liver tumor embolization, ablation and surgical resection require precise segmentation of the liver from CT images. Due to the complex shape and the large size of this organ, the manual segmentation is time consuming. In order to increase the effciency of the clinical work, automatic segmentation methods are needed. A computerized liver CT segmentation system should take less time and should segment the liver accurately. It should be consistent and should provide a system to radiologist which is self explanatory and easy to operate [3-4].

There are many approaches for liver image segmentation. Most of the automated liver segmentation methods are based on region-growing, active contour or surface level-set or voxel classification algorithms, which were adapted to liver segmentation and connected with

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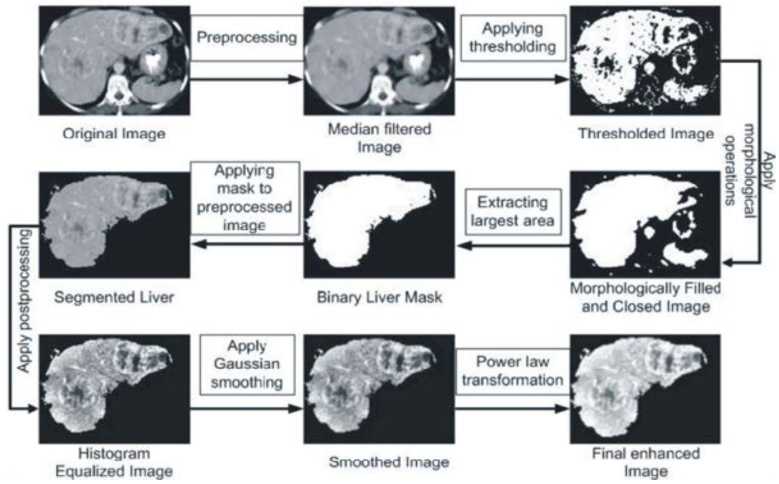


Fig. 1: Flow diagram of Computerized System for Liver CT Segmentation and Enhancement

some pre- and post-processing operations. Since the intensity as well as the boundary gradient of the liver varies from one part to the other, the methods are usually constrained with statistical shape or volume model. Zalthen *et al*. used a voxel-based region-growing algorithm to extract the portal vein, but the algorithm requires a manually set initial seed point and is therefore not fully automatic. The portal vein skeleton was calculated utilizing methods of Malandain and Bertrand and is corrected by pruning vessel segments that do not confirm with a set of predetermined properties. There are also may liver image enhancement methods. Histogram equalization (HE) is normally used to improve contrast,which generates an image whose pixels of gray levels are as equal as possible.But for the original CT image, HE often makes the whole image too bright to see. In recent years, contrast limited adaptive histogram equalization (CLAHE) has been used in medicalimages processing. However, it is easy to introduce artificial boundaries at the region where gray levels have great difierences [6].

A computerized liver CT segmentation system should consist of multiple phases including noise removal, liver region segmentation and liver region enhancement. In this paper, we propose a computerized system for liver image segmentation. Our system segments the liver region by using three phases, preprocessing, global threshold and post processing. The paper is organized in four sections. In section 2, proposed method is explained. Section 2 also presents the step by step techniques required for computerized liver CT segmentation system. Experimental results of tests on theimages and their analysis are given in Section 3 followed by conclusion in Section 4.

**Proposed System:** A systematic overview of the proposed technique is shown in Figure 1. In summary, given a liver CT image, the first step removes the noise from the image, the second step segments the liver portion from the CT image and in the third step post processing using adaptive histogram equalization, gaussian smoothing and gray level transformations takes place. As a result of these steps, we get a final segmented and enhanced liver CT image. Figure 2 shows flowchart of proposed technique [7].

**Preprocessing:** Preprocessing of liver CT image is the first step in our proposed technique. Preprocessing of an image is done to reduce the noise and to enhance the image for further processing. The purpose of these steps is basically to improve the image and the image quality to get more surety and ease in segmenting the liver. Steps for preprocessing are as follows:

Image is converted to gray scale.

A 3x3 median filter is applied on liver CT image using equation 1 in order to remove the noise.

$$\bar{f}(x,y) = median_{(8,t)\in Sxy}\{g(s,t)\} \quad (1)$$

Figure 3 shows the original liver CT image and preprocessed image.

**Liver Segmentation:** After enhancing the liver CT image, the next step of our proposed technique is to segment the liver region from liver CT image. Segmentation is done to separate the image foreground from its background. Segmenting an image also saves the processing time for

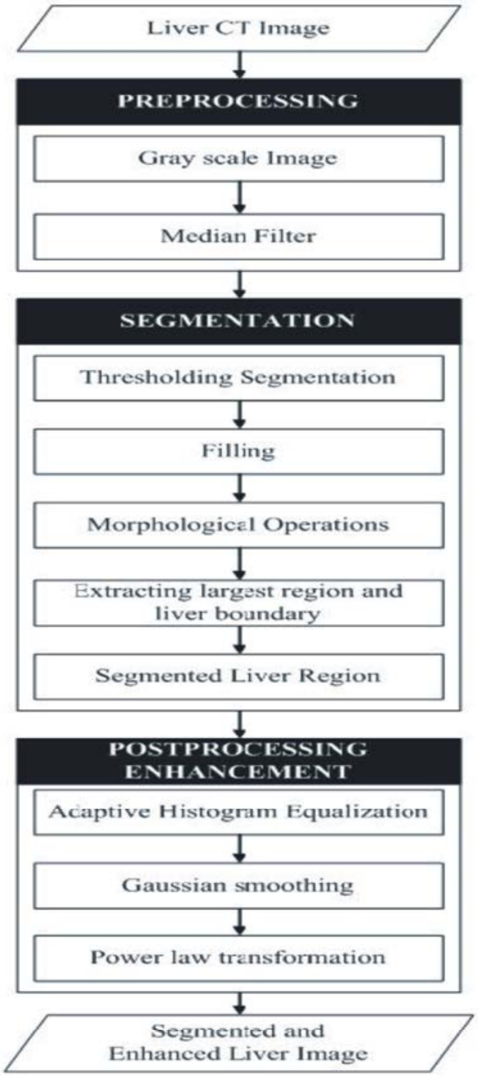


Fig. 2: Flowchart of proposed technique

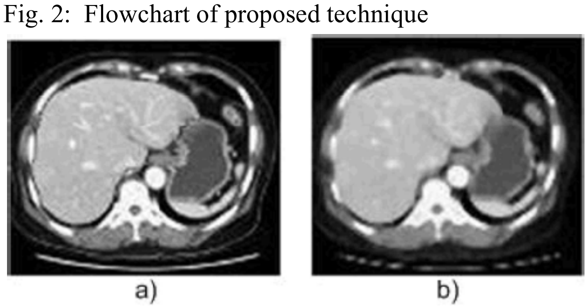


Fig. 3: Preprocessing: a) Original Image b) Median Filtered Image

further operations which has to be applied to the image. We have used segmentation using a global threshold in order to segment the liver CT image. Afterwards some morphological operations are applied on the image to obtain the final segmented liver region. The basic steps for liver CT segmentation are as follows:

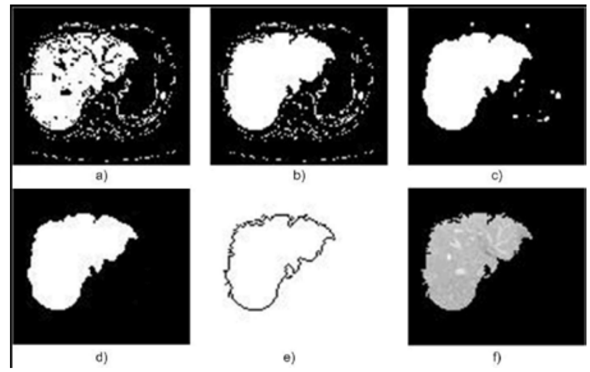


Fig. 4: Segmentation: a) Thresholding, b) Morphological Filling, c) Morphological Closing, d) Binary Liver Mask, e) Liver Boundary, f) Segmented Liver Region

Select a global threshold value for the whole CT image.

Apply the threshold value to the preprocessed image to convert the image to binary and the thresholded image is obtained. Morphological close operation is applied on the thresholded image to fill in holes and small gaps in the image. Reserve the block whose area is the biggest and set the others to zero using 8-connected neighbors.

The binary liver mask is obtained using the above step.

Extract the liver boundary by setting a pixel to 0 if its 4-connected neighbors are all 1’s, thus leaving only boundary pixels.

Multiply the original liver CT image with the liver masked image to obtain the final segmented liver region with gray level values as those of original image.

Figure 4 shows the threshold image, filled image, image after applying morphological operations, liver mask image, boundary extracted image and final segmented image [8-9].

**Postprocessing:** After segmenting the liver region from liver CT image, several post processing operations are applied on the image to enhance the liver region so that area of focus can be clearly highlighted. These post processing operations include adaptive histogram equalization, gaussian smoothing and gray level transformations. The basic steps of post processing are as follows:Adaptive histogram equalization is applied on the segmented image. Adaptive histogram equalization is an image enhancement technique which is capable of improving the image contrast and brings out fine details of an image [10-11].

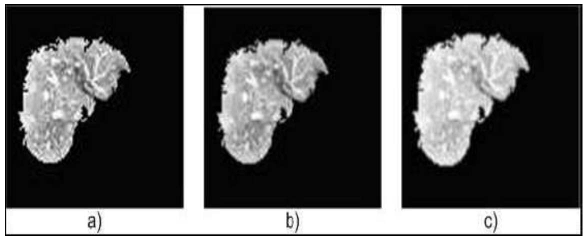


Fig. 5: Post processing: a) Adaptive Histogram Equalization, b) Gaussian smoothing, c) Power law transformation

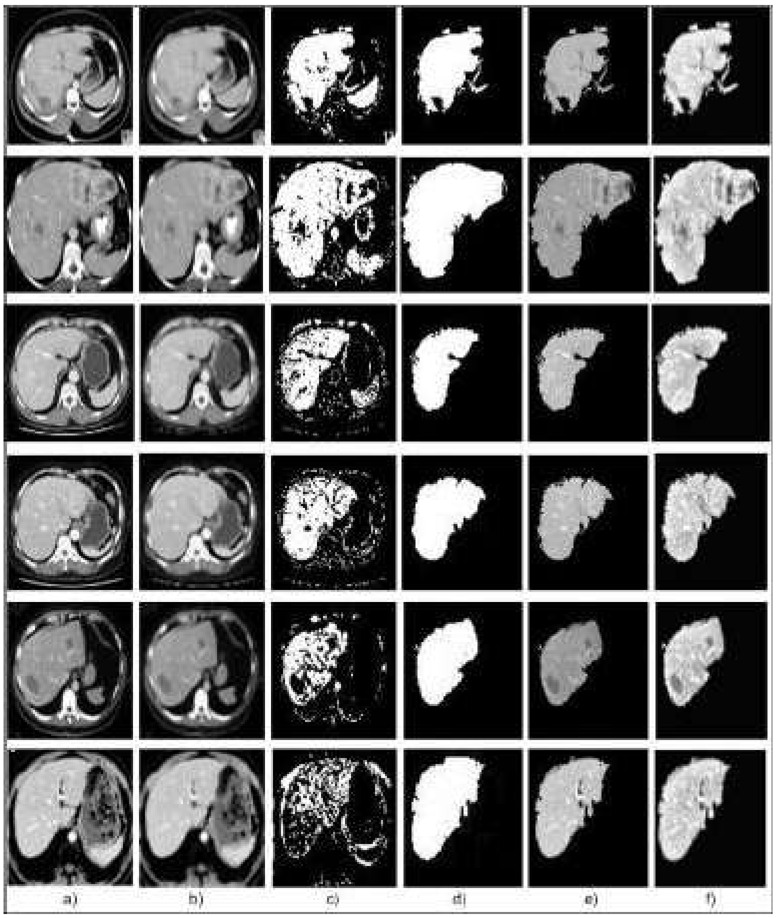


Fig. 6: Experimental Results: a) Original Images, b) Preprocessing, c)Threshold Segmentation, d)Binary Liver Mask, e)Segmented Liver, f)Postprocessing

A 7x7 gaussian low pass filter with =0.5 is applied on the histogram equalized image using equation 2 in order to smooth the image.

$$h_g(x,y) = e^{-(x^2+y^2)/2\sigma^2} \tag{2}$$

Power law transformation is applied on the smoothed in order to adjust the gray levels of an image using equation 3.

$$S=cr^{\gamma} \tag{3}$$

where s is output gray level value, r is input gray level value, is gamma and it is a constant value but its value changes in different scenarios and c is the constant. The enhanced segmented liver region is obtained using the above enhancement techniques.

The enhanced segmented liver region is obtained using the above enhancement techniques. Figure 5 shows the adaptive histogram equalized image, smoothed image and power law transformation applied image [12].

**Experimental Results:** The tests of proposed technique are performed with respect to the liver region segmentation accuracy using 100 images of different patients. Theimages are of size 512x512 pixels, eight bits per color channel. In order to check the accuracy of automated segmented liver region, liver region from allimages is segmented manually by the hepatologist and oncologist. The manually segmentedimages are used as ground truth. The true positive fraction is the fraction of number of true positive (pixels that actually belong to liver region) and total number of liver region pixels in the CT image. False positive fraction is calculated by dividing false positives (pixels that don't belong to liver region) by total number of non liver region pixels in the CT image [13-19].

Figure 6 shows the experimental results for different liver CT images. It shows that proposed method have extracted the liver region accurately and enhanced the liver region to highlight the point of focus.

## CONCLUSION

Identification and segmentation of a liver from images is challenging due to the very low contrast between the liver and other organs. In this paper liver segmentation and enhancement is done using CT images. The proposed method segments the liver using global threshold and then by identifying the largest area. Contrast of the liver region is improved by using adaptive histogram equalization and power law transformation. The proposed method is invariant in terms of size and shape of liver region. Experimental results show that our method performs well in enhancing, segmenting and extracting liver region from CT images.

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