Automatic Segmentation of the Liver in CT Images using the Watershed Algorithm based on Morphological Filtering

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ABSTRACT

Liver segmentation is one of the most basic and important parts in computer-aided diagnosis for liver CT. Although various segmentation methods have been proposed for medical imaging, most of them generally do not perform well in segmenting the liver from CT images because of surface features of the liver and difficulty of discrimination from other adjacent organs. In this paper, we propose a new scheme for automatic segmentation of the liver in CT images. The proposed scheme is carried out on region-of-interest (ROI) blocks that include regions of the liver with high probabilities. The ROI approach saves unnecessary computational loss in finding the accurate boundary of the liver. The proposed method utilizes the composition of morphological filters with a priori knowledge, such as the general location or the approximate intensity of the liver to detect the initial boundary of the liver. Then, we make the gradient image with the weight of an initial liver boundary and segment the liver region by using an immersion-based watershed algorithm in the gradient image. Finally, a refining process is carried out to acquire a more accurate liver region.

Keywords: Morphological operation, Edge detection, Watershed algorithm, Region merging

1. INTRODUCTION

The liver cancer is one of the most common internal malignancies worldwide. The hepatocellular carcinoma is common in Asia and the metastasis is common in the west. The liver cancer is one of the leading deaths. Currently, the only confirm diagnosis for the liver cancer is needle biopsy. The needle biopsy, however, is an invasive technique and generally not recommended\textsuperscript{1}. Computed tomography (CT) and magnetic resonance imaging (MRI) have been identified as accurate noninvasive imaging modalities in the diagnosis of the liver cancer. These medical images are interpreted by radiologists. However, image interpretation by humans is limited due to nonsystematic search patterns of humans, the presence of structure noise in the image, and the presentation of complex disease states requiring the integration of vast amounts of image data and clinical information. Recently, computer-aided diagnosis (CAD), defined as a diagnosis made by a radiologist who uses the output from a computerized analysis of medical images as a “second opinion” in detecting lesions, assessing extent of the disease, and making diagnostic decisions, is used to improve the interpretation
component of medical imaging. Research in CAD for both mammogram and chest radiographs is a rapidly growing field, but CAD research for the liver cancer is insufficient because liver segmentation that plays an important role for CAD is difficult. This is mainly due to the fact that there are other organs or tissues adjacent and close to the liver which makes segmentation more difficult.

In this paper, we propose the automatic segmentation algorithm of the liver in abdomen CT images by using a prior-knowledge and a watershed algorithm based on the morphological filters. After we present the proposed algorithm in Section 2, experimental results on several applications are presented in section 3, and our conclusions are drawn in Section 4.

2. PROPOSED METHODS

2.1 Overview of the proposed algorithm
The proposed scheme can be divided into four parts: pre-processing for image simplification, initial liver detection, block-based segmentation, and post-processing for refining of the result. The entire framework of our proposed scheme is illustrated in Figure 1.

![Figure 1. Block-diagram of the algorithm](image)

2.2 Pre-processing
The pre-processing is based on a priori knowledge, such as the general location of the liver and the general intensity of the liver. The liver region is generally located in the left side of the CT image and sequential CT images. Also, the general average and standard deviation of the liver intensity are almost homogeneous between patients. Thus, in the pre-processing we use the general information of the location and the intensity of the liver.

Firstly, we divide the abdomen CT image of the size of 512x512 into 64x64 blocks. And, the right-bottom region ('Rd' region except 'd1' block) which has not generally the liver region is reduced. Then, we set the first ROI blocks.
Figure 2 shows the first ROI blocks. Two-level image threshold is performed on the first ROI blocks by using general intensity threshold values of the liver.

![Diagram of First ROI Region](image)

Figure 2. First ROI Region

### 2.3 Initial Liver Detection

For the initial liver detection, the filter based on mathematical morphology (MM) is used. This set theoretic, shape oriented approach treats the image as a set and the kernel of operation, commonly known as structuring element (SE), as another set. Different standard morphological operations namely dilation, erosion, opening, closing etc. are basically set-theoretic operations between these two sets. The shape and the size of the SE play important role in detecting or extracting features of given shape and size from the image. Here, erosion and dilation with a flat structuring element are used in constructing a morphological filter as

\[
(f \ominus B_n)(x, y) = \min\{f(x+l, y+m) | (l, m) \in B_n\} \\
(f \oplus B_n)(x, y) = \max\{f(x-l, y-m) | (l, m) \in B_n\}.
\]  

(1) \hspace{2cm} (2)

For processing objects based on their shape as well as size we incorporate a second attribute to the structuring element which is its scale. Multiscale filtering are defined, respectively, as

\[
(f \ominus mB_n)(x, y) = \{(f \ominus B_n) \ominus B_n) \cdots \ominus B_n)(x, y)\}
\]

(3)

\[
(f \oplus mB_n)(x, y) = \{(f \oplus B_n) \oplus B_n) \cdots \oplus B_n)(x, y)\}
\]

(4)

where \(m\) is an integer representing the scale factor of the structuring element \(B\). Multiscale filtering is performed by using the composition of \(m\)th order morphological erosion and dilation operations with multisize structuring elements of the 5x5 and 3x3 flat size. Morphological filtering is operated on the first ROI region in the threshold image. Therefore, multiscale filtering by reconstruction in its first step eliminates bright features that do not fit within the SE and unconnected small features. In the second stage, it dilates iteratively to restore the contours of components that have not been completely removed by its first step. The performance of \(m\)th order multiscale filtering in the threshold image reduces the circumferential object of the liver, preserves the shape of the liver and detects the initial liver region.
The result of the initial liver detection processing is set to the second ROI region.

### 2.4 Block-based Segmentation

For ease of segmentation, the second ROI region is simplified with the morphological closing operation by a reconstruction of closing. The simplified image exhibits that the detailed textures of the original image are smoothed out, but the object boundaries are preserved.

The spatial gradient of the simplified image is approximated by the block-based edge enhancement processing. Through image simplification, the inside of each homogeneous region has small gradient. On the other hand, large gradients are induced along region boundaries among different homogeneous regions in the image. In edge enhancement processing, homogeneous region is enhanced by using the result of the initial liver detection and the edge detection algorithm. The result of the initial liver detection is the weighting factor for the enhancement of the border. This gradient image is used for the input image to detect the watershed lines.

Watersheds are one of the classics in the field of topography. In the field of image processing and more particularly in mathematical morphology, the image is often interpreted as a geographical surface in mathematical morphology, and its gray level is regarded as altitude. As for geographical surfaces, image structure exhibits inclines, hills, and plateaus over the image plane. Usually, a semantic region is distinguished by its inclines from surrounding contiguous regions in the image. The gradient exhibits large values at the inclines. So a watershed algorithm is applied to the gradient image to partition the image into homogeneous intensity regions within the initial liver region. Several number of a watershed algorithm have been proposed in the literature. In this paper, we use an immersion-based watershed algorithm since this algorithm is the simplest and computationally efficient.

The watershed algorithm is a region-growing algorithm, and it assigns pixels in the uncertainty area to the most similar neighbor region started from local minima with some segmentation criterion such as difference of intensity values. The final result of the algorithm is a tessellation of the input gradient image according to its different catchment basins.

![Watershed flooding](image)

Figure 3. Watershed flooding

Figure 3 depicts a two-dimensional graphical illustration of the watershed algorithm in an intuitive way. The local gradient minima are detected and used as seeds for region growing. In the image, these local minima are derived from homogeneous intensity regions. As the tessellation of the gradient image is immersed, each catchment basin in filled up...
from its lowest altitude selected as a seed. When the surface of the water in each catchment basin reaches the top of the crest, a dam is made for the water not to overflow into the nearby catchment basins. Last, the water surface in each catchment basin reaches the same level but is confined within the region encompassed by the crest lines or dams built on the crest in the gradient image. Then each region is assigned a unique label.

The watershed algorithm is highly sensitive to gradient noise. That fact yields many catchment basins, resulting in oversegmentation. Since the watershed detection could result in oversegmentation, the region merging algorithm based on intensity homogeneity should be incorporated to solve the oversegmentation problem. In this step, the statistical information of the initial liver region and the segmented liver region of the original image is used.

2.5 Post-processing

Finally, in the post-processing, region refining is performed by using the average and standard deviation of the segmented image through the comparison with initial liver region. And then, we can extract the liver region from the original image.

3. EXPERIMENTAL RESULTS

Liver segmentation described has been experimented with three abdomen 512x512 CT images of three patients. Each sample shows six images which are original image, the result of initial liver detection, gradients approximation, the result of the watershed detection, region merged image, and final result through Figure 4 to Figure 6.

Figure 4 (a), Figure 5(a) and Figure 6(a) show the original image of the abdomen CT image whose size is 512x512. Each sample is entered contrast media. Figure 4 (b) shows the two-level threshold image in the pre-processing. Threshold value is set by the statistical information of the liver. The other organs and tissues are reduced by thresholding. Figure 4 (c), Figure 5(b) and Figure 6(b) depict the result of the initial liver detection by performing the morphological operation. All of the other organs and tissues except the liver region are reduced by using the multiscale structural elements on the morphological filter. Also, we could obtain the result of maintaining the original size and shape of the liver.
Figure 4. The experimental result of the Patient 1: (a) original image, (b) threshold image, (c) initial liver detection, (d) gradients approximation, (e) watershed detection, (f) region merging, (g) final result

Figure 4(d), Figure 5(c) and Figure 6(c) show the result of the gradients approximation on the second ROI blocks. This is used as the marker in the watershed algorithm. The boundary information of the initial liver detection is the weight value for the gradients approximation. The gradients approximation is weighted by the edge enhancement processing with this value. Then, the watershed algorithm is performed on this gradient image. Figure 4(e), Figure 5(d) and Figure 6(d) show the result image of the watershed detection. Each different gray level depicts the different region. Finally, Each region is merged by comparing the statistical information of the same location between the original image and the segmented region. This is to solve the oversegmentation problem of the watershed algorithm. The result of region merging depicts in Figure 4(f), Figure 5(e) and Figure 6(e).
Figure 5. The experimental result of the Patient 2: (a) original image, (b) initial liver detection, (c) gradients approximation, (d) watershed detection, (e) region merging, (f) final result.
Finally, the final segment image is refined by using the statistical information of the original image and the result of the initial liver detection. You can see clearly the result image is the complete liver region in Figure 4(g), Figure 5(f) and Figure 6(f).

Figure 6. The experimental result of the Patient 3: (a) original image, (b) initial liver detection, (c) gradients approximation, (d) watershed detection, (e) region merging, (f) final result
4. CONCLUSIONS

In this paper, we suggested the automatic segmentation algorithm of the liver by using the watershed method was based on prior knowledge and the morphological filter in the abdomen CT image. The proposed algorithm decreased the needless computational time and efforts by reducing the other organs and tissues except the liver. This is obtained by performing two-level thresholding based on the block-based ROI by using general features of the liver and the statistical information in CT images. Also, the morphological filter using the multiscale structural element detects the initial liver boundary and that result is used for the weighting factor of the edge enhancement. And the result of the edge enhancement is used to be the marker for a watershed algorithm. An immersion-based watershed algorithm segments each region by detecting the watersheds lines through the immersion of the surface from the minima. These segmented regions are refined by using the statistical information of the original image and the result of the initial liver detection. The final result is compared to the segmented image by the radiological doctor and we knew that the fault error is almost not existed. This algorithm is the effective automatic segmentation algorithm of the liver in CT images for the first step of the CAD system.

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