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Automatic liver segmentation in MRI images using an iterative watershed algorithm and artificial neural network

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ABSTRACT

Precise liver segmentation in abdominal MRI images is one of the most important steps for the computer-aided diagnosis of liver pathology. The first and essential step for diagnosis is automatic liver segmentation, and this process remains challenging. Extensive research has examined liver segmentation; however, it is challenging to distinguish which algorithm produces more precise segmentation results that are applicable to various medical imaging techniques. In this paper, we present a new automatic system for liver segmentation in abdominal MRI images. The system includes several successive steps. Preprocessing is applied to enhance the image (edge-preserved noise reduction) by using mathematical morphology. The proposed algorithm for liver region extraction is a combined algorithm that utilizes MLP neural networks and watershed algorithm. The traditional watershed transformation generally results in oversegmentation when directly applied to medical image segmentation. Therefore, we use trained neural networks to extract features of the liver region. The extracted features are used to monitor the quality of the segmentation using the watershed transform and adjust the required parameters automatically. The process of adjusting parameters is performed sequentially in several iterations. The proposed algorithm extracts liver region in one slice of the MRI images and the boundary tracking algorithm is suggested to extract the liver region in other slices, which is left as our future work. This system was applied to a series of test images to extract the liver region. Experimental results showed positive results for the proposed algorithm.

1. Introduction

Today, imaging techniques, such as magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET) are very important in the medical diagnosis process. A hepatic MR is a new diagnostic method that has experienced important advances. It produces high quality images and is one of the standard instruments for the diagnosis of liver pathologies, such as cirrhosis, liver cancer, and fulminant hepatic failure [1]. These advances include rapid scanning, new sequences of images with a high spatial resolution and more specific contrast for each type of lesion [2,3]. Fast and suitable algorithms for segmentation have an important role in the diagnosis, classification and quantitative description of diseases in various tissues, including liver tumors [4]. For example, in clinical surgery, accurate segmentation of the liver using MRI images is important for automated liver perfusion analysis, which provides important information about the blood supply to the liver [5]. Accurate liver segmentation in abdominal MRIs is challenging because the gray-level distribution of surrounding organs is not highly distinguishable. Therefore, the boundary regions between the liver and adjacent tissues generally have uniform intensity distributions, which often lead to the oversegmentation of the liver. Additionally, the vasculature inside the liver commonly leads to segmentation leakage [6].

To date, most research has been conducted on liver segmentation in CT images. Only a few studies have focused on MRI images. The primary reason that abdominal MRI research has been limited is that these images are more affected by artifacts. Moreover, they have a low gradient response, which makes accurate liver segmentation very difficult [7].

Zhang et al. [8] proposed an automatic liver segmentation method for CT images that was based on a statistical shape model (SSM) integrated with an optimal-surface-detection strategy. The method included three steps: first, the average liver shape model was determined by CT volume data via a 3D generalized Hough transform. Then, subspace initialization of the SSM was performed using intensity and gradient profiles. Finally, the shape model was reformed to adapt to the liver contour through an optimal-surface-detection approach based on graph theory.

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Badakhshannoory and Saeedi [9] proposed a model-based validation scheme for organ segmentation in CT scan volumes. In this method, instead of using the organ's prior information directly in the segmentation process, the information was utilized to validate a large number of potential segmentation outcomes that were generated by a generic segmentation process. For this purpose, an organ space was generated using the principal component analysis approach.

The authors of Ref. [10] proposed an automatic liver segmentation system by combining several phases of the contrast-enhanced CT images. The method employed a region-growing algorithm facilitated by pre- and postprocessing functions, which incorporated anatomical and multi-phase information to eliminate over- and undersegmentation.

Foruzan et al. [11] employed a knowledge-based technique for liver segmentation in CT images. To estimate the initial liver boundary, the method utilized a technique based on the anatomical knowledge of liver and its surrounding tissues. Furthermore, a multi-step heuristic technique was employed to segment the liver from other tissues in multi-slice CT images.

The authors of Ref. [12] proposed a liver segmentation method using a gradient vector flow (GVF) snake in CT images. This method utilized a snake algorithm with a GVF field as its external force. To improve the performance of the GVF snake in the segmentation of the liver contour, an edge map was obtained using Canny edge detector, followed by modifications using a liver template and a concavity removal algorithm.

The authors of Ref. [13] proposed a liver segmentation method from contrast-enhanced CT images. In this method, the two-step seeded region growing (SRG) method was applied on the level-set speed images to define the initial liver boundary. The first SRG efficiently divides the CT image into a set of discrete objects according to the gradient information and connectivity. The second SRG detects the objects belonging to the liver by using a 2.5-dimensional shape propagation.

Zhao et al. [14] proposed a liver segmentation algorithm in CT images, where a thresholding method was used to remove the ribs and spines in the input image. Additionally, the initial liver region was segmented using a fuzzy C-means clustering algorithm and morphological reconstruction filtering. Then, a multilayer perceptron (MLP) neural network was employed for the segmentation.

The authors of Ref. [15] proposed an automatic liver segmentation method in abdominal CT images. At first, the liver tissue is roughly distinguished by using a statistical model-based approach. Then, a force-driven optimized active contour (snake) [16,17] is applied to obtain a smoother and finer liver contour.

Different algorithms have also been proposed for liver segmentation in MRI images. Chen et al. [5] employed a multiple-initialization level set method (LSM) to overcome the leakage and oversegmentation problems in liver segmentation from MRI images. They first evolved the multiple-initialization curves separately using a fast marching method and LSMs, which were then combined with a convex hull algorithm to obtain a rough liver contour. Finally, the contour was refined again using global level set smoothing algorithm to determine the precise liver boundary.

The authors of Ref. [18] proposed a liver perfusion analysis based on active contours and chamfer matching (CM) [19,20] that were employed for liver segmentation and to align the slices in the MRI series, respectively. To apply CM, a prior liver shape image was employed to assist in the liver shape extraction and remove artifacts.

Gloger et al. [21] proposed a three-step liver segmentation method using LDA-based probability maps for multiple contrast MR images. The method is based on a modified region growing approach and a thresholding algorithm. In this method, all available MR-channel information for different weightings was used to identify liver tissue and position probabilities in a probabilistic framework. The method utilized a multiclass linear discriminant analysis to generate the probability maps for the segmentation.

Yuan et al. [6] proposed an automatic liver segmentation algorithm based on fast marching and improved fuzzy clustering methods in abdominal MRI images. This method includes four successive steps. First, the fast marching method and convex hull algorithm were applied to roughly extract the liver's boundary and topology. This step provides a basic estimation for subsequent calculations. Second, an improved fuzzy clustering method, combined with multiple-cycle processing, was designed to refine the segmentation result. Third, on the basis of the segmentation results, the liver is visualized by the marching cube (MC) method.

Middleton and Damper [22] proposed a MRI segmentation algorithm based on the combination of neural networks and active contour models. In this method, a perceptron neural network was trained to classify each image pixel as either a boundary or a non-boundary. Then, the resultant binary image was used to define the external energy function for the snake. Consequently, by minimizing the snake energy, the final result was obtained.

Most of the existing methods on liver segmentation focused on CT images. Accurate liver segmentation in abdominal MRIs is difficult because the gray-level distribution of surrounding organs is not highly distinguishable. Boundary regions between the liver and adjacent tissues generally have uniform intensity distributions, which often lead to the oversegmentation of the liver and make the automatic segmentation more difficult. Existing methods on liver segmentation in abdominal MRIs are generally semi-automatic and automatic approaches suffer from the segmentation leakage or oversegmentation.

In this paper, we propose a new method for automatic liver segmentation in abdominal MRI images. The algorithm is fully automatic and contains several stages, including preprocessing, segmentation, feature extraction and liver-region extraction. The preprocessing stage is applied to enhance the main edges of the image regions while suppressing the image noise. We then used a morphological watershed transform [4,23,24] for image segmentation because of its efficient segmentation properties. Among the various medical image segmentation methods, watershed algorithm, which is based on morphological mathematics, plays an important role. It is widely used in histology in many different ways. However, when a pure watershed transform is applied to MRI images directly, it causes oversegmentation. To overcome the problem of oversegmentation, the iterative watershed algorithm was combined with trained neural networks for image segmentation. The neural networks are trained to extract some features from the input image. The features are also extracted from the segmented image using a watershed transform. The outputs of the watershed transform are compared with the neural networks' outputs, and the difference is used to adjust the required parameters of the algorithm sequentially. To obtain optimum parameters, the parameters are gradually changed in several iterations.

The proposed algorithm deals with the extraction of the liver region in one slice of the MRI images. The slice is randomly selected from slice numbers 25–35 that have larger liver region. When the liver region is obtained for one slice, the boundary tracking algorithm may be used to extract the liver region in other slices.

The organization of the paper is as follows: Section 2 describes the proposed algorithm for liver segmentation, Section 3 represents the experimental results, and finally, we conclude the paper in Section 4.