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3D active surfaces for liver segmentation in multisequence MRI images

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ABSTRACT

Biopsies for diagnosis can sometimes be replaced by non-invasive techniques such as CT and MRI. Surgeons require accurate and efficient methods that allow proper segmentation of the organs in order to ensure the most reliable intervention planning. Automated liver segmentation is a difficult and open problem where CT has been more widely explored than MRI. MRI liver segmentation represents a challenge due to the presence of characteristic artifacts, such as partial volumes, noise and low contrast. In this paper, we present a novel method for multichannel MRI automatic liver segmentation. The proposed method consists of the minimization of a 3D active surface by means of the dual approach to the variational formulation of the underlying problem. This active surface evolves over a probability map that is based on a new compact descriptor comprising spatial and multisequence information which is further modeled by means of a liver statistical model. This proposed 3D active surface approach naturally integrates volumetric regularization in the statistical model. The advantages of the compact visual descriptor together with the proposed approach result in a fast and accurate 3D segmentation method. The method was tested on 18 healthy liver studies and results were compared to a gold standard made by expert radiologists. Comparisons with other state-of-the-art approaches are provided by means of nine well established quality metrics. The obtained results improve these methodologies, achieving a Dice Similarity Coefficient of 98.59.

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1. Introduction

Medical imaging is a powerful diagnostics technique for locating and characterizing organs and related pathologies in medical practice. In case of liver, diagnostic confirmation is often performed by percutaneous or surgical biopsies. Nowadays, these invasive techniques can be partially replaced by medical imaging techniques such as Computerized Tomography (CT) and Magnetic Resonance Imaging (MRI), with obvious benefits for the patient. This makes it crucial to provide radiologists with new methods and tools for medical image understanding [1–5]. Accurate liver segmentation on these images directly enhances diagnosis efficiency and provides radiologists and surgeons with a robust tool for intervention planning.

Many approaches to liver segmentation have achieved reasonable success in recent years, mainly based on semi-automatic methods over CT images requiring user interaction. For instance, some works in liver segmentation over CT images [6,7] employ level set based techniques to incorporate

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regularization in the segmentation problem [8–10]; use statistical models that map the existing prior knowledge [11]; introduce textural information [10,12,13], and use atlas with different approaches. In the recent years, more automatic methods have been developed, such as in References [14–16], which propose deformable models, capable of adapting well to organs such as liver that can present complex shapes and high variability. Although most of the referred methods for CT could be exported to MRI images, the majority of these works are developed ad-hoc for CT images and performance in MRI images is typically worse. Therefore, ad-hoc CT or MRI segmentation is usually tackled. Automatic liver segmentation in MRI is a challenging problem due to some artifacts and characteristics of these images, such as the partial volume effect [17], the presence of noise or the low contrast and edge resolution of the liver in relation with adjacent tissues.

In all the approaches over CT images, only one sequence is used as input in the segmentation problem. On the contrary, MRI acquisition techniques are based on the response of the tissue to different electromagnetic fields. Each configuration determines specific imaging sequences that provide different functional responses of the tissues. This permits radiologists the use of different sequences at the same time to obtain complementary and valuable diagnostic information.

Even if it is usual in clinical practice, the automatic and combined use of these multiple sequences remains challenging. Unfortunately, there exist few methods that propose a multichannel approach in MRI [18–21]. A detailed review of these methods is provided in section 2.2. These proposed multisequence approaches lack in general the ability to integrate multisequence information with its spatial distribution: the main idea is usually to treat the problem as a straightforward extension to higher dimensions. In our work, we propose to transform the multidimensional information in the input into only one sequence with enhanced contrast that allows better segmentation. This way, the dimensionality of the problem is not increased.

In this paper, we propose a novel method for multichannel MRI automatic liver segmentation. On the one hand, the representation of the multisequence data is proposed by means of a sole compact descriptor through a multivariate Gaussian statistical model based on the appearance of the organ. This approach gathers spatial distribution of the multi-dimensional intensity values and is able to capture the variability of the data. On the other hand, the proposed method consists of the minimization of a 3D volumetric active contour (active surface) model by means of an extension of the dual approach to the underlying variational problem. This work extends Chambolle's algorithm [22] for 3D segmentation. The proposed 3D active surface approach naturally integrates volumetric regularization in the model. These two novel contributions allow the embedding of the 3D spatial variability of the multisequence on a 3D compact framework that ensures accurate and fast volume segmentation. This novel method was tested on 18 healthy liver studies and results were compared to a gold standard provided by expert radiologists. This allowed the extraction of nine well established metrics for comparison with other state-of-the-art methods.

The rest of the paper is structured as follows. Section 2 provides further detail on the related works. Section 3 describes the proposed method. Section 4 details the validation tests and results. Section 5 is devoted to discussion, and in section 6 the conclusions are gathered.

2. Related work

In this section, the previous works that are closely related to ours are described in detail. First, a review of recent methods for 3D liver segmentation is developed. Then, multichannel approach is reviewed. Next, different models of active contours proposed in the literature are analyzed. Finally, minimization methods are enumerated.

2.1. 3D liver segmentation

Several works have been developed specifically for 2D and 3D liver segmentation in MRI images. Level set techniques have been applied to this problem. Chen et al. make an attempt to deal with the main limitation of the level set methodologies, which are initialization-dependent [23]. They propose a method where three level sets are initialized as close as possible to the final solution. Then, a specific post-processing to extract a well-segmented region is applied, and final results are merged together. Although this method provides good results according to evaluation metrics, it remains semi-automatic, thus needing interaction with the user. A more successful and promising solution is the one proposed by Göçeri et al. in Reference [24] where a fully automated level set approach is detailed. The method defines automatically an initial contour, and computes weight values of each term in the applied energy functional at each iteration during evolution, dealing with two problems that are common to level set techniques at the same time, that is, the initialization need and the terms updates. However, the efficiency of the regularization of the level set function could be increased to get more successful results. In other works, mainly deformable models based on different approaches over active contours are developed. Yuan et al. develop a MRI specific liver segmentation method that combines fast marching approach and fuzzy clustering [25]. The main drawback of this method is the same as in the level set framework, i.e., they need a good initialization close to the solution.

There are other few fully automatic methods performing 3D segmentation over MRI images. Gloger et al. develop a fully automatic three-step 3D segmentation approach in MRI based upon a modified region growing methodology and a further thresholding technique [26]. For dimensionality reduction, they employ multiclass linear discriminant analysis and generate probability maps then used for segmentation. Finally, they incorporate prior knowledge to refine the segmentation results. In Reference [27], 3D liver segmentation is proposed in three stages. First, a preprocessing stage is applied to T1-weighted MRI to reduce noise and produce the boundary-enhanced image. This enhanced image is used as a speed function for a 3D fast-marching algorithm to generate an initial surface that roughly approximates the shape of the liver. A 3D geodesic-active-contour segmentation algorithm refines the initial surface to determine the liver boundaries. Deformable models, as active contours, are capable of segmenting elements with complex

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