computer methods and programs in biomedicine 114 (2014) 11–28

journal homepage: www.intl.elsevierhealth.com/journals/cmpb

Liver segmentation in MRI: A fully automatic method based on stochastic partitions

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ARTICLE INFO

Article history:
Received 28 November 2012
Received in revised form
20 December 2013
Accepted 24 December 2013

Keywords:
Magnetic resonance imaging
Liver segmentation
Mathematical morphology
Stochastic partitions
Watershed transform

ABSTRACT

There are few fully automated methods for liver segmentation in magnetic resonance images (MRI) despite the benefits of this type of acquisition in comparison to other radiology techniques such as computed tomography (CT). Motivated by medical requirements, liver segmentation in MRI has been carried out. For this purpose, we present a new method for liver segmentation based on the watershed transform and stochastic partitions. The classical watershed over-segmentation is reduced using a marker-controlled algorithm. To improve accuracy of selected contours, the gradient of the original image is successfully enhanced by applying a new variant of stochastic watershed. Moreover, a final classifier is performed in order to obtain the final liver mask. Optimal parameters of the method are tuned using a training dataset and then they are applied to the rest of studies (17 datasets). The obtained results (a Jaccard coefficient of 0.91 ± 0.02) in comparison to other methods demonstrate that the new variant of stochastic watershed is a robust tool for automatic segmentation of the liver in MRI.

1. Introduction

Fully automatic liver segmentation in medical images is currently an unsolved problem [1]. An accurate liver segmentation has a direct application in the planning, monitoring, and treatment of different types of pathologies such as cirrhosis or hepatocellular carcinoma diseases. In these cases, hepatic tissue anomalies are treated using qualitative comparison, which is related to physician experience; however, quantitative measures are not widely used. Liver segmentation is the first step to calculate objective measurements and liver/lesion ratios for decisions regarding treatment and planning for the patient. The segmentation of internal organs is also essential for image-guided surgery and virtual reality scenarios for medical training [2–6]. In addition, the liver segmentation can help in hepatic steatosis quantification because the results of this segmentation can be correlated to measure fat fractions [7].

In most applications mentioned above, due to the high accuracy required, a segmentation of the liver is carried out in images with high spatial resolution, i.e., Computed Tomography (CT) or Magnetic Resonance Images (MRI) [8,9]. Currently, some efforts are focused on the segmentation of the liver in other types of images (such as PET or ultrasound images) that are less damaging for the patient than the CT images and that are cheaper for hospitals than MRI. However, the low spatial resolution of these images is a disadvantage and, in some

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0169-2607/$ – see front matter
http://dx.doi.org/10.1016/j.cmpb.2013.12.022

cases, even with manual corrections, the segmentation is not accurate enough for image-guided surgery or liver volumetry applications that radiologists or surgeons require [10,11]. In the literature, there are more segmentation methods that are applied and validated for CT than for MRI. MRI generally has more artefact effects and a lower gradient response and is more costly for hospitals; however, since it is a non-ionizing radiation, it is less damaging for the patient in comparison with CT. The authors of several studies support the benefits (or the additional information) of MRI considering it to be a primary diagnostic imaging modality for liver lesion detection or for measuring hepatic steatosis [7,12–16]. For example, the segmentation of the liver in MRI is important in automating liver perfusion analysis, which provides important information about the blood supply to the liver [17]. In any case, hepatic MR certainly is an alternative to CT images for the diagnosis of liver disease offering benefits that make this image technique interesting for clinical purposes. For this reason it is necessary to advance in the development of methods for liver segmentation in MRI in a way similar to the advances in CT methods.

The liver segmentation methods found in the state-of-the-art in MRI are based mainly on level-set methods [17–22], where the drawbacks of these algorithms (difficult training, high computational cost, or high user iteration) are noticeable. Specially, in [18], a level-set method (a fast marching algorithm) and fuzzy theory are applied in the liver segmentation task, but the computational cost of this algorithm needs to be improved (as the authors themselves recognize) and, additionally, non-uniform intensity problems are not solved. In [19,20], level-sets and probabilistic maps are used, and a training process is required with a high user iteration for manual segmentation. In [21], another level-set method called active contour is applied in T1 MR images of the liver, and the radiologist's knowledge is required to define the region of interest. Finally, in [22], active contours are also applied in T2 MR images, but the results, though promising, are not accurate in some cases. Other methods based on graylevel properties (region growing, thresholding, *k*-means, etc.) produce poor results in images of this type because the great intra-study differences make difficult the generalization of these algorithms. In [9], authors use a region growing method combined with threshold techniques and prior knowledge that requires a training step with manual segmentation.

In the current paper, the performance and the validation of a new liver segmentation method that is based on the watershed transform and that is applied to MRI is presented. The goal is to obtain a fully automatic method that requires less of the clinician's time, has enough accuracy and robustness for medical environments, and has a reasonable computational cost. The watershed transform is a segmentation tool that is based on graylevel and contour properties of the image. This tool extends each regional minimum of the image as far as its topography allows. An over-segmentation problem usually appears due to the large number of regional minima in the image. There have been improvements in the original watershed transform in order to reduce its drawbacks. These include using marker-controlled watershed paradigm [23] as well as hierarchical watershed paradigms such as the waterfall algorithm [24]. It must be specify that here the standard framework of watershed transform based on the flooding algorithm is adopted despite to there are other alternative frameworks based on a continuous formulation using topographic distance [25,26]; the topological watershed based on discrete geometry tools [27,28]; graph-based watershed using minimum spanning-tree algorithms [29,30]; the power watershed algorithm [31]; the viscous watershed [32]; etc.

With the marker-controlled algorithm, a set of markers imposes the new minima, and the number and position of output regions can be controlled and the over-segmentation problem is reduced. The definition of these markers is not an easy task for the segmentation of the liver, which is a large organ that has an enhanced vessel tree that produces high internal gradients. The manual definition of these markers is inefficient and is not a practical option in clinical environments due to the potential benefits of the algorithm (such as low user interaction) decrease [33]. To deal with problems of this kind, the use of a new variation of the stochastic transform proposed by [34] is carried out in this paper. This variation is necessary because when the original stochastic transform is applied in MR images of the liver, it enhances internal edges with respect to the external edges of the liver, which is not useful for our purpose. The purpose of the new variant of the stochastic watershed proposed in this work is to obtain a more significant probability density function of contours by taking into account the contrast between adjacent regions thanks to a region-based model. Besides presenting this new version of stochastic watershed, another contribution of this work is the combination of pre-processing, marker extraction, and post-processing filters. This makes possible the liver segmentation of 3D studies in a fully automated and accurate way and with a low computational cost. These features convert the method into a usable tool for clinical purposes.

There have been other liver segmentation algorithms where the watershed transform has been used due to its easy user initialization/interaction, its reasonable computational cost, its intuitiveness, and the accurate results achieved in other casuistic (type of images, organs, etc.). In [35], the watershed transform is combined with neural networks to train and tune watershed parameters for liver segmentation purposes. This training algorithm requires manual segmentation, and since the method is only used for 2D image segmentation, the particularities of a 3D volume are not taken into account. In [36], after applying a pre-processing step, the watershed transform is applied but regions with similar intensities may be incorrectly merged due to problems of intensity that are produced by lesions or by illumination that is not uniform.

In our application, the final goal of the segmentation of the liver is to add the 3D model of the liver into a 3D model with other abdominal organs of a patient previously segmented with own algorithms [37,38]. This virtual 3D model will be registered and merged thanks to augmented reality algorithms by using an image of the patient that will be taken with an external video camera. The system will be applied in order to place trocars in the patient's body in which the minimum accuracy required is approximately 2 cm [39].

The rest of the paper is divided into three sections. The first section describes a technical explanation of the watershed transform, the contribution of this work, and