Chapter 10
Abdomen CT Image Segmentation Based on MRF and Ribs Fitting Approach

Huiyan Jiang, Zhiyuan Ma, Mao Zong, Hiroshi Fujita and Xiangrong Zhou

Abstract Aiming at the segmentation of liver image with fuzzy edge, a new algorithm based on Markov Random Field and ribs fitting approach is proposed. The new algorithm consists of three main steps. Firstly, an abdominal image is pre-processed to fit ribs and remove the obstructive region. Then, lifting wavelet transform is adopted to decompose an image in different resolutions, and an image segmentation algorithm based on MRF is manipulated to the low frequency sub-images; lastly, morphology operation is adopted to obtain the liver region. The algorithms of the initial and multi-level segmentation in wavelet domain are K-means and MAP/ICM. Several experiments have been carried out and the experimental results show that the proposed algorithm has a good robustness and higher segmentation accuracy than the traditional MRF approach.

Keywords Image segmentation · Markov random field · Ribs fitting · ICM · Wavelet transform

10.1 Introduction

With the rapid development of modern medical technology, digital medical image has been widely used in disease diagnosis for clinical doctors and experts. The accurate segmentation of diverse tissues in the CT image is not only a necessary premise before extracting features of diseases, but also a basic of the image three-dimensional reconstruction and the medical image visualization [1].

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W. Du (ed.), *Informatics and Management Science III*, Lecture Notes in Electrical Engineering 206, DOI: 10.1007/978-1-4471-4790-9_10,

Human anatomy of different individuals is distinct, and the accuracy and time of the medical image segmentation approach are highly demanded by the clinical application. For this reason, there are massive methods proposed in research literatures, such as threshold-based method, edge-based method, clustering method, region-based method, and Markov Random Field (MRF)-based method, Level Set method, etc. The threshold-based method is widely used in image segmentation with simple structures, but it is sensible to noise and the threshold; Edge-based methods depend on the edge detect operator to find the edge of an image, and these edges identify discontinuous locations of gray-level, colour and texture in an image [2, 3]. The edge-based method is commonly combined with some prior knowledge to avoid the effect of noise [4]. The most frequently-used clustering methods are K-means clustering and FCM clustering. Both of them need an initial cluster centre which greatly influences the final segmentation result, and the algorithm possesses a bad robustness; Region-based methods can effectively eliminate the noise by taking into account both the similarity of the pixels and the spatial adjacent relationships among them [5]. However, it is sensible to the chosen of the initial seed; MRF-based approach is a kind of region-based algorithm, which takes into account connections of pixels with their neighbour pixels. It sufficiently considers the mutual relationships among pixels. MRF-based algorithm usually models an image in a suitable model, and makes use of the equivalence of Gibbs-Markov to achieve image segmentation. The algorithm commonly uses some optimization algorithms to achieve robustness result, like Iterative Conditional Mode (ICM), Mean Field Annealing (MFA) and Simulated Annealing (SA), etc. Different optimization algorithms will significantly affect the segmentation result. Level set is a sort of curve evolution approach, which owns good robustness. However, the curve evolution time of level set is long and the segmentation accuracy of image with fuzzy object edge is low [6].

This paper presents a new medical image segmentation algorithm based on MRMRF model with ribs fitting approach [7]. Firstly, an original image is pre-processed to implement ribs fitting with a series step, like threshold process, morphology operation, centre demarcation, and curve fitting. Secondly, a three level LWT is executed to an original image [8, 9]. Then we use this result to accomplish the multi-level segmentation of the destination area. During the modelling of MRF, Finite Gauss Matured Model (FGMM) and Potts model are respectively used to characterize the feature field and label field, Expectation—Maximization (EM) is adopted to estimate the parameters in the models [10, 11]. During the multi-level segmentation procedures, we choose the ICM algorithm and make use of the equivalence between the Maximum a Posterior (MAP) and energy minimization. We use a variable weight to combine the feature field and the label field in each iteration procedure, which can efficiently coordinate the potency between the feature field and the label field [12, 13]. Lastly, we manipulate the segmentation result in MRF model with some morphology operation to revise the result. Figure 10.1 shows an outline of the proposed algorithm. LF is short for low frequency.

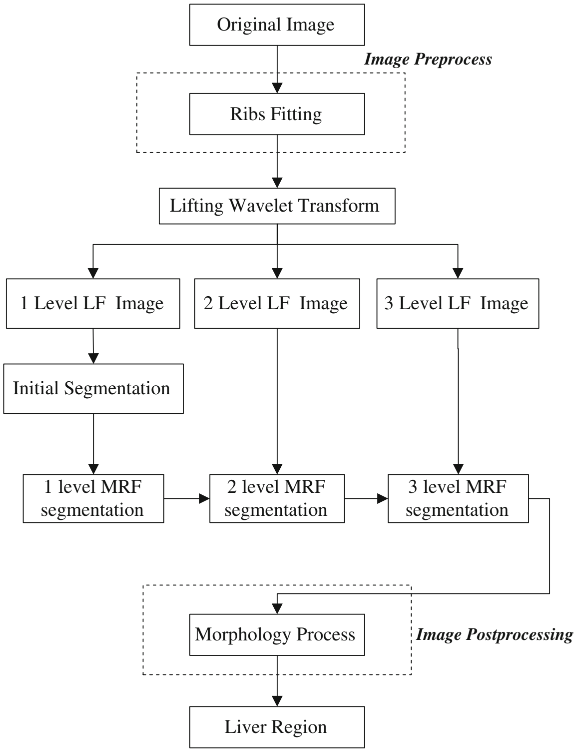

Fig. 10.1 The outline of the proposed algorithm

The rest of the paper is organized as follows: in the next section, a fully describe of the proposed algorithm is introduced, including the image pre-process with threshold process, morphology operation, centre demarcation, and curve fitting, the image segmentation with image lifting wavelet transform, the modelling of MRF in wavelet domain, the image post-processing with morphology operation. In Sect. 10.3 the validity of the proposed algorithm compared with other methods is given. Some conclusions are given in Sect. 10.4.

10.2 The Proposed Algorithm

The proposed algorithm consists of three modules: image pre-process, image segmentation based on MRF approach, and image post-processing based on morphology method.

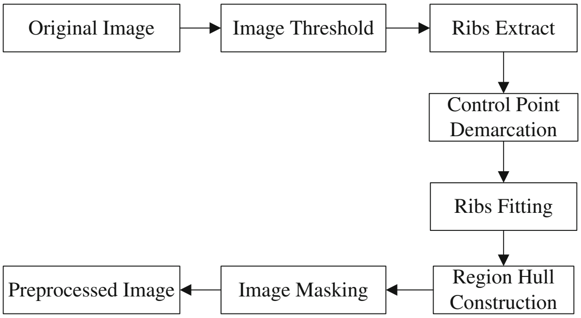

Fig. 10.2 Flow of the image pre-process procedure

10.2.1 *Image Pre-Process*

Image pre-process is an important step in image segmentation. The flow of the pre-process procedure is shown in Fig. 10.2. During the procedure, firstly a threshold is chosen to separate ribs in an original image, as the luminance of ribs is higher than other regions. Secondly, region proportion is based to wipe out other regions except of ribs. Thirdly, according to different image, we choose several control points automatically or manually. Fourthly, we construct a hull by the control point and get a mask image. Lastly, after getting the mask image, we can obtain a pre-processed image.

10.2.2 *Image Segmentation Based on MRF Approach*

According to MAP criterion, the image segmentation based on MRF can be formulated as:

$$\begin{aligned} \hat{x} &=38; \arg\max_{x}\{P(W=\omega, X=x)\} \\ &=38; \arg\max_{x}\{\prod_{n=0}^{J-1}\prod_{(i,j)\in I_{2^n}} P(\omega_{ij}^{(n)}|x_{ij}^{(n)})P(x_{ij}^{(n)}|x_{\eta_{ij}}^{(n)})\} \end{aligned} \tag{10.1}$$

The Eq. (10.1) can be translated into Eq. (10.2) according to the equivalence of energy minimization and MAP criterion. In this paper, we use ICM-MAP to achieve the energy minimization based on the Eq. (10.2).

$$\hat{x} = \arg\min\{\sum_{n=0}^{J-1}\sum_{(i,j)\in I_{2^n}}[E_{\omega_{ij}^{(n)}|x_{ij}^{(n)}} + E_{x_{ij}^{(n)}}]\} \tag{10.2}$$

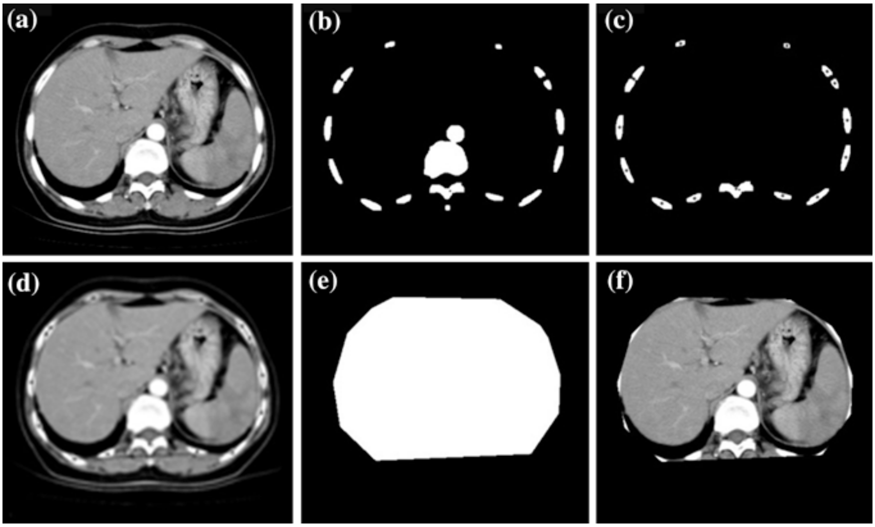

Fig. 10.3 Results of image pre-process

10.2.3 Image Post-Processing Based on Morphology Method

Morphology method is a useful tool in image process, which can effectively wipe out diminutive regions in an image. During our work, when an image is segmented with MRF, a morphology open operation is used to remove the organs connects with the left lobe of liver, and a morphology close operation is used to modify the segmentation result.

10.3 Experimental and Analysis

The experimental data is 30 abdomen CT image with format of DICOM derived from a 64 row CT machine in a domestic large hospital which space resolution is 512×512. Figure 10.3 gives the pre-processed result of one set of abdomen CT image segmentation. (a) is an original image, (b) is the result after image threshold process, (c) is the result of ribs extract with control points (d) is the result of ribs fitting, (e) is the result of hull construction, and (f) is the pre-processed image.

We carry out experiments with liver CT images to demonstrate the performance of the proposed segmentation approach, and compare the proposed results with the results of some traditional methods. Figure 10.4b shows the segmentation result using single-scale MRF without pre-process procedure. The boundaries of regions are not very smooth, and many pixels around the left lobe are misclassified, which is shown in some white rectangles. Figure 10.4c shows the segmentation result of

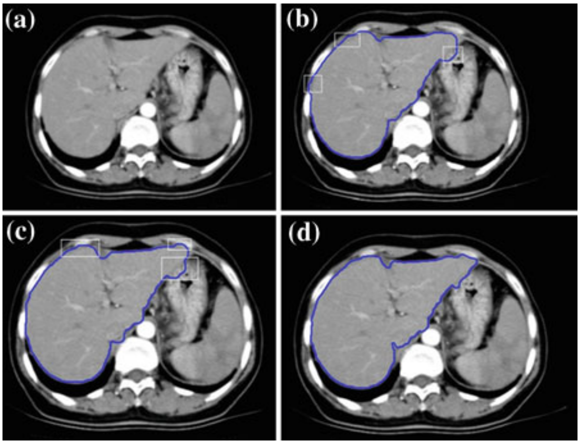

Fig. 10.4 Comparison of segmentation results on abdomen CT image

Table 10.1 Comparison of performance among the above algorithms

Method	Iteration time	Time/s	Accuracy (%)
SMRF	12	65.1	72.6
MRMRF	8	51.2	63.6
NMRF	4	32.4	85.7

applying multi-scale MRF without pre-process procedure, the boundaries of liver in the right is rough, and the pixels around the left lobe are also misclassified. As shown in Fig. 10.4d, the result of the proposed algorithm demonstrates a visually significant improvement and robustness to noise, and preserves better edge information than the former two approaches. The number of misclassified pixels is less than those of the contrastive algorithms.

Table 10.1 shows an average case of 30 sets of abdomen CT images in time, iteration times and segmentation accuracy. SMRF is short for the single scale MRF approach, MRMRF is short for the multi-scale MRF approach, and NMRF is short for the proposed algorithm. The segmentation accuracy is shown in the Eq. (10.3). In Eq. (10.3), S_1 denotes the target liver region produced by the proposed algorithm, S_2 denotes the liver region manually partitioned by a doctor.

$$precision = \frac{S_1 \cap S_2}{S_1 \cup S_2} \tag{10.3}$$

10.4 Conclusions

Aiming at the segmentation of liver image with fuzzy edge, this paper proposes a new medical image segmentation algorithm based on MRF and ribs fitting algorithm. We characterize the segmentation problem as a kind of optimization problem.

Firstly, we manipulate an image with several steps, which aims to remove some regions connected to ribs. Secondly, we use lifting wavelet transform to characterize an image in wavelet domain. Then, we accomplish initial and multi-level segmentation to low frequency sub-image. During the configuration of MRF, FGMM and Potts model are respectively used to establish the feature field and label field, and EM algorithm is used to estimate the parameters in the model. Lastly, morphology technique is used to obtain the liver region. Experimental results show that the proposed algorithm possesses a good robustness, and the segmentation accuracy is higher than the traditional MRF approaches. However, there still exists some limitations in the proposed algorithm, and the segmentation accuracy still needs to be improved aiming at some CT image with complicated organs.

Acknowledgments The research is supported by the National Natural Science Foundation of China (No. 50834009 and No. 60973071).

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