

Liver Segmentation on CT Images. A Fast Computational Method Based on 3D Morphology and a Statistical Filter

Fernando López-Mir^{1*}, Pablo González¹, Valery Naranjo¹, Eugenia Pareja², Mariano Alcañiz^{1,3}, Jaime Solaz-Mínguez⁴

¹ Instituto Interuniversitario de Investigación en Bioingeniería y Tecnología Orientada al Ser Humano, Universitat Politècnica de València, I3BH/LabHuman, Camino de Vera s/n, 46022 Valencia, Spain

² Unidad de Cirugía Hepatobiliopancreática y Transplante, Hospital universitari i politècnic La Fe, Valencia, Spain

³ Ciber, Fisiopatología de Obesidad y Nutrición, CB06/03 Instituto de Salud Carlos III, Spain

⁴ Hospital Clínica Benidorm

{ferlomir,vnaranjo}@labhuman.i3bh.es, www.labhuman.com

Abstract. The purpose of this paper is the segmentation of the liver tissue in computed tomography (CT) images and the comparison with several literature methods. Several expert radiologist restrictions such as automation, an easy user-interaction, and a low time-cost were taken into account for selecting the final algorithm. Thirty public dataset have been used to estimate the accuracy of the algorithm, twenty for training and ten for testing our method. A Jaccard index of 0.89, an average distance of 2.06 mm, and a runtime of 0.54 seconds per image state a promising efficiency but a poor efficacy. For this reason, user-assisted tools were used in a final step to demonstrate that this fast computational method with minimal user corrections (in some required dataset) remains runtime efficient and enough accurate for the liver segmentation purpose.

Keywords: Liver Segmentation, Computer Tomography Images, fast computational method

1 Introduction

Liver segmentation in CT images is currently an unsolved problem[1]. An accurate liver segmentation has a direct application in the planning, monitoring,

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an treatment of different types of pathologies such as cirrhosis or hepatocellular carcinoma diseases. In these cases, hepatic tissue anomalies are treated with a qualitative comparison and with physician experience; however, quantitative measures are not extended. Liver segmentation is the first step to help surgeons or radiologists to delimit lesions in organ tissue, and thus liver/lesions ratios and measures can be calculated in treatment or planning decisions.

The liver segmentation method proposed in this paper is included within the framework of the HepaPlan project [2]. The aim of HepaPlan is the development of a planning system for hepatic surgery.

After the liver tissue extraction, internal structures (hepatic veins and arteries, or biliary ducts) and lesions are segmented. These segmented structures are obtained from different studies of the same patient, and, therefore, a registration step is required to submit this information in a common 3D space. The correct segmentation and registration of these liver structures is required to obtain several measures (such as tumour volume or area), ratios (liver/tumour volume), and tumour position in Couinaud classification. This paper presents the first stage of this hepatic surgery planner: the CT liver extraction. The proposed method is based on a 3D region growing algorithm because of its easy user-interaction (only a seed point is needed) and its low computational cost. Our method was tuned with twenty public dataset that were provided with manual reference and it was tested with ten dataset whose manual segmented is not public. Currently, this is the same methodology that the most authors follows to validate their liver segmentation algorithms [1, 3].

Segmentation methods in liver can be classified according to several criteria: user-interaction, input image type, algorithm properties, etc. According to the algorithm properties, the methods can be classified in greylevel-based and contour-based methods. Contour-based methods in liver segmentation generally have better results but a more complex interaction, initialization, and/or training process is required in order to obtain the desired results. These characteristics can be inappropriate in a clinical environment. Probabilistic atlases, deformable models, statistical shape models or level-sets are algorithms used in liver segmentation that are based on contour properties [1, 4–6].

Greylevel methods have a lower computational cost but algorithms are less robust to noise and gradient changes. Thresholding algorithms, classifiers as k-means, or region growing methods belong to this group of algorithms [7, 8]. Efficient pre- and/or post-processing steps are needed in order to reduce noise and adjacent organs connections in algorithms of this type to carry out an accurate segmentation but this can not be enough in some cases. To minimize this lack of accuracy, our system introduces optional tools to make small corrections in the liver segmentation mask. Automatic segmentation was carried out in the twenty training dataset, and studies without enough accuracy were corrected by 3 experts. In these cases, the final time-cost increase but anyway it is lower in comparison with other automatic algorithms, and the segmentation accuracy increases enough for radiologist requirements.

The rest of the paper is divided into three sections. Section 2 reminds some basic tools used in our algorithm and it explains the developed algorithm in this work. Section 3 presents the final results and section 4 presents a discussion of our conclusions and outlines future work. The primary contribution of this paper is the design and validation of some pre- and post-processing steps in order to perform an algorithm for the segmentation of the liver in CT images which has the advantages of a low computational cost and not training requirements. Automatic errors are solved with user-assisted tools and the final results are more time-cost efficient than automatic methods in any case.

2 Method

Region growing methods are based on neighbourhood grey levels to expand an initial seed (or group of seeds) to obtain a final mask. With this initial seed (or seeds), a pixel is added to the mask (in our case the liver mask) if it fulfils two conditions: it is connected to the pixels that have already been labelled as liver and it satisfies some similitude criterion (different similitude criteria define different region growing algorithms). In our case, this criterion is defined as $f(\mathbf{x}) \in m_0 \pm k * \sigma_0$, where $f(\mathbf{x})$ is the intensity of a new candidate pixel with coordinates $(\mathbf{x} = (x, y))$, m_0 and σ_0 are the arithmetic mean and the standard deviation of the pixel values of an initial liver mask and k is a tolerance parameter. This formulation is extensive to 2D images and 3D volumes, only the connexion criteria between voxels changes. If the algorithm begins with a seed point (and not with an initial mask), m_0 and σ_0 is calculated using a neighbourhood around this seed point.

Mathematical morphology is a non-linear processing technique in spatial structures that is based on maxima and minima operators [9]. Erosion and dilation are the two basic operators:

$$\begin{aligned} \text{Dilation} : [\delta_B(f)](\mathbf{x}) &= \max_{\mathbf{b} \in B(\mathbf{x})} f(\mathbf{x} - \mathbf{b}) \\ \text{Erosion} : [\varepsilon_B(f)](\mathbf{x}) &= \min_{\mathbf{b} \in B(\mathbf{x})} f(\mathbf{x} + \mathbf{b}) , \end{aligned} \quad (1)$$

where $B(\mathbf{x})$ (or structuring element) is a subset of \mathbb{Z}^n centred at point (\mathbf{x}) with a particular size and shape.

Other filter based on mathematical morphology that is used in this paper is the reconstruction by dilation. The reconstruction by dilation of an image $g(\mathbf{x})$ from a marker image $f(\mathbf{x})$ is defined as a geodesic dilation of f with respect to g until idempotence:

$$R_g^\delta(f) = \delta_g^{(i)}(f) , \quad (2)$$

where $\delta_g^{(i)}$ is such that $\delta_g^{(i)}(f) = \delta_g^{(i+1)}(f)$, and where $\delta_g^{(i)}(f) = \delta_g^{(1)}(\delta_g^{(i-1)}(f))$ with $\delta_g^{(1)}(f) = \delta_B(f) \wedge g$, [10].

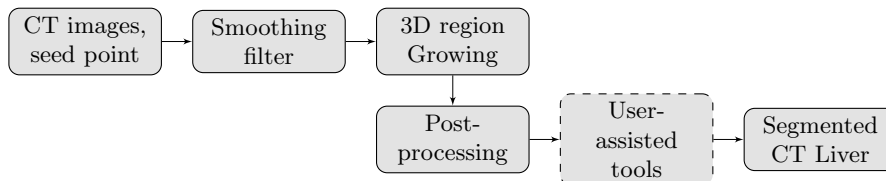


Fig. 1. Algorithm segmentation flowchart.

The block diagram of our algorithm is presented in Fig. 1. The first purpose of the algorithm is to obtain a CT volume with a liver tissue as uniform as possible but preserving the gradient between adjacent organs.

Several smoothing filters were evaluated: a curvature flow filter (CF) [11], a morphological center filter (MC) [12], and an adaptive filter (AF) proposed in this paper that is based on first-order statistics of the image, such as the arithmetic mean (m) and the variance (σ) of the graylevel values of the liver. This filter changes the pixel intensity as:

$$f(\mathbf{x}) = \begin{cases} m_5 & \text{if } m_5 \in m \pm \sigma \\ f(\mathbf{x}) & \text{otherwise,} \end{cases} \quad (3)$$

where m_5 is the greylevel arithmetic mean of the neighbourhood of radius 5 and m and σ are a initial estimation of the greylevel arithmetic mean of the liver and its standard deviation. These parameters (m, σ) are calculated using a region growing 2D with a seed point selected by the user in one image where the liver appears as large as possible and with homogeneous greylevels in the liver tissue. For this region growing 2D, the k parameter is extracted experimentally ($k = 1.2$) and the m_0 and σ_0 parameters are calculated in a 25 neighbourhood centred in the initial seed point. Each pixel in the final mask of this 2D region growing is considered for calculating the m and σ statistics that the adaptive filter needs. After, this adaptive filter based on first-order statistical parameters is applied in the whole 3D study as (3). Several experiments demonstrate that the adaptive filter obtains a more uniform grey-level in the liver, preserving better its boundaries.

In the next step, a 3D region growing is applied to the smoothed CT volume (Fig. 2a). The seed points are the whole mask obtained as result of the previous 2D region growing, so m_0 and σ_0 parameters have the same value than m and σ in the adaptive filter. The tolerance parameter ($k = 1.35$) is extracted empirically.

In the next stage, post-processing filters are applied to obtain the final result. First, the holes are closed in all 2D images with a morphological reconstruction by dilation (Fig. 2b) [10]. After that, a 3D erosion is applied with a cylindrical structuring element of size 2 (Fig. 2c). The erosion step is carried out to eliminate connexions between the liver and organs as the heart, the stomach or the kidneys with similar greylevels than the liver. Every object is labelled, the largest is selected, and a 3D dilation with the same structuring element than the previous

erosion is carried out to recover the original size of the liver (Fig. 2d). The choice of this structuring element has been preferred, instead of a cube or a sphere, due to liver and adjacent structures morphology, and after the comparison and evaluation of the effect on the results of the other structuring elements.

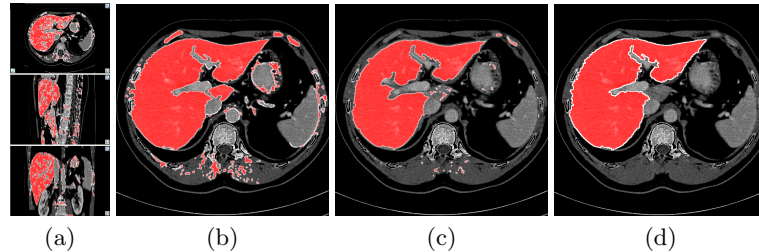


Fig. 2. Images in different stages of the algorithm. (a) After RG 3D; (b) After filling holes; (c) After 3D erosion; (d) After final dilatation

Finally, the mask is filtered with the Fourier coefficient technique [13] as previously proposed in [14] to smooth the contour, obtaining the final liver mask.

3 Results

The goodness of our method was evaluated with 30 public studies as the most authors follows to validate their algorithms [3]. A collection of 20 studies are provided with manual reference in order to tune the algorithm. Other 10 dataset are provided (without manual reference) to submit and then an independent observer evaluate the liver segmentation method with five coefficients and a system score [1]. This approach ensures the validity and independence of the results. The size of each image was 512×512 pixels in x and y . The number of slices of each volume varied from 64 to 348, depending on the dataset. Pixel spacing was between 0.55 and 0.88 mm in x/y direction and slice distance was between 1 and 3 mm.

In all cases the five coefficients used to obtain the goodness of the method are: Volumetric Overlap Error (VOE) or Jaccard coefficient (JC), Relative Volume Difference (RVD), the Average Symmetric Surface Distance (ASSD), Root Mean Square Symmetric Surface Distance (RMSD) and Maximum Symmetric Surface Distance (MSSD),[1].

The influence of the noise reduction (or smoothing) filter was calculated by applying different smoothing filters and obtaining the five coefficients in the 20 training dataset. Table 1 shows the arithmetic mean of the five coefficients for the twenty dataset when each filters is applied in the pre-processing step.

Table 2 shows the arithmetic mean (m) and the standard deviation (σ) of the five coefficients of the 10 test studies that are provided by [1],[3].

Table 1. Results with different smoothing filters.

Smooth. filter	VOE(%)	RVD(%)	ASSD(mm.)	RMSD(mm.)	MSSD(mm.)
MC	15.99	1.93	3.75	7.88	52.95
CF	14.41	7.23	3.55	7.86	53.48
AF	11.91	-5.02	3.03	6.95	53.49

Table 2. Final results of 10 test and 20 training dataset.

	VOE(%)	RVD(%)	ASSD(mm.)	RMSD(mm.)	MSSD(mm.)
$m_{test}(\sigma_{test})$	11.17(6.18)	-7.34(6.47)	2.06(1.21)	4.22(2.66)	29.15(11.32)
$m_{train.}(\sigma_{train.})$	11.91(4.24)	-5.02(6.78)	3.03(.96)	6.9(2.71)	53.5(24.9)

The same coefficients were obtained with the 20 training dataset and the 20 manual references as is shown in Table 2. The runtime average of the 30 dataset (20 training and 10 test) is 0.54 seconds per image.

A final step is carried out in our system when accuracy is not enough. The 20 segmented masks by our algorithm of the training dataset were shown to 3 experts. They pointed out that seven had enough accuracy, there were discrepancies with 9 dataset, and 4 of these dataset were not accurate enough for any of them. For this reason, HepaPlan software allows to make corrections in those dataset that experts consider appropriate. Two basic tools are provided: erase and paint. The arithmetic mean of the five coefficients of the 20 training dataset (with user-assisted corrections in the required dataset) can be observed in table 3. The average time-cost increases to 7 seconds per image when these corrections were carried out in some of these 20 training dataset. The second row is a lineal extrapolation to the 10 test dataset.

Table 3. Final results of 20 training dataset with manual corrections. Approximation of 10 test dataset.

	VOE(%)	RVD(%)	ASSD(mm.)	RMSD(mm.)	MSSD(mm.)
Train.	6.7	-1.63	1.14	2.29	27.8
<i>Test</i>	6.28	-2.38	0.77	1.4	15.25

4 Conclusions

A liver tissue segmentation method in CT images is presented in this paper. A 3D region growing algorithm has been evaluated with promising results. The selection of this method is based on the easy user-interaction, the automation (only a seed point introduced by the user is needed), and the low time cost. These are typical requirements in a medical environment. A pre-processing filter to reduce noise is applied due to intrinsic CT images properties. An adaptive

filter based on statistical parameters is used instead of other filters because it gets the best results (Table 1). After, a post-processing step is carried out to refine the final results. An averaged VOE coefficient of 11.17 ± 6.18 (or Jaccard index of 0.89 ± 0.04) and a point to point distance of (2.06 ± 1.21) mm. demonstrate that results are promising if the high level of automation of the method (only one seed point is needed) is taken into account. Despite this, opinion of different experts is that the accuracy of several 3D masks is not enough for future purposes. A negative RVD means that a sub-segmentation is carried out in the general algorithm. This is due to lesions in the liver boundaries in which the hole closing filter has not effect. While this problem is being solved, HepaPlan software incorporates user-assisted tools that can improve in 40-50% the final results while the time-cost remains lower than the most author algorithms. One hospital dataset is about 120 images, so 12 minutes would be necessary in the worst case and one minute if the automatic segmentation is enough accurate.

In [1], results are provided with the same ten test dataset (whose manual segmentation is not published). Four methods have a VOE less than 10% and five are between [10-12.5%]. Only one author has a VOE greater than 20%. Most of them have an ASSD less than two millimetres. The problem of these nine methods are the high computational cost, only one method has a low computational cost (less than one minute). The other disadvantage of these methods is the training of statistical shape models (when a manual interaction is required in some cases) or the initialization of level set methods. Figure 3 summarizes results of our method (automatic algorithm and automatic algorithm with experts corrections in some dataset) and some information published in [1] about runtime (it is the average time to segment one image test volume) and the VOE coefficient (all coefficients follow a similar pattern). The algorithms inside zone 1 and 2 ($VOE \lesssim 7$) achieves enough accuracy, equivalent to human performance [1], besides algorithms in zone 1 are faster than those in zone 2.

In [7] a region growing method is applied to liver segmentation and a runtime of 3.53 seconds per image is obtained. A VOE of 26.4% and a ASSD of 10.2 mm is given by one author that applies a region growing algorithm in the comparison presented by [1]. Other authors have a Jaccard coefficient of 0.86 [6], or the VOE is greater than 14% [15].

We are currently studying ways to improve the main problem of our algorithm: the segmentation of lesions in the liver boundary. Our efforts are also focused on the detection of other structures as the heart or the ribs that could be confused as liver [4]. In addition, we are working on hepatic tree segmentation.

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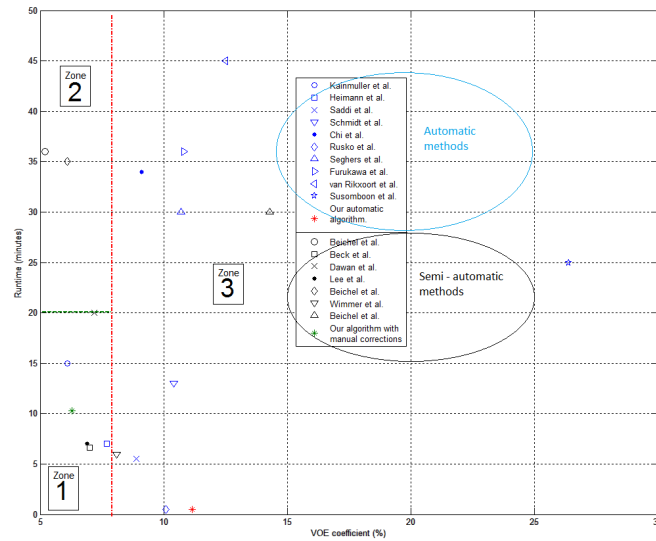


Fig. 3. Comparison of runtime and a goodness measure.

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