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Semi-automatic detection of hepatic tumor in computed tomography images

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Abstract. In this work, the main purpose is develop a computational segmentation strategy for liver tumor semiautomatic detection. This strategy considers three-dimensional computed tomography images and it consists of techniques application that, on the one hand, diminish the noise and detect the edges of the objects present in those images and, on the other hand, generate the liver tumor morphology. For this, the sequence of techniques composed of gaussian smoothing, gradient magnitude, median filter, region growing and binary morphological dilation are used. The value obtained, for the metric called Dice score, show a good correlation between manual segmentation, performed by a hepatologist, and the tumor segmentation obtained using the proposed technique. This type of segmentation is the extreme utility for the characterization of hepatic tumors and the planning of the clinical behavior to be followed in the treatment of this human liver disease.

1. Introduction

The liver is an organ located below the diaphragm, on the right side of the abdomen. It is the largest solid organ of the human body [1]. It has a particular vascularization, the blood arrives in effect, in two ways: the hepatic artery and the hepatic portal vein. This blood leaves the liver through the hepatic veins, tributaries of the inferior vena cava [1]. Its main functions are three: it extracts the essential nutrients for digestion, such as carbohydrates, lipids and proteins, secreting bile; stores energy in the form of sugar so that the body can use it; and it filters and eliminates the toxins coming from what we consume, for example, alcohol and medicines.

The liver is made up of cells that cover their blood vessels, cells that cover the small ducts in the liver called bile ducts, and additionally, cells called hepatocytes. When uncontrolled cell growth occurs in the liver they can form several types of malignant (cancerous) and benign (non-cancerous) liver tumors [2]. The most frequent type of hepatic tumors is hepatocellular carcinoma, which begins in the main type of liver cells (hepatocytes). Other types of liver tumors are presented in Figure 1. The modalities of medical imaging play a crucial role in the diagnosis of focal lesions of the liver, for

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example, the ultrasound examination helps to visualize and differentiate liver lesions, to determine their location and position with respect to the vascular system.

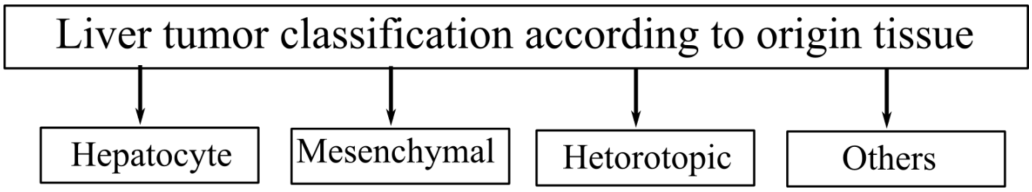


Figure 1. Liver tumor brief classification.

On the other hand, computed tomography (CT) and multilayer computed tomography (MSCT) are the primary diagnostic method for liver tumors; whereas using the magnetic resonance we can visualize, in a very precise way, the vascular neoplastic infiltration, which greatly facilitates the planning of an additional treatment. Finally, the usefulness of the nuclear emission modality varies according to the type of tumor [2].

The segmentation of liver tumors is a problem of great interest because the three-dimensional (3D) segmentation of hepatic tumors from MSCT images is a prerequisite for computer-assisted diagnosis, treatment planning and cancer control of liver. On the other hand, several works related to the segmentation of liver tumor, which are presented at next. In this sense, Wu, *et al.* [3], propose a semi-automatic method for the segmentation of liver tumors in computerized tomography images, which is based on a fuzzy media C algorithm and a graphic cuts technique. For this, a seed was used from which the volume of the tumor was extracted using algorithms of region growing, trying in this way to reduce the computational cost in the process. The segmentation process continues, labeling the foreground and background regions automatically in order to incorporate the fuzzy kernelized algorithm that allowed to increase the segmentation accuracy of the spatial information about the graphics cuts. The work used public clinical data (called 3Dircadb), which included 15 different CT images of liver tumors. Once the data set was evaluated, results were obtained that showed an average error of volumetric superposition of 29.04% and a Dice coefficient (Dc) of 0.83, with an average processing time of 45 seconds per tumor.

In addition, Chlebus, *et al.* [4], propose an automatic method for the segmentation of hepatic tumors in CT images, for which a completely convolutional two-dimensional (2D) neural network was used as basis, performing a post-process stage based on objects. The experimental work included a challenger training data set containing 131 abdominal CT. The results obtained with this model achieved a similar segmentation, in the detected tumors, comparing it with human performance, and generated a Dc of 0.69 compared to 0.72 in the human-made process, however the execution of the detection is lower with 63% compared to 92% of the latter. This technique focused on the segmentation of liver tumors, and gives us a double contribution to this task. The first contribution is that it provides a detailed description of the method developed and its evaluation. The second contribution is that the results obtained in the human performance are informed with the training data, to place them in perspective with respect to the quality of the segmentation of the automatic methods. In this paper, the main purpose is to generate a semi-automatic strategy for the morphology of the hepatic tumor or liver tumor presents in three-dimensional (3D) computed tomography images. This strategy is based on the use of: a) filters bank (gaussian, gradient magnitude and median filters), for addressing the problems linked to noise, artifacts and low contrast that affect the images quality b) segmentation techniques called region growing and binary morphological dilation algorithm necessaries for generating the liver tumor morphology.

2. Materials and methods

2.1. Dataset

A three-dimensional MSCT database was used, which has a voxel number of 512 x 512 x 172. Manual segmentation of the hepatic tumor by a hepatologist is also available.

2.2. Computational strategy proposed
In Figure 2, a schematic diagram is presented that synthesizes the computational algorithms that make up the semi-automatic technique for the segmentation of the liver tumor.

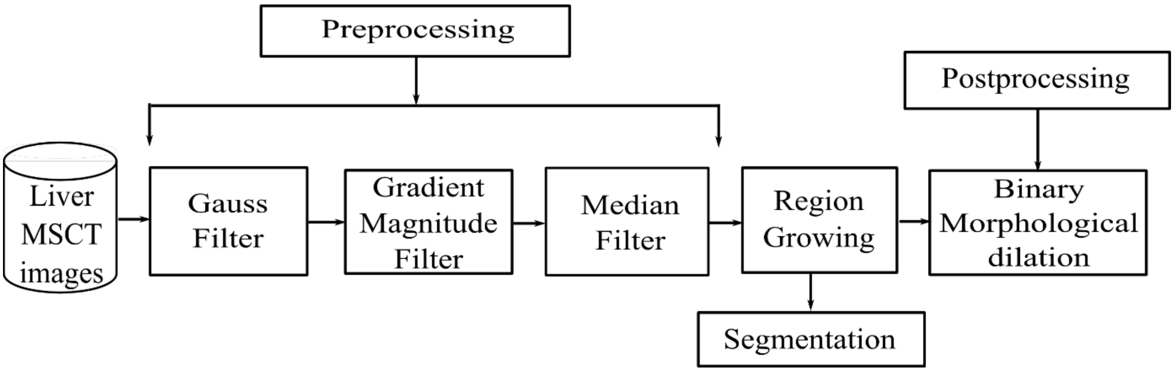


Figure 2. Block diagram of the proposed strategy.

2.2.1. Pre-processing. The main steps of this stage are: a) Generating a Gaussian image (I_g) processing each original image (Io) with a Gauss filter [5]. The role of this filter is to minimize the Poissonian noise present in the images. b) Obtaining a gradient image (I_MG) processing each image I_g with a filter called gradient magnitude [6,7]. The role of this filter is to detect the edges of the image under study. c) Getting a median image (I_m) processing each I_MG image with a median filter [7,8]. The role of this filter is to address the noise present in the images introduced by the gradient magnitude filter. The tuning parameter of this filter is the size of the neighborhood.

2.2.2. Segmentation. At this stage, the region growing technique and dilation filter are applied.

a) Region growing technique (RG). The RG partitions an image (f) into regions (Ri) whose voxels are connected according to certain predefined criteria based on connectivity and the similarity of the image. The most popular predefined criterion is given by Equation (1) [9]. The RG needs a seed voxels into an initial neighborhood (Iv).

$$\left|f(i,j,k) - \mu_{R_i}\right| < k\sigma_{R_i} \tag{1}$$

being: f (i, j, k) the gray levels of Iv, μ_{R_i} the average gray levels of a Iv of arbitrary shape and size, k an arbitrary scalar and σ_{R_i} the standard deviation of an arbitrary neighborhood of Iv. The RG tuning parameters are the initial neighborhood size (r) and k parameter that controls the amplitude of the range of intensities considered to accept or reject a voxel in a region. Such parameters must undergo a tuning process.

b) Postprocessing. A binary image is generated processing the segmentation of the liver tumor with a filter called binary morphological dilation. This filter has the purpose of compensating the modification of the borders, introduced by the Gaussian filter [10,11].

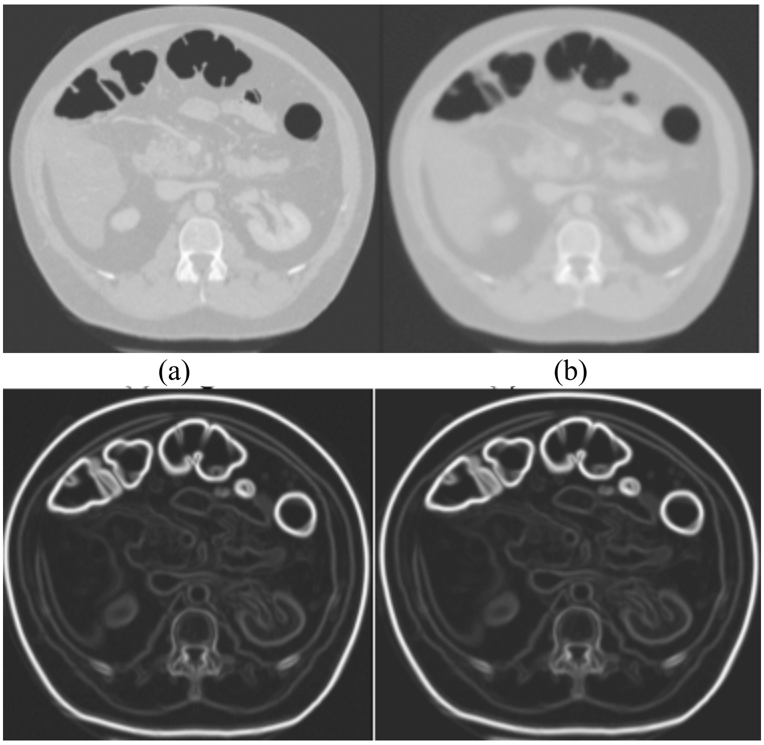
3. Results
The tuning process, for a particular filter, stops when the optimum value for its parameters is obtained, that is, when the values for which the best segmentation is generated are identified. The metric considered in the present investigation was the Dice coefficient (Dc) [12]. It is a metric used to compare the segmentations of the same 2D or 3D image, obtained by different methodologies. In the medical context, it is generally considered that the Dc establishes how similar, spatially, are manual segmentation and automatic segmentation.

The interpretation of Dc values is the manual segmentation and the automatic one matching when the Ds is 1 and they no matching at all when the Dc is zero. In this sense, normally, values of Dc over 0.75 are okay, in the medical routine.

In this paper, the maximum Dc generated was 0.7985, and it allowed establishing the optimal parameters of the computational algorithms that make up the proposed technique, which are described below:

- Gauss filter: obtained as kernel size (3x3x3) and standard deviation 2.
- Median filter: the size of the kernel was corresponding with (3x3x3).
- Region growing: the parameters were r = 1 and k = 4.
- Dilation filter: the size of the kernel was (9x9x9).

Figure 3 shows a 2D view of both the original tumor and the processed versions after applying the proposed technique to the database considered.



(a) (b) (c) (d)

Figure 3. Preprocessing stage results. (a) Original. (b) Gauss filter. (c) Gradient magnitude filter. (d) Median filter.

In Figure 3, we can appreciate an excellent performance of bank of filters applied over the original images, especially, the role of the gradient magnitude filter in the border detection task. Additionally, is easy to observe the reduction of noise generated by the Gauss and median filters.

On the other hand, Figure 4 illustrates a 2D view the segmented tumor liver by RG, a dilated version of this segmentation and a 3D view of this tumor.

In Figure 4, it is possible observing that the region growing technique gives a preliminary liver tumor segmentation, which is refined using the morphological binary dilation filter. Finally, we can observe an excellent 3D representation of the liver tumor, which is useful for calculating the volume occupied by this kind of tumor.

(a) (b) (c)

Figure 4. Segmentation results. (a) RG segmentation. (b) Dilation filter. (c) Segmented tumor: 3D view.

4. Conclusions

In this paper, a novel semi-automatic strategy for liver tumor segmentation has been presented. This strategy is capable of addressing the problem of noise, artifacts and low contrast observed in computed tomography images using, for this, an adequate group filtering techniques and segmentation techniques based on RG and binary morphological dilation algorithm.

The post processing stage generates 3D digital representations and thus obtain a realistic model of the anatomical structure of the liver tumor, present in MSCT images.

In clinical procedures, both the volume occupied by the tumor and its location are of vital importance as a support to the hepatologist for its diagnosis, classification and activation of treatment protocols, according to the dimensions and characteristics of the liver tumor.

Additionally, in this research, manual and automatic liver tumor segmentations were compared and the Dc value obtained suggests that the semi-automatic strategy developed has a good performance when liver tumor segmentation is performed.

In the future, it is planned to generate an automatic strategy using smart operators and to validate the proposed strategy with a significant number of databases in order to estimate the robustness of the aforementioned technique.

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