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Smart operator for the human liver automatic segmentation, present in medical images

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Abstract. The segmentation of the human body organ called liver is a highly challenging problem due to the noise, artifacts and the low contrast exhibited by the anatomical structures located around the liver and that are present in digital images, generated by any modality of medical images. The main modalities are: ultrasound, nuclear emission, magnetic resonance and the gold standard called multi-slice computed tomography. In this paper, with the objective of to address this problem, we consider multi-slice computed tomography images and we propose an automatic strategy based on two phases. In the first phase, a digital filtering bank is used for diminishing the noise effect and the artifacts impact in the quality of images. In the second phase, called liver detection, we use a smart operator based on least squares support vector machines for generating both the morphology and the volume of liver. The application of this strategy allows generating the morphology of the liver in a precise and efficient manner as it was demonstrated by the metrics used to assess its performance. These results are very important in clinical-surgical processes where both the shape and volume of liver are vital for monitoring some liver diseases that can affect the normal liver physiology.

1. Introduction

The liver is an organ located below the diaphragm and on the abdomen right side. It is the largest solid organ of the human body [1]. It has a particular vascularization; the blood arrives to the liver 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. Its main functions are: a) extracting the essential digestion nutrients (such as carbohydrates, lipids and proteins), b) secreting bile, c) it stores energy in the form of sugar that the body can use, d) it filters and eliminates the toxins coming from what we consume such as alcohol and medicines, for example [1].

In this investigation, we chose multi-slice computed tomography (MSCT) modality to generate the liver morphology and to obtain the liver volume, which is a very important parameter in surgical routine called liver transplantation [2-4].

Some researchers have addressed the issue of liver and tumor segmentation. In this sense, Kim *et al.* [5] developed a method based on fusion images for segmenting hepatocellular carcinoma on MSCT images. The segmentation method reached a maximum sensitivity of 97.7%. Muthuswamy *et al.* [6] present an automatic computational scheme for liver contour segmentation, considering MSCT images. This scheme uses a strategy based on thresholding technique, bilateral filters, fuzzy-C means



clustering technique and label connected component and optimization algorithms. They report a maximum Dice score (Ds) of 0.9318. This result is very precise due to the Ds is a metric with values among 0 and 1; being the best results values near to 1.

Finally, Tacher *et al.* [7], proposes a region growing and radial base functions algorithm for automatic liver-tumor segmentation reporting an average Ds of 0.74.

In our paper, we use MSCT images and propose a computational strategy, based on the application of a filter bank and segmentation techniques, for liver automatic segmentation. The importance of this kind of research is the possibility of generate automatic strategies for detecting and monitoring efficiently some pathologies linked to human liver.

2. Materials and methods

2.1. Dataset

One three-dimensional (3D) MSCT liver dataset was used and it was supplied by the Instituto de BioIngeniería y Diagnóstico S.A., Venezuela. The 3D image size is 512x512x100 voxels. Additionally, liver manual segmentation (ground truth) generated by a hepatologist, is available.

2.2. Proposed computational strategy

Figure 1 shows a block diagram of the automatic computational strategy (ACS), proposed in this paper, for segmenting the liver.

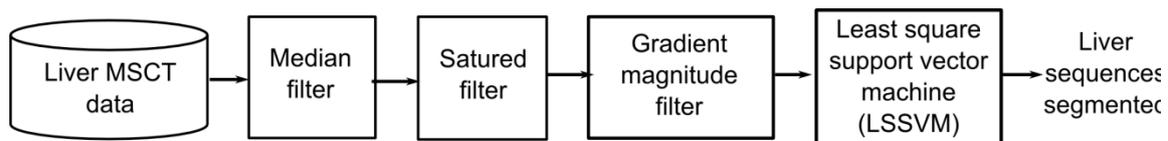


Figure 1. Block Diagram of the proposed strategy (ACS) for liver segmentation.

2.2.1. *Pre-processing.* The filters showed in Figure 1, are described at next.

- Median filter (MF). The median filter uses the median statistical definition for smoothing information and it is required in contexts where the borders preservation is crucial. In this sense, MF has an observation window typically odd and it considers window sizes reported in [8].
- Saturation filter: A saturated image (I_s) is obtained using the arithmetic addition of I_o and I_m [9].
- Gradient magnitude filter (GMF). In this work, an approach based on finite differences was used for GMF computational implementation [9]. This filter generates a smoothed version, called I_{GM} , calculating the three-dimensional gradient magnitude of I_s , using the mathematical model given by Equation (1).

$$I_{GM} = \left(\left(\frac{\partial I_s}{\partial i} \right)^2 + \left(\frac{\partial I_s}{\partial j} \right)^2 + \left(\frac{\partial I_s}{\partial k} \right)^2 \right)^{1/2} \quad (1)$$

being: i, j, k the spatial directions in which the gradient is calculated and $\left(\frac{\partial I_s}{\partial i}, \frac{\partial I_s}{\partial j}, \frac{\partial I_s}{\partial k} \right)$ the partial derivatives of I_s .

The computational cost (time of calculations) of the continuous model for GMF, given by the Equation (1), is very expensive. By this reason an approach based on central finite differences is used, in this paper, for modelling computationally the GMF [10].

2.2.2. *Segmentation.* This stage involves two steps: liver contour detection and a filler algorithm. These steps are presented at next.

- Least square support vector machine (LSSVM). A LSSVM is used in order to obtain all contours that contain the liver. The specialized literature, view for example reference [11], establish that the LSSVM ought to be trained with 30% of total images and it must be validated with 70% of total images. In this sense, the total images that belong to the database, used in this paper, is split considering 30 axial view images for training stage (training images set) and 70 axial view images for validation (validation image set). Then the following processes are applied:
 - Training stage: Using the value proposed in [8], in this paper, we consider circles, with radius 10 pixels, are used to cover the information both liver contours and no-contours of liver, presents in the training images set. The training examples are labelled input vectors which components are statistics features such as: media, median, variance and standard deviation of the densitometric information included in training circles. The LSSVM hyper-parameters (σ and γ) are tuned until the LSSVM's performance reaches the minimum relative error (Re). This error is computed considering the matching between automatic and manual circles localization based on theirs centers.
 - Validation stage: At the beginning, 70 images unseen during the training are presented in the input of trained LSSVM in order to detect the circles centers that represent the liver contours. Then, a B-spline algorithm traces the contour edges considering these centers.
- Filler algorithm (FA). A FA is used in order to generate the put white information inside of liver contours detected with trained LSSVM.

During the tuning process, the liver segmented is compared with the ground truth traced by hepatologist. The Ds is used in order to estimate the matching between these structures [12].

3. Results

A maximum Ds of 0.92 is obtained from the tuning, which generated the optimal parameters for LSSVM hyper-parameters ($\sigma = 1.00$ and $\gamma = 0.50$). For this Ds, the size of median neighborhood was (5x5x5), it represents the optimal value for ns parameter in this research which was obtained heuristically.

Figure 2 shows axials views of a liver original image and the images linked to digital processing developed with the ACS. Notice the excellent visual performance developed by the pre-processing techniques over the liver MSCT images.

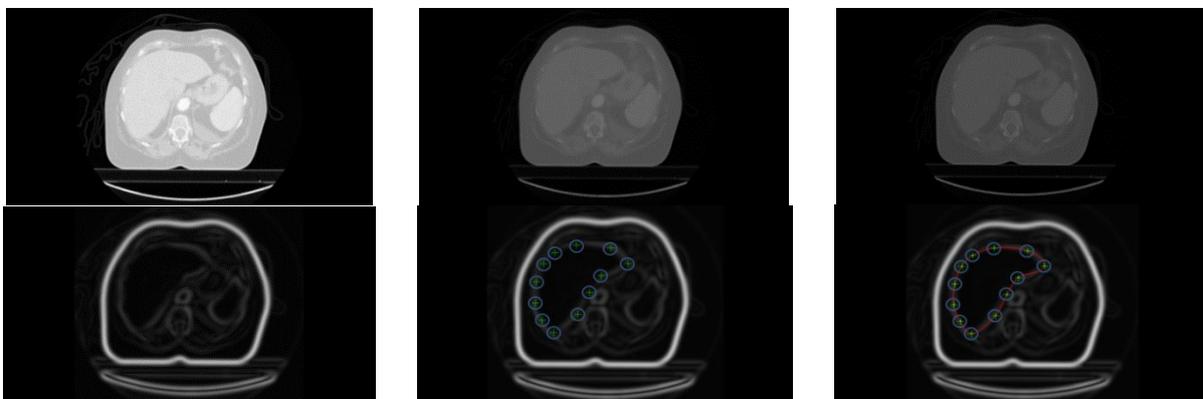


Figure 2. Axials views about effect of the ACS over liver dataset. First row: Original image (Left), Median Filter (center) and Saturated image (Right). Last row: Gradient image (Left), Markers (center) and Final contour (Right).

Figure 3 shows 3D view of liver morphology generated using reconstruction technique. This kind of results is relevant because the automatic technique, proposed in this paper, is able to generate the liver morphology which is necessary for liver quantification.

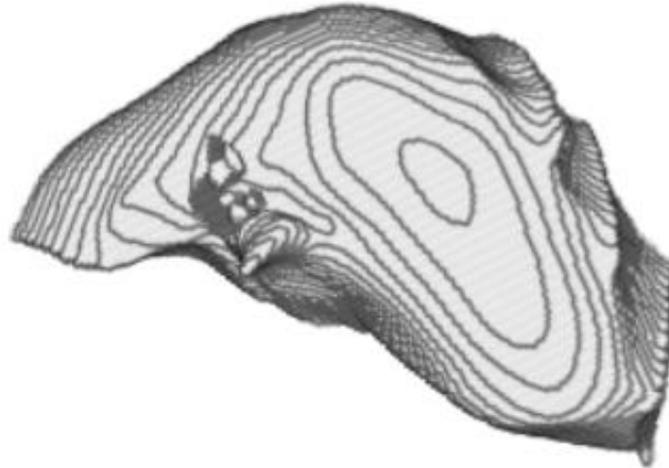


Figure 3. Liver 3D representation generated by clustering of liver contours detected with LSSVM.

Finally, Table 1 shows the volume values considering its automatic segmentation.

Table 1. Clinical parameters associated with segmented liver.

	Liver
Volume (cm ³)	1634.45

Using the 3D liver representation is possible to realize the liver volume quantification. Simply, the liver voxels number is multiplied by the voxels dimensions for calculating the liver volume. In the clinic context, this volume is an important parameter for performing the liver transplantation in humans.

In this section, it is necessary pointed that the D_s is a metric with values between 0 and 1. This metric is better when its value is closest to 1 [12]. In a medical image segmentation context, this means that the manual segmentation and the automatic one matching when the D_s is 1 and they no matching at all when the D_s is zero. In this sense, normally, values of D_s over 0.75 are good accepted, in the medical routine.

According to the results of this paper, the maximum D_s value obtained for the liver segmentation was 0.9200. This value is comparable with 0.9318 that was the D_s obtained in [6]. So, we can say that the ACS, developed in this research, had a good performance segmenting liver.

4. Conclusions

In this paper, a novel automatic strategy for liver segmentation was developed using an adequate group of pre-processing techniques (filters bank) and a smart operator, based on LSSVM. The considered bank of filters (median, saturated and gradient magnitude filters) let us address the noise and the artifacts problems, present in MSCT images; whereas the LSSVM had a good performance with the low contrast problem doing possible precise 3D liver segmentation.

In this research, manual and automatic liver segmentation were compared and as results the D_s value obtained suggests that the ACS developed has a good performance when the liver segmentation is performed. The liver segmentation is a crucial step in a surgical procedure called liver transplant because this kind of segmentation allows obtaining liver volume and considering this volume, and

others parameters, the specialized personal in the medical context can decided which patients can receive this organ via transplantation.

It is planned, for the future, to use the ACS in the segmentation of an important number of liver datasets.

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