A space-occupying lesion automatic quantification from abdominal contrast-enhanced computerized tomography images

Cuantificación automática de lesión ocupante de espacio a partir de tomografía computarizada contrastada del abdomen

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Abstract

Space-occupying lesions represent a health high risk of subjects affected by this kind of pathology. From a medical point of view, the volume occupied by each of these lesions constitutes the most important descriptor when addressing them, and especially for the respective decision-making process that guides their control, mitigation or elimination. In such context, this paper proposes a strategy based on computer-aided image processing techniques to extract the three-dimensional morphology of a space-occupying lesion, of the amoebic liver abscess type, and calculate its volume. In this sense, in order to attenuate poissonian noise and improve the abscess edge information, the abdominal contrast computed tomography images are preprocessed using a Gaussian filter, an edge detector and a median filter, sequentially. Then, a clustering algorithm based on region growing procedure is applied to the enhanced images, obtaining the space-occupying lesion three-dimensional shape. Additionally, the Dice coefficient is considered as a metric to establish the correlation between the shapes, automatic and manual lesion, the latter described by a mastologist. Then, in order to characterize the liver abscess, its volume is quantified considering both the voxels occupied by the lesion obtained by applying of the computer-aided image processing, and the physical dimensions of the voxel. Finally, the automatically calculated volume is compared to that generated manually by the medical specialist. The results reveal an excellent correspondence between manual results and those produced by the proposed technique. This type of technique can be used as a resource not only to obtain, precisely, the value of the aforementioned descriptor, but also to monitor the process of the abscess evolution by means imaging control.

Keywords: Computerized tomography; space-occupying lesion; imaging filters; clustering techniques, Dice coefficient.

Resumen

Las lesiones que ocupan espacio representan un alto riesgo para la salud de los sujetos afectados por este tipo de patología. Desde el punto de vista médico, el volumen ocupado por cada una de estas lesiones constituye el descriptor más importante al abordarlas, y especialmente para el respectivo proceso de toma de decisiones que guía su control, mitigación o eliminación. En este contexto, este artículo propone una estrategia basada en técnicas de procesamiento de imágenes asistidas por computadora para extraer la morfología tridimensional de una lesión que ocupa espacio, del tipo de absceso hepático amebiano, y calcular su volumen. En este sentido, para atenuar el ruido poissoniano y mejorar la información del borde del absceso, las imágenes de tomografía computarizada de contraste abdominal se preprocesan utilizando un filtro gaussiano, un detector de borde y un filtro de mediana, secuencialmente. Luego, se aplica un algoritmo de agrupamiento basado en el procedimiento de crecimiento de regiones a las imágenes mejoradas, obteniendo la forma tridimensional de la lesión que ocupa espacio. Además, el coeficiente Dice se considera como una métrica para establecer la correlación entre las formas, lesión automática y manual, la última descrita por un mastólogo. Luego, para caracterizar el absceso hepático, su volumen se cuantifica considerando tanto los vóxeles ocupados por la lesión obtenida mediante la aplicación del procesamiento de imágenes asistido por computadora, como las dimensiones físicas del vóxel. Finalmente, el volumen calculado automáticamente se compara con el generado manualmente por el médico especialista. Los resultados revelan una excelente correspondencia entre los resultados manuales y los producidos por la técnica propuesta. Este tipo de técnica puede usarse como un recurso no solo para obtener, precisamente, el valor del descriptor mencionado anteriormente, sino también para monitorear el proceso de evolución del absceso mediante el control de imágenes.

Palabras clave: Tomografía computarizada, lesión que ocupa espacio, filtrado de imágenes; técnicas de agrupamiento; coeficiente de Dice.

Introduction

Space-occupying lesions are pathological structures that have a recognizable volume and that can affect nearby structures. Such lesions can form a mass or deformities at the level of the organs of the abdominal cavity that can be tumor and non-tumor. The space-occupying lesions of the abdominal cavity comprise two groups, namely non-neoplastic and neoplastic. Abscesses are of the non-neoplastic infectious type, meanwhile, the hematomas, suture granuloma, endometriosis and endometriomas, nodular fasciitis, and intra-abdominal sclerosing mesenteritis are space-occupying lesions non-neoplastic non-infectious. Neoplastic space-occupying lesions include lipomas, vascular tumors, leiomyomas, neurofibromas and schwanomas, fibromas and benign fibrous histiocytoma, benign pigmented lesions, solitary fibrous tumor, granular cell tumors, myofibroblastic tumor, fibromatosis and desmoid tumor, myoepithelial carcinoma, adenocarcinoma, soft tissue sarcomas, melanomas, and lymphomas[1].

Currently, in clinical routine, the imaging exploration of the organs in the abdominal cavity for disease assessment, preoperative diagnosis, planning and control is preferably performed using computed tomography (CT) imaging[2-4]. The quantification of a space-occupying lesion from the detection of its three-dimensional shape, as well as the determination of important clinical descriptors such as the volume occupied by the lesion, is possible with this three-dimensional imaging modality. For the space-occupying lesion of non-neoplastic infectious kind, such as the abscess, the volume measured is an important factor in making surgical decisions involving the percutaneous transorgan drainage.

In the process of quantifying space-occupying lesion in the abdominal cavity from contrast-enhanced CT images, the first task is detecting the shape of the ~~pathological~~ lesion. Then, the volume of the structure can be computed[5]. In the field of computer science, specifically in the discipline of digital image processing, the process of detection object structure into three-dimensional images is called segmentation[6]. Various procedures have been proposed in the literature for the segmentation of morphopathology of different structures present in the explored abdominal cavity using CT imaging[7-9]. In this sense, in the present work a procedure for the automatic quantification of a space-occupying lesion from abdominal contrast-enhanced computerized tomography images is proposed.

Materials and Methods

Data Source

In this work, a database acquired using contrast multi-slice CT supported by a General Electric LightSpeed VCT Iris medical image system is considered. The three-dimensional image is quantified at 12 bits with a whole dimension of 512´512´76 image elements, which have a spatial size of 0.548828´0.548828´2.49998 mm. Figure 1 shows the sagittal, axial and coronal views of abdominal contrast CT image.

Figure 1. Computerized tomography with contrast of abdomen. The sagittal, axial and coronal views.

Image filters pipeline

Gaussian Filter

This linear filter is an image smoothing filter, whose application generates a blur effect on the edges of the original data. Being a linear filter, its computational implementation can be performed using a convolution process. In this sense, the discrete Gaussian distribution defined in the three-dimensional space by standard deviations at each dimension (s_i, s_j, s_k) is used to construct the convolution kernel required in the convolution process[10]. The filter algorithm then requires two parameters, namely, kernel size and standard deviations, both of which are three-dimensional arrays.

Median Filter

Meanwhile, this is a non-linear filter used to attenuate noise in the image. Each three-dimensional image element (voxel) located at the neighborhood center is located at the same location and replaced by the median of the elements in such neighborhood. The median is calculated sorting the intensities of the original image into the neighborhood and selecting the intensity located at the middle of the sorted array[11]. A single parameter related to the neighborhood size is required for the computational implementation of the median filter.

Gradient Magnitude Filter

With the idea to obtain a precise representation of the edges of the multiple structures contained in the abdominal image, a simple gradient magnitude operator is incorporated into the pipeline filter. The computational implementation considers a numerical finite difference scheme to estimate the gradient magnitude at each three-dimensional image element[12].

Clustering Algorithm

Algorithm Initialization

The clustering algorithm requires the definition of a seed voxel for its operatively. In order to locate this seed image element, a procedure previously reported is used[13]. In this sense, a least square support vector machine[14] (LSSVM) is developed using a MatLab toolbox called LS-SVMlab v1.8 (Available from: https://www.esat.kuleuven.be/stadius/lssvmlab/). The hyperparameters that control the LSSVM performance ($\mathbf{g}$ and $\mathbf{s}^2$) are tuning by cross-validation[6].

Region Growing Procedure

From the seed voxel, a region grows clustering the neighborhood voxels that fulfill the following uniformity criterion: if the difference in between the intensity of a voxel into neighborhood and the mean value of intensities of voxels into neighborhood is within a range defined by the product of a multiplier (positive constant) and the standard deviation (±)

of the image intensities into neighborhood. The parameters that control the performance of the clustering algorithm correspond with the multiplier and the neighborhood size, and they are also tuned by means of cross validation[15].

Dice Coefficient

In three-dimensional image processing, the Dice coefficient being a statistic used to compare the similarity of two objects. This statistic allows quantifying the degree of overlapping between two volumes. The coefficient expresses the probability that a part of one object is in the other object, quantified as the ratio of the number of matching parts between the two objects and the total number of objects[16].

The Dice coefficient is considered in quantifying the differences between the shape of the hepatic lesion identified with the computational approach and the shape described by the specialist. The statistic is incorporated both the process of tuning the optimal parameters of the image processing techniques as the validation of the shape finally detected.

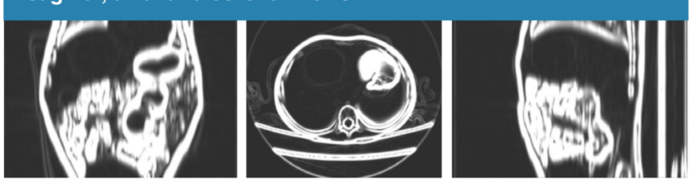
Results

The image of the computerized tomography with contrast of abdomen considered in the current work is initially processed by the filters pipeline. In this sense, a Gaussian filter with a kernel size 3´3´3 of and standard deviation equal to the standard deviation of the original image is first applied. The filter kernel size is chosen with the criterion of the minimum valid three-dimensional size and the standard deviation with an isotropic approach (s_i, s_j, s_k) = (2, 2, 2). The results obtained for applying this smoothing filter are shows in Figure 2.

Figure 2. Gaussian filter results. The sagittal, axial and coronal views.

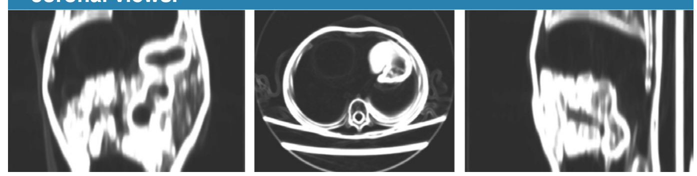
The second filter into pipeline corresponds with a gradient magnitude operator, which is computationally implemented using an approach based on finite differences. The linearity and separability properties of this filter are exploited for its implementation, thus, the filter output is obtained convolving the Gauss filter image with the finite difference kernel given by [-1, 0, 1]. Figure 3 shows the CT image after applying of second filter considered into the pipeline.

Figure 3. Results of the gradient magnitude filter. The sagittal, axial and coronal views.



The filter pipeline output is obtained applying a median filter to the results of the two previously filters considered in the filtering sequence. The median filter is implemented considering the concept of statistical median[17,18]; therefore, it has a single tuning parameter called median neighborhood size. Initially, an isotropic approach of odd values of possible values of the median neighborhood size is assumed, namely (3´3´3), (5´5´5), (7´7´7), (9´9´9) and (11´11´11). The optimal value of the median neighborhood size is tuned by means of cross validation, selecting as optimal size that yielded the maximum Dice Coefficient of space-occupying lesion obtained after running the clustering algorithm, in this case (5´5´5).

Figure 4 Filters pipeline output. The sagittal, axial and coronal views.

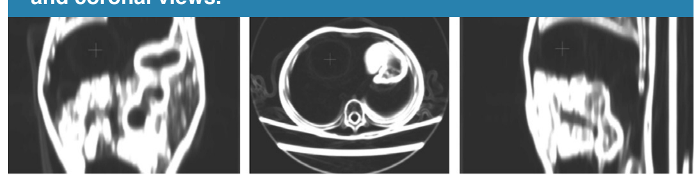


Once preprocessed the CT image, the seed voxel must be established. This procedure requires that the hyperparameters that control the performance of the LSSVM are tuned. Using also the cross validation, and considering as a metric the Euclidean distance between the centroid of the reference image (selected by the clinical expert) and the centroids of the validation images constituted by the images from the database, located between the equator and the base of the liver. Table 1 shows the ranges considered for the hyperparameters in the cross validation, the step sizes with which such hyperparameters are varied and the optimal values obtained. Figure 5 shows the location of the seed image element obtained.

Table 1. Optimal values of LSSVM hyperparameters.

	g	s^2
Range	(0,100]	[0,50]
Step size	0.25	0.25
Optimal value	9.5	1.25

Figure 5. Location of seed voxel. The sagittal, axial and coronal views.



The parameters that control the performance of the region growing technique are tuned by means of cross validation, considering the values shown in Table 2, and selecting as optimal parameters those parameters that yielded the maximum Dice Coefficient. The results of the clustering are shown in Figure 6.

Table 2. Optimal values of clustering algorithm parameters.

	Neighborhood size	Multiplier
Range	(0,20]	[0,10]
Step size	1	0.1
Optimal value	1	3.60

Figure 6. Results of clustering algorithm. The sagittal, axial and coronal views.

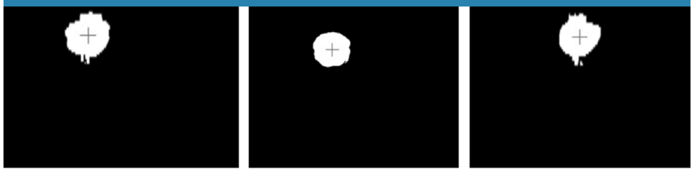
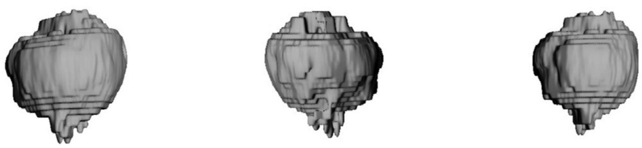


Figure 7 shows the three-dimensional space-occupying lesion detected in the contrast computerized tomography of the abdomen and that clinically corresponds with an amebic liver abscess.

Figure 7. Three-dimensional views of the amebic liver abscess detecting form contrast CT of abdomen.



Finally, from the three-dimensional spatial information obtained that morphologically described the space-occupying lesion in the liver; the volume of the hepatic abscess is quantified obtaining a measured value of 39.04 mL.

Conclusions

The research performed allowed the development of a computational approach that allows the space-occupying lesion to be quantified automatically, in contrast-enhanced computed tomography images acquired from a patient with liver abscess.

The filtering pipeline composed by three images filters, namely, a Gaussian filter, a border detector and a median filter, allowed to attenuate the CT images poissonian noise and enhancing rim of the liver abscess. Likewise, the procedure used for the analysis and selection of the region of interest in the enhanced CT images, and that allows discriminating, what image spacial spatial information belongs or not to pathological abdominal lesion, is based on region growing clustering technique.

The space-occupying lesion shape obtained using the clustering procedure is validated by means of the comparison with the manually reproduced shape by a specialist. Then, the validated shape is used to quantify the volume, which is considered as a clinical parameters useful to characterize the liver lesion.

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