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Renal lithiasis detection in uro-computed tomography using a non-parametric technique

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Abstract. Renal lithiasis is the pathology that causes nephritic colic, which is one of the most frequent reasons for consultation in emergency medical services. According to the size, location, hardness and number of stones present in the urinary system, usually in the human kidney, it is established to which form of treatment is suitable for the patient. These kidney stones can be analyzed by means of biopsy or imaging modalities such as computed tomography images. This type of images has challenging problems called noise, artifacts and low contrast. In this paper, in order to address these problems, a non-parametric semi-automatic computational technique is developed for detecting kidney stones, present in computed tomography images, using digital image processing techniques based on a smoothing filter and an edge detector. Finally, the size and position of the stones present in the images are calculated and a precision metric is considered to compare the manual segmentation, performed by an urologist, and the one generated by the NPCT, obtaining an excellent correlation. This technique can be useful in the renal lithiasis detection and if it is considering this kind of computational strategy, medical specialists can establish the clinic or surgical actions oriented to address this pathology.

1. Introduction

Renal lithiasis is the pathology caused by the presence of stones or stones inside the kidneys or the urinary tract. It is the cause of nephritic colic, which is one of the most frequent reasons for consultation in emergency medical services [1].

The segmentation of kidney stones is a problem of great interest because the three-dimensional (3D) segmentation of this stones, from multi-slice computed tomography (MSCT) images, is a prerequisite for computer-assisted diagnosis, treatment planning of the kidney pathologies [2]. However, the MSCT images have as main disadvantage the artifacts generation and noise that affect the image quality [3]. The main imperfection is the stair-step artifact, which dramatically deteriorates the appearance of such objects and can affect the dimensions especially of small structures present in the images acquired under this modality [4].

On the other hand, several works related to the segmentation of kidney stones, which are presented at next. In this sense, Liu, *et. al.* develops a fully computer-aided diagnostic system to detect kidney stones in computed tomography images. The sensitivity of the method obtained was 90% [5].



Ebrahimi, *et. al.* proposes to improve the quality of the image in the detection of kidney stones in computed tomography images. The results show that the program has an accuracy of 84.61%, which suggests the potential of the program in terms of diagnostic efficiency for the detection of kidney stones [6].

Sujata, *et. al.* develops a prototype of computer-aided diagnosis for the early detection of kidney stones. The proposed work is implemented in MATLAB with the development of an initial prototype with stone precision detection of 92% [7].

In this paper, the main purpose is to generate a semi-automatic technique (SAT) for kidney stones (KS) segmentation in MSCT images. This technique is based on the application of a filter bank (gradient magnitude and gaussian filters) and region growing technique in order to generate the 3D kidney stone morphology. The filter bank is necessary for address the problems of the aforementioned imperfections of MSCT images. This technique can be useful in the detection and monitoring KS for establishing the main actions oriented to address this type of pathology.

2. Materials and methods

2.1. Dataset

A three-dimensional MSCT dataset was used. It has a voxel number of 512 x 512 x 30. Manual segmentation of the kidney stone by an urologist is also available.

2.2. Computational strategy proposed

In Figure 1, a schematic diagram is presented. It synthesizes the computational algorithms that make up the SAT for the segmentation of the kidney stone. In this figure, the computed tomography dataset matches with the dataset described in the 2.1 section of this paper. The other elements, shown in Figure 1, will be explained in the sections 2.2.1 and 2.2.2.

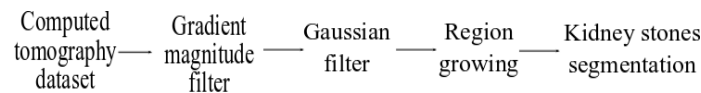


Figure 1. Block diagram of the proposed strategy.

2.2.1. Pre-processing. The main steps of this stage are: (i) Gradient magnitude filter (GMF). In this work, an approach based on finite differences was used for GMF computational implementation [8]. This filter generates a smoothed version, called GM_I , calculating the three-dimensional gradient magnitude of O_I , using the mathematical model given by Equation (1) [9].

$$GM_I = \left(\left(\frac{\partial O_I}{\partial i} \right)^2 + \left(\frac{\partial O_I}{\partial j} \right)^2 + \left(\frac{\partial O_I}{\partial k} \right)^2 \right)^{1/2}, \quad (1)$$

being: i, j, k the spatial directions in which the gradient is calculated and $\left(\frac{\partial O_I}{\partial i}, \frac{\partial O_I}{\partial j}, \frac{\partial O_I}{\partial k} \right)$ the partial derivatives of O_I . It is important to note that 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].

(ii) Gaussian filter. This filter smooths an image by convolving it with a Gaussian kernel using as standard deviations, the standard deviation of GM_I [11]. A discrete Gaussian distribution represented by the mentioned kernel, with arbitrary size, can be used. The kernel values are obtained according to Pascal's triangle. In this research, the size of its kernel is arbitrarily set to (3x3x3).

2.2.2. Segmentation. In this stage the region growing (RG) technique is applied. The RG partitions an image (f) into regions (R_i) whose voxels are connected according to certain predefined criteria based

on connectivity and similarity of the image. The most popular predefined criterion is given by Equation (2) [8]. The RG needs a seed voxel into an initial neighborhood (I_v).

$$|f(i, j, k) - \mu_{R_i}| < m\sigma_{R_i}, \quad (2)$$

being: $f(i, j, k)$ the gray levels of I_v , μ_{R_i} the average gray levels of a I_v of arbitrary shape and size, m an arbitrary scalar and σ_{R_i} the standard deviation of an arbitrary neighborhood of I_v . The Equation (2) represents the most popular predefined criterion due its simplicity and effectiveness [10]. 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 [11]. During the tuning process, the KS segmented is compared with the manual segmentation traced by a urologist. The Ds is used in order to estimate the difference or matching between these structures [12].

3. Results

First, we present qualitative results using original and preprocessed images in two-dimensional (2D) and 3D views. Then the quantitative results are shown considering mainly the results accuracy and optimal parameters obtained by the algorithms present in the proposed SAT.

3.1. Qualitative results

Figure 2 shows a two-dimensional (2D) view of both the original image and the processed images after applying the proposed technique to the dataset considered. In Figure 2, we can observe the effects generated by filter bank application. A qualitative analysis reveals that the considered filters generated high quality images reducing the noise and producing a high contrast between the anatomical structures. In Figure 2(a), we can observe the excellent performance of gradient magnitude filter for generating the contours of aforementioned structures. In Figure 2(b) we can see the borders of KS and the others anatomical structures; while in Figure 2(c) the gaussian filter generates a suitable representation of an image with less noise when it is compared with the original image.

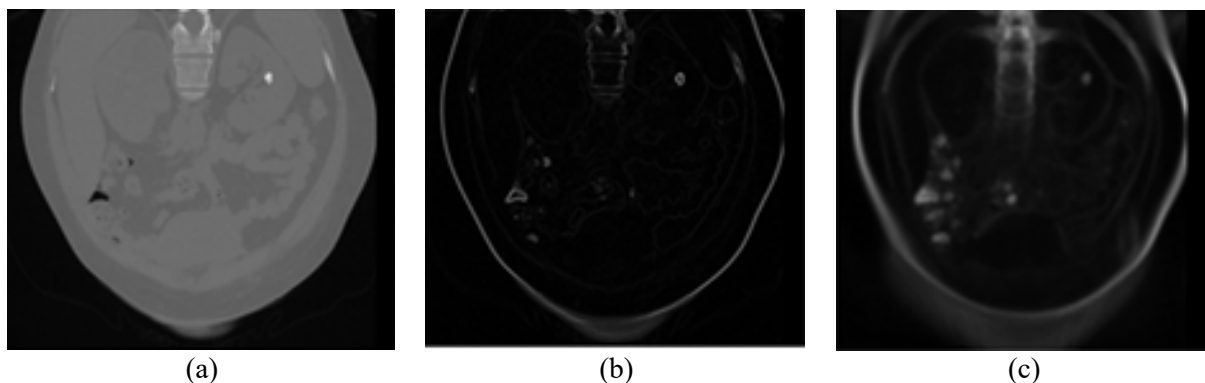


Figure 2. Preprocessing stage results, (a) original image, (b) gradient image, (c) gaussian image.

On the other hand, Figure 3 illustrates the results of the segmentation process developed using region growing technique. In this figure, we can observe an excellent representation of segmented kidney stone morphology in both 2D and 3D views.

3.2. Quantitative results

When the tuning process was performed the kidney stone was characterized considering its volume. So, the volume occupied by the automatically segmented kidney stone was 3.14 cm^3 ; while the volume, reported by the clinical expert, (obtained considering the manual segmentation) was 3.07 cm^3 .

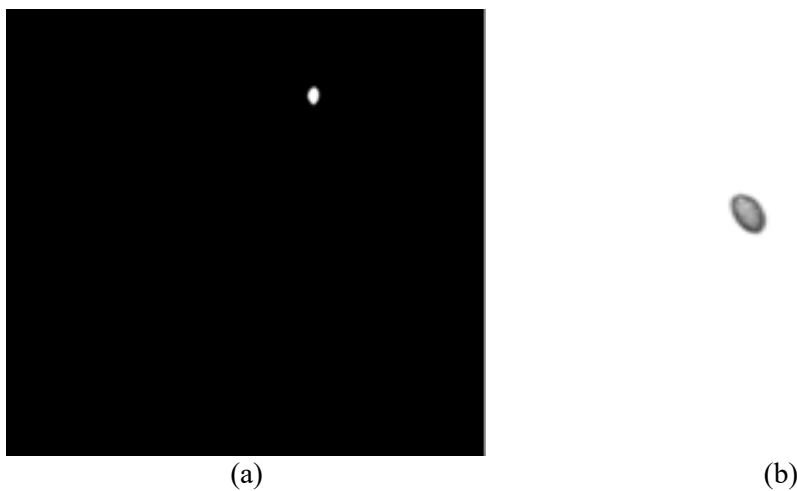


Figure 3. Kidney stone segmented: (a) 2D view, (b) 3D view.

The percentage relative error, considering these volumes, was 12.28%. This error represents an accuracy of 87.72%. Additionally, the maximum Dice coefficient generated was 0.8772. This result allowed establishing the optimal parameters of the computational algorithms that make up the proposed technique. They were: Region growing: $r = 1$ and $k = 6.5$.

Additionally, the Table 1 shows comparative information about the accuracy obtained both in this paper and in others researches, reported in the specialized literature.

Table 1. Comparison using accuracy values for kidney stone segmentation.

Authors	Technique	Accuracy (%)
Lui, <i>et. al.</i> [5]	Flow and attributes	90.00
Ebrahimi, <i>et. al.</i> [6]	Geometric principles	84.61
Sujata, <i>et. al.</i> [7]	Region growing	92.00
Rodríguez, <i>et. al.</i> (Our technique)	SAT	87.72

The information analysis presented in Table 1, let us to affirm that SAT was outperform by the results reported by Liu, *et. al.* [5] and Sujata, *et. al.* [7]; whereas the computational technique proposes in this paper generated a higher accuracy value than that reported by Ebrahimi, *et. al.* [6]. Our technique is very efficient and let us obtains result with a similar accuracy that the result reported in [5].

4. Conclusions

A semi-automatic technique, available for detecting kidney stone in a precise and efficient manner, has been presented. This technique was based in the application of median and gradient magnitude filters in order to address the noise problem and the region growing technique for generating the 3D kidney morphology, presents in MSCT images.

The three-dimensional representation of kidney stone is useful for the detection and monitoring of kidney diseases; as well as for the planning of medical treatments and clinical-surgical procedures linked to this pathology.

On the other hand, it is expected that the segmentation generated by the proposed method can be useful to promote, deepen and potentiate the study of the real anatomy of the structures linked to the renal lithiasis.

In the immediate future it is planned to validate the proposed technique with a significant number of databases in order to estimate the robustness of the aforementioned technique.

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