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Objective Analysis of Simple Kidney Cysts from CT Images

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Abstract — ***Simple kidney cysts* analysis from CT images is nowadays performed in a direct visual and hardly reproducible way. Computer-aided measurements of simple kidney cysts from CT images may help radiologists to accomplish an objective analysis of the clinical cases under observation. We propose a semi-automatic segmentation algorithm for this task. Experiments performed on real datasets confirm the effectiveness and usefulness of the proposed method.**

Keywords: Computer-Aided Image Analysis, Segmentation, Computer Tomography, Simple Kidney Cysts

I. INTRODUCTION

Kidneys are small but crucial organs, located in the upper part of the abdomen. Kidneys filter wastes and extra fluid from the blood to form urine and regulate several vital parameters [1]. A cyst is a pouch of tissue that can form anywhere in the body. Kidneys cysts are typically filled with fluid [2]. There are different categories of kidney cysts. The most common one, especially associated with aging, is the *simple kidney cyst* (Fig. 1).

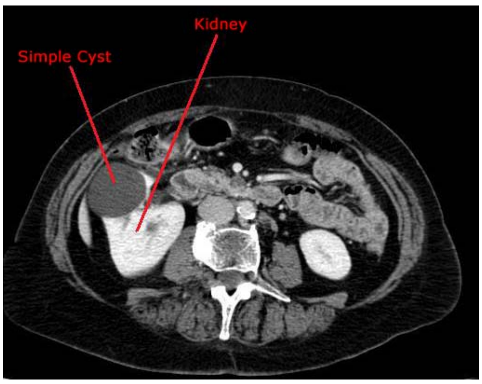

Figure 1. Example of simple kidney cyst.

Most often, simple cysts do not cause symptoms or harm the kidney. In some cases, however, pain could occur when cysts volume comprimes other neighboring organs. Cysts may, occasionally, become infected or suddenly start to bleed. Cyst presence rarely impairs kidney functionality. Correlation between presence of simple cysts and high blood pressure have been observed, although the cause-and-effect relationship is not yet well understood. Asymptomatic simple cysts do not need in most of the cases, any treatment. When treatment is required the most common procedures are puncturing. This invasive action is aimed to drain the cyst and to fill it with a solution containing alcohol to make the tissue harder. Very large cysts may eventually require surgery for their removal [2]. Kidney cysts can be diagnosed using computerized tomography (CT) scans [3]. The discovery and measurement of kidney cysts is performed by the trained radiologist through direct visual inspection of the CT slices of the lower abdomen. To monitor in time the evolution (measuring variations in size, density and location) of cysts, objective evaluation of all the relevant parameters is needed.

A basic computer-aided system may support the extraction of objective information asking the radiologist to manually label all of the pixels belonging to the simple kidney cysts in all the CT slices. Manual segmentation coupled with DICOM information [10] can be used to extract volumetric information about the cysts. This naïve approach, however is an error prone and time consuming task. The repeated results obtained in this way by different radiologists with a different kind of training and expertise show an unacceptably high variance. Other related acquisition drawbacks of such sytems are the following: the acquired data is aften noisy and in most technologies the ranges of data values of different tissues often overlap. This is especially true for soft tissues and trabecular bone in aged patients, where osteoporosis degenerates the bone density and thus the intensity of the bone is decreased. Thus, data values cannot be uniquely associated with specific tissues i.e., the data cannot be partitioned using Hounsfeld Units (HU) values alone. This rules out global as well as local thresholding techniques. Moreover, defining a similarity function between neighbouring pixels is hard, since the same tissues often have uneven values in different positions. Hence, region-growing, or edge detection algorithms are unable to effectively cope with this data. Although a large variety of segmentation methods have been developed for medical image processing, ad-hoc solution are often preferred especially to properly detect complex structures, such as vessel, brain, or skeletal structures.

To partially overcome these difficulties, in this paper we propose a semi-automatic approach to segment a simple kidney cyst. Effective computer-aided systems for the medical domain requires a full understanding of the semantic of the data [6,7,8,9]. This can be accomplished only by an interdisciplinary joint work that involves different competences (e.g., physician, radiologist, computer scientist, etc.). We propose a segmentation method that starts with an initial rough segmentation of a cyst in only one 2D slice from the full stack of the volume scan. This may be quikly done by a radiologist. This initial step may be done quickly: the quality of the initialization does not greatly affect the quality of the final segmentation, hence granting good repeatabilty properties of the measurement. More precisely the proposed computer-aided system requires that the radiologist draws a rough internal boundary of each cyst in only one slice of the CT data. The segmentation is then automatically refined: first on the slice where the radiologist has drawn his segmentation hypothesis and then on all neighborhood slices of the considered CT stack. Both refinement and propagation do not require any other user intervention. The final segmentation is coupled with the DICOM information of the CT data to produce an objective measures about volume, density and location of the segmented simple kidney cyst.

Experiments performed on a datasets of CT scans confirm the effectiveness and usefulness of the proposed approach.

II. Semi-Automatic Segmentation

The proposed algorithm can be summarized as follows:

Step 1. Segmentation of the simple kidney cyst on the initial slice (Fig. 2).

Step1.1. Rough segmentation of a simple kidney cyst by direct user intervention.

Step1.2. Filtering of the initial slice by making use of a bank of filters. For each filter response statistical information relative to the pixels within to the rough segmented region are computed and collected.

Step1.3. Binarization. Gaussian distributions are properly fitted [4] to the statistical information obtained in Step 1.2. This is done separately for each filter response. Windowing on the response values is performed on each of these informative channels in a such way that the 99,7% of the filtered Gaussian is considered as positive evidence.

Step1.4. The masks obtained at Step 1.3 are combined with a conjunction operator (AND). A morphological regularization [5] is used to obtain the final refined segmentation of the cyst section in the slice under consideration.

Step 2. Propagation of the segmentation to all the other slices. Given the segmentation on the slice *i*, the segmentation of the slice *i+1* [*i-1*] is performed as follows. A first rough segmentation of the new slice is obtained performing the Step 1.3 and 1.4 above. The segmentation uses the Gaussian distributions fitted on the mask that has been refined on the previous slice. Gaussian distributions of the filter responces are once again sampled on the rough mask obtained insofar. Using these new distributions Step 1.3 and Step 1.4 are repeated to obtain a refined mask on the new slice. Information about the center of the mass, as well as the diameters of the segmentation are used to stop the propagation.

The proposed algorithm make use of a bank of filters that includes a set of Gaussian filters and a set of derivative of Gaussian filters with different orientations; we used also the relative position of each pixels with respect to the position of the center of mass, the size of the cyst segmented in the adiacent slice, and the Hounsfield units (HU) values.

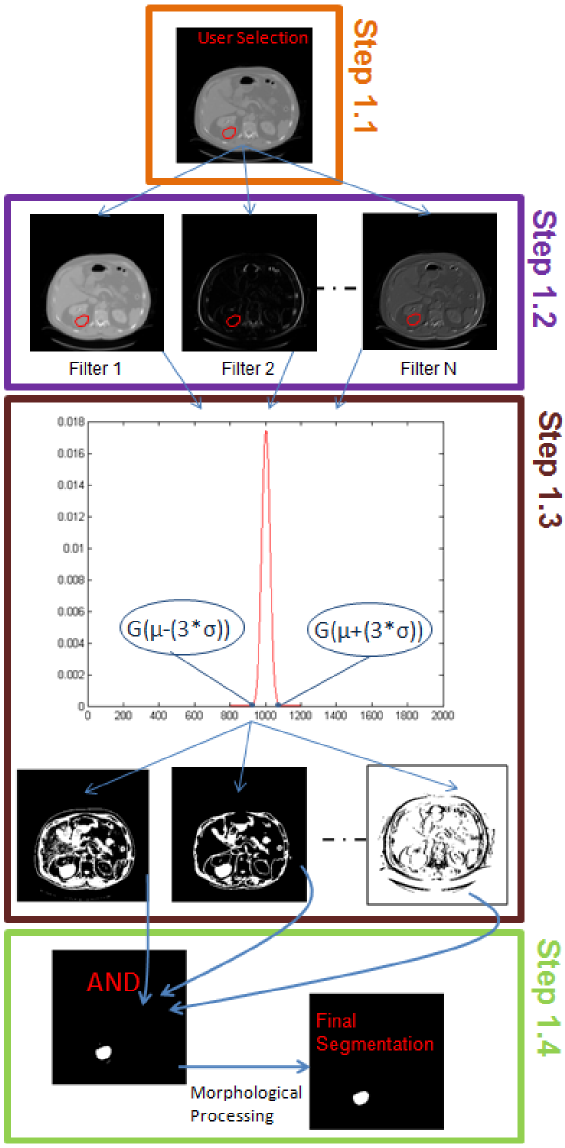

Figure 2. **Step 1.1:** a rough segmentation of the simple kidney cyst is done by the user on a 2D slice. Pixels inside the red region are considered belonging to the cyst. **Step 1.2:** The initial slice is processed whit a bank of

filters producing different channels. **Step 1.3:** A binary mask for each channel obtained in the previous step is computed. For each pixel the probability to be within a cyst or not is estimated through a Gaussian distribution whose parameters (μ,σ) are estimated in the previous step. A pixel is considered belonging to a cyst if the associated value on the considered channel is within the interval [μ+3*σ, μ+3*σ]. This process is applied independently for each filter response. **Step 1.4:** To obtain the final segmentation on the initial CT slice, the binary masks obtained at the step 1.3 are combined and refined through morphological operation.

Figure 3. Example of critical case for semi-automatic segmentation. Two simple kidney cysts are just one next to the other. This makes the separation of the two cysts and the delineation of their boundaries a challenging task.

III. Case Studies

The datasets of CT scans used in our experiments are from eight different clinical cases observed at Vittorio Emanuele Hospital in the year 2008. CT data are acquired with different settings of parameters (e.g., section thickness). The acquisition of the CT data have been perfomed with standard protocol after injection of a contrast agent. Critical cases with more than one cysts (e.g., cysts that are close each other as in Fig. 3) have also been considered in the experiments.

IV. Experimental Results

To asses the performance of the proposed semi-automatic segmentation, we have built a computer-aided systems implementing 1) a naïve approach for segmentation (pixel-wise manual segmentation) and 2) the method discussed in Section II.

First, a experienced radiologist performed a pixel-wise classification of the simple kidney cysts within the considered datasets. Fifteen simple kidney cysts have been labeled. The labeled datased, coupled with the DICOM information about CT scans (e.g., thickness), have been stored together with the extracted information about volume, location (i.e., centre of the mass) and density of the cysts. The labeled dataset have been used as benchmark to test the performances of the proposed semi-automatic segmentation.

We asked to another radiologist to perform the segmentation by using the computer-aided module that implements the proposed method. Each cyst has been segmented three times. The radiologist choose the stanting slice that make his duty easier (i.e., Step 1 of the algorithm described in previous Section).

The segmentation results (Fig. 4, Fig. 5) have been stored and compared with the segmentation of the benchmark datasets. The average pixel-wise categorization performance was about 96%. Main errors occured in correspondence of slices that have been segmented as last slices in the propagation. The obtained results match in terms of cysts location and density of the cysts.

V. Conclusion and Future Works

Objective analysis of CT images is becoming of increasingly of interest for radiologists. This paper proposes a semi-automatic segmentation algorithm useful to extract objective information of simple kidney cysts from CT scans.

Experiments results on real datasets confirm the effectiveness and usefulness of the proposed method.

Future works will include a complete study of intra and inter operator deviation and a characterization of the proposed system with respect to the average values obtained on the same dataset by different trained operators. Moreover, the segmentation of cysts on other organs will be considered.

Acknowledge

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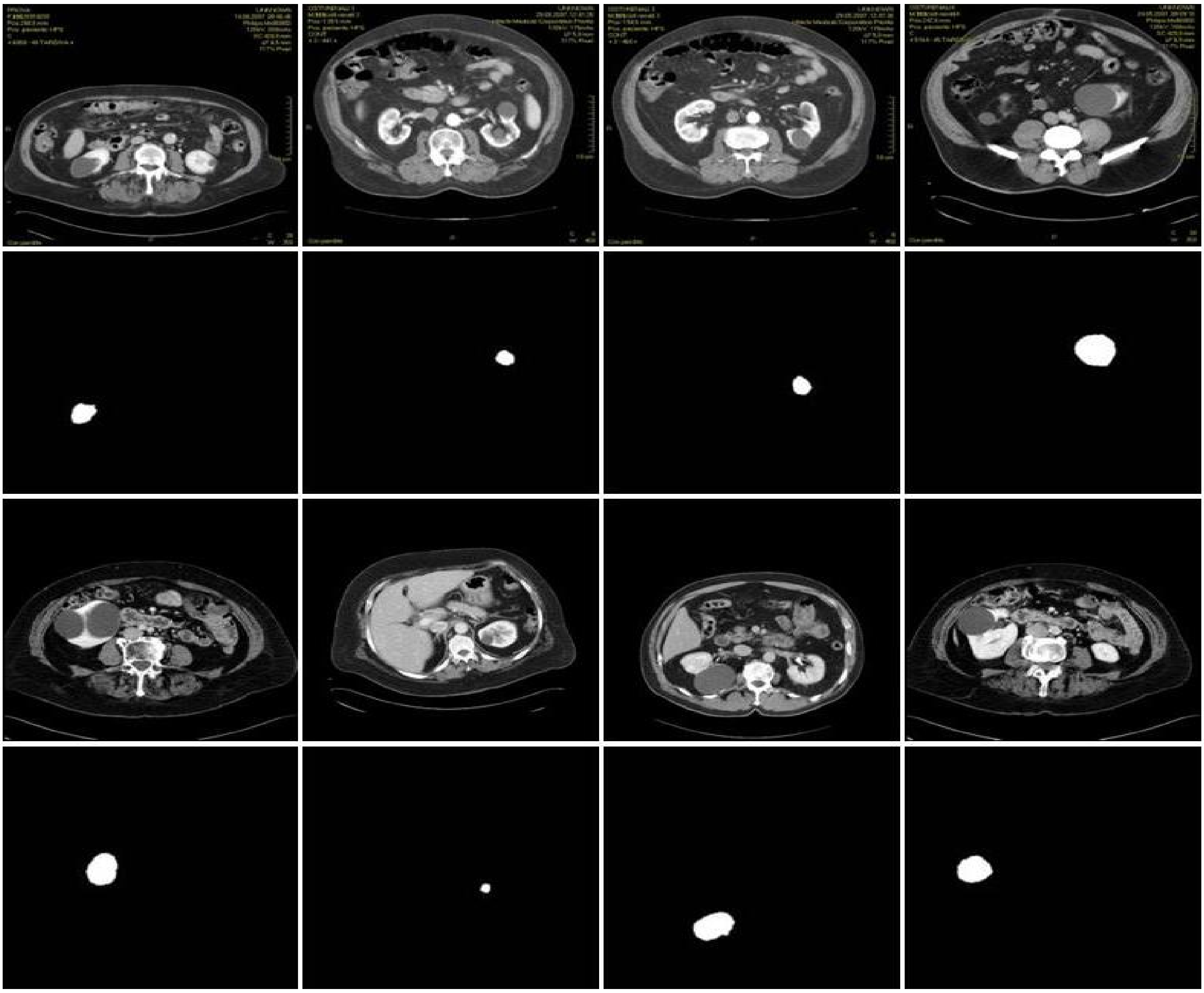

Figure 4. CT slices, and corresponding segmentation results, of eight different simple kidney cysts considered in the experiment.

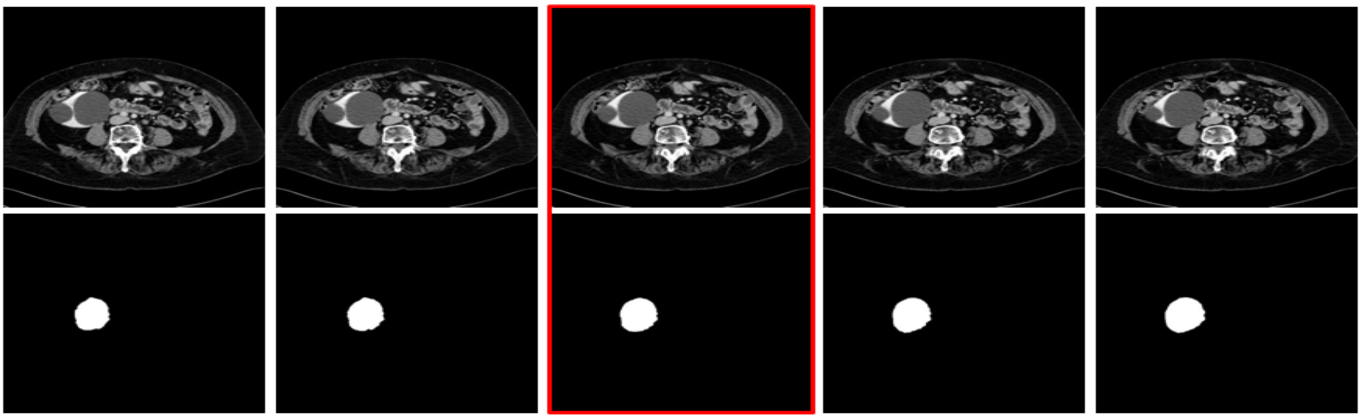

Figure 5. Segmentation results on a critical case shown in Figure 3. The initial slice is marked with red border.