

An image preprocessing method for kidney stone segmentation in CT scan images

Nilar Thein

*Department of Electrical Engineering and Information
Technology
Universitas Gadjah Mada
yogyakarta, Indonesia
nilarthein.mti13@mail.ugm.ac.id*

Hanung Adi Nugroho

*Department of Electrical Engineering and Information
Technology
Universitas Gadjah Mada
yogyakarta, Indonesia
adinugroho@ugm.ac.id*

Teguh Bharata Adji

*Department of Electrical Engineering and Information
Technology
Universitas Gadjah Mada
yogyakarta, Indonesia
adji@ugm.ac.id*

Kazuhiko Hamamoto

*Department of Information Media Technology
Tokai University
Tokyo, Japan
hama@keyaki.cc.u-tokai.ac.jp*

Abstract—In 3D medical imaging, anatomical and other structures such as kidney stones are often identified and extracted with the aid of diagnosis and assessment of disease. Automatic kidney stone segmentation from abdominal CT images is challenging on the aspects of segmentation accuracy due to its variety of size, shape and location. The performance of 3D organ segmentation algorithm is also degraded by the image complexity containing multiple organs and because of their huge size. The current need is a preprocessing algorithm to assist the segmentation process. The objective of the present study was to develop reader independent preprocessing algorithm for kidney stone detection and segmentation in CT images. Three thresholding algorithms based on intensity, size and location are applied for unwanted regions removing such as soft-organ removing, bony skeleton removing and bed-mat removing. The digitized transverse abdomen CT scans images from 30 patients with kidney stone cases were included in statistical analysis and validation. As validation data for analysis, the estimation of coordinate points in stone region was measured independently by expert radiology. Experimental results prove that the proposed preprocessing algorithm has 95.24% sensitivity as the evaluation parameter. So, it can reduce the noise and unwanted regions in each procedure with good detection.

Index Terms—preprocessing algorithm, kidney stone detection, unwanted regions removing

I. INTRODUCTION

Kidney stone problem (nephrolithiasis) is a common type of urological disease with a high recurrence rate of 10 % after one year, 50 % over a period of 5-10 years and 75 % over 20 years period in [1]. Over the last 20 years (1991-2011), the prevalence rate of kidney stones disease in China has increased nearly twice from 5.95 % until 10.63 % which has been documented in mainland China in [2]. In early stage of this disease, it is impossible to realize the problem because of non-specific symptoms. And, it can be noticed only after starting the sign of organ damage in [3]. Moreover, kidney

disease is a progressive disease that damaged the kidneys leading to be permanent and undone problem. Therefore, it is vital to identify kidney stone disease before the permanent damage is done. If the stone problem is caught in the early stage, kidney disease can be treated very effectively. So, stone diagnosis is vital not only treatment of kidney disease but also management of recurrent stone formation.

Over the past few years, 3D medical image processing is used as a vital role in computer-aided diagnosis, leading to assist radiologist in evaluating medical imagery or in recognizing abnormal findings in a medical image. Traditional test (blood test, urine test and biopsy) and imaging test (ultrasound, CT and MRI) are used to diagnose kidney stone disease. According to the consideration based on time taken, cost, information gained on diagnostic test, imaging test using computer tomography (CT) has become the most common one among diagnostic tests in [4].

But, stone diagnosing on CT is still having a challenge in segmentation because of its complicated structures of interest in abdomen CT. In heterogeneous nature of the tissues, lack of clear boundaries, similarities among the adjacent organs, noise, partial-volume effect, accurate segmentation of the organs is a difficult problem. Therefore, preprocessing method plays a vital role for improving the performance of 3D image segmentation.

This study developed a user independent preprocessing algorithm leading to accurate segmentation of kidney stone diagnosis in CT images. Specifically, the study (1) developed a method for soft organs removing; (2) developed a method for bony skeleton removing; (3) developed a method for bed mat removing and noise reducing in a digital CT scan images.

II. MATERIALS AND METHODS

A. CT image acquisition

All CT examinations included were performed with CT scan image of 30 patients. CT had demonstrated a kidney stone in the kidney or outside of kidney (anywhere in the abdominal cavity). These digitized transverse abdomen CT scans images were taken with Toshiba Aquilion 64slice CT Scanner and obtained from No_2, Military Hospital, Yangon. The number of slices for each patient has between 500 slices and 600 slices with variable kidney stone sizes and locations through their CT scan.

B. Proposed Methods

To investigate and implement the proposed method, the available dataset and MATLAB computing is used for implementation. It can be seen many organs in abdominal, such as soft organs (stomach, gallbladder, intestines, liver, pancreas and spleen), hard organs (kidney stone, vascular calcification and bones) and blood vessels in “Fig. 1”. Therefore, removing unneeded disturbance from CT images is basically one of the critical tasks in image segmentation. In this study, the pre-processing method is focused on removing unneeded disturbance based on prior knowledge of the input DICOM image. In the following processes, the effective and efficient methods has been applied to develop each process of the proposed scheme.



Fig. 1. Kidney stone in CT slice

1) *Soft-organ removing*: The first step in the proposed segmentation method is removing soft organs from the abdominal cavity. Strength of CT is its ability of significant intensity (Hounsfield scale) differences between soft organs and hard organs. Soft-organs have low intensity values while others have high intensity values. Moreover, the range of HU value of kidney stone is regarded between 200 HU to 2800 HU in [5] in [6]. Therefore, the soft organs in the image are removed using intensity-based thresholding with two threshold value, T_a and T_b .

- Step 1, Select two constant threshold values, T_a and T_b , manually, in “(1)”.

$$g(x, y) = \begin{cases} 1 & \text{if } T_a \leq g(x, y) \leq T_b \\ 0 & \text{if else} \end{cases} \quad (1)$$

- Step 2, Segment the image into two group of pixels $g(x, y)_1$ and $g(x, y)_2$, using T_a and T_b .
- Step 3, Develop the new image with $g(x, y)_1$ and without $g(x, y)_2$.

2) *Bony skeleton removing*: After removing soft organs from the images, there are still left many high-intensity regions such as bed-mat, bones, vascular calcification, stones and noise. Among these unwanted regions, a largest structure is bony skeleton which is comprised of rib cage, vertebral column and pelvic cage. The size of kidney stone can also grow as large as the size of golf balls in [7]. Therefore, the size of bony skeleton is completely difference in kidney stone size. And, it can be eliminated by finding the largest area of objects in the image. For bony skeleton removing, we develop the following algorithm:

- Step 1, Calculate the area of each 3D object in the image using the following equation,:

$$Area(A) = \text{Number of voxels in an object} \quad (2)$$

- Step 2, Find the maximum object area O_{max} .
- Step 3, Segment the image into two group of pixels $g(x, y)_1$ and $g(x, y)_2$, using O_{max} as the following equation.

$$g(x, y) = \begin{cases} 1 & \text{if } O_{max} = g(x, y) \\ 0 & \text{if else} \end{cases} \quad (3)$$

- Step 4, Develop the new image with $g(x, y)_2$ and without $g(x, y)_1$.

3) *Bed-mat removing and noise reduction*: Finally, bed-mat and some noise remained in image are extracted for kidney stone segmentation. Area-based thresholding is not available to eliminate the unwanted objects which are similar in size of stone. Therefore, location-based thresholding has been developed to eliminate bed-mat, vascular calcification and some noise that are remained after bony skeleton removing. Bed-mat is extracted using location-based thresholding method in the X, Y and Z direction. As the exact location, bed-mat is located at the behind of bony skeleton and is closed to the end of Y-direction in “Fig. 2”. Moreover, the kidney stones can form anywhere in the urinary tract, kidney and bladder which are exactly located in the enclosed region of the bony skeleton. So, bed-mat has been cut out in the image by regarding X, Y and Z location manually. The proposed location-based thresholding can provide not only bed-mat removing but also noise (is located in front of the bony skeleton) reduction. Although the proposed method is not robust, it can completely remove bed-mat with noise reduction.

C. Implementation

In order to assist the segmentation process, the proposed preprocessing has been developed in “Fig. 3”. The stages of implementation of the proposed scheme are present as follows:

Loading the input DICOM file is started the proposed process. The method used in this process will remove all of unwanted regions of each slice in the input data, produce 3D segmented object smoothly and accurately.

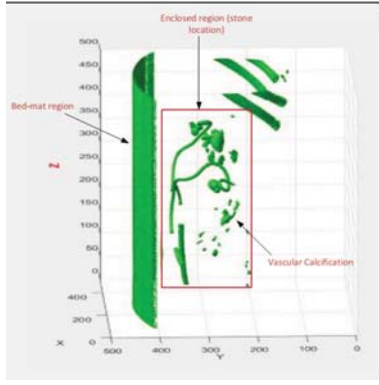


Fig. 2. Location of bed-mat, stone, vascular calcification and bones on CT

Soft-organ removing: Because of distinct intensity range between the stone and other low-intensity organs, intensity-based thresholding become the optimal method to remove soft organs. Large object with high intensity value (stone and bone) are easier to detect and segment compared with small ones with low intensity values. Therefore, stone and bone can be extracted among other soft tissue and organs using intensity-based thresholding.

Bony skeleton removing: The area of bony skeleton is largest one among all hard organs of the abdomen CT scan. So, size (area)-based thresholding can remove the boney skeleton completely form the image.

Bed-mat removing and noise reduction: From the residues of boney skeleton removal process, some objects (stent, vascular calcification and a piece of bones) around the segmented stone and bed-mat also exist as noise. Among them, bed-mat and some pieces of bones are distant apart with the stone. Therefore, location-based thresholding can delete these unneeded parts for stone segmentation. Finally, the proposed algorithm can produce the output by reducing many unneeded region. The output of the proposed will be a support for accurate segmentation process.

D. Evaluation Parameters

According to analysis of evaluation parameters in [8], an evaluation parameters, sensitivity, is used in this study for proposed pre-processing algorithm: The sensitivity can be calculated using TP and FN rate as shown below:

$$Sensitivity = \frac{TP}{TP + FN} \quad (4)$$

TP is used for kidney stone, which are correctly detected. FN is used for kidney stone, which are not detected.

III. RESULTS AND DISCUSSION

A. Data Analysis and Prototype Application

Data analysis for this study was tested on abdominal CT images which are based on the incidence of kidney stone. The experiments were carried out on a PC with Intel(R) Core(TM) i7-7700HQ CPU @ 2.80 Hz, 8 GByte of RAM, and the computations were performed under MATLAB 9.0 (R2016a).

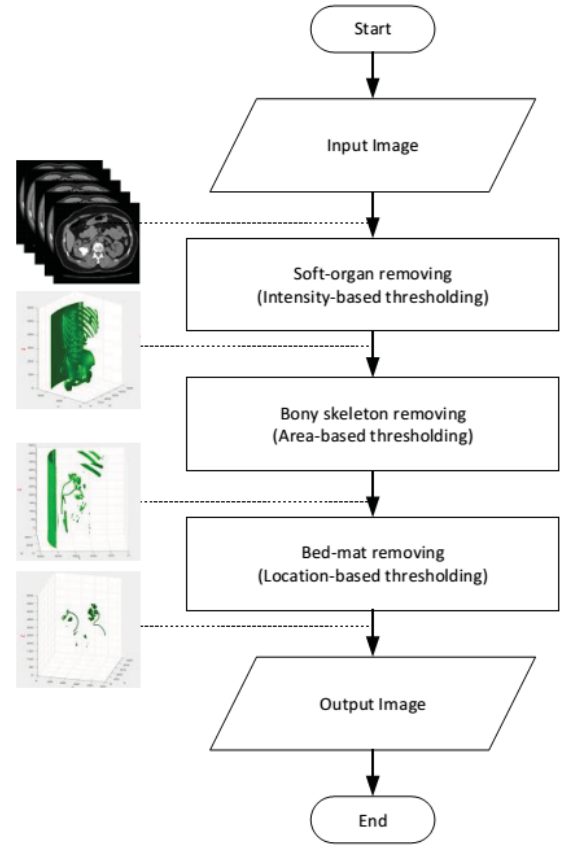


Fig. 3. Flow chart of the proposed algorithm

Seventy five CT scan images with DICOM format were used for testing. Reference manual detection, coordinate points estimation in stone region, were created by expert radiologist. We computed our preprocessing with the reference detection to evaluate our method.

B. Performance Evaluation

The proposed preprocessing algorithm consists of segmentation using simple thresholding method and morphological operation which are used step by step relies on the prior knowledge of the CT image.

Working on 550 slices of abdominal CT image of a patient, our experiments demonstrated that the proposed algorithm is removed unwanted regions step by step in “Fig. 4”. The first image, “Fig. 4(a)”, is the resulted image after soft-organ removing, the second image, “Fig. 4(b)”, is the resulted image after bony skeleton removing, and the third image, “Fig. 4(c)”, is the resulted image after Bed-mat removing. “Fig. 4(a)” illustrated the result of intensity-based thresholding that can completely remove all soft organs such as liver, kidney, pancreases etc. in the abdominal CT image. “Fig. 4(b)” gave the result of size (area)-based thresholding that can also

remove the bony skeleton, the biggest object in the image. But, it is unable to extract some remaining objects in the image, bed-mat, stone, stent and other fragmented bones. “Fig. 4(c)” provides the result of location-based thresholding that can remove bed-mat and many fragmented bones from the image. Therefore, the program produces 3D result without many distributed regions that can assist to improve the performance of next segmentation process.

TABLE. I shows the result of each process in the proposed algorithm. After loading 500-600 slices, it is constructed the original image which is consists of over 500000 labels. In soft-organ removing process, the algorithm can remove all soft organs from the abdomen CT image and reduce the unwanted objects up to 4300 labels in average. In second process, bony skeleton removing, the algorithm removes the bony skeleton and some bones but the average of the remaining labels is about 400. In the last process of the proposed algorithm, it can remove most of unwanted regions and produce the output of the preprocessing. The final output is clear in visualization and remains only an average of 25 labels in an image. Therefore, the proposed preprocessing algorithm can significantly reduce the unwanted regions that will be efficient and effective to improve the next segmentation process. As execution time analysis, the proposed algorithm takes about 60 second (in average) for overall process of the algorithm.

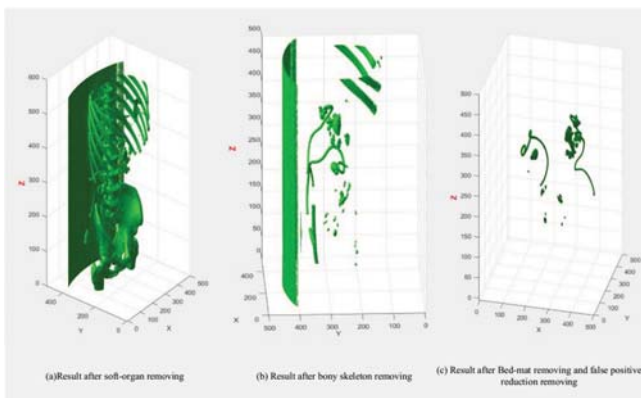


Fig. 4. Results of each step from the proposed preprocessing method.

TABLE I
AVERAGE RESULT OF ALL 30 PATIENTS IN EACH STEP

Mean value of the proposed algorithms results for 30 patients			
Soft-organ removing	Bony skeleton removing	Bed-mat removing and false positive reduction	Total execution time
4303 labels	380 labels	25 labels	60 sec

C. Accuracy

The program output and manual record arranged to valid the performance of the algorithm. Validation experiments were performed on real CT data from 30 patients. From these results, we got 60 true positive and 3 false negative. The sensitivity, the performance of the proposed technique has been

calculated using in “(4)”. The result for algorithm, sensitivity is 95.24%. It is found that this method works unneeded regions removing with a significant true positive (stones) detecting. It gives a clear output image for segmentation although there are still remain false positive.

IV. CONCLUSIONS

This proposed preprocessing method for kidney stone segmentation will provide good support in detecting kidney stone. Intensity-based thresholding can produce the output image without any soft regions. Area-based thresholding can delete the bony skeleton from the image. Location-based thresholding can reduce many false positive and bed mat region. Because of using thresholding methods based on the prior knowledge of the image, the proposed scheme is simple and easy to understand for segmentation. Moreover, the proposed thresholding methods correctly remove the unneeded region and provide the output image in a clear form. According to performance analysis, the detection ability of the program is efficient with high sensitivity (sensitivity is 1). The result we found is good and satisfactory. As limitation, the proposed schemes will weak in robustness because it is completely relines the prior knowledge of the input image. We plan to explore more robust preprocessing process and to develop the accurate method for kidney stone segmentation.

ACKNOWLEDGMENT

This paper was supported by the aid of JICA/AUN Seed-Net.

REFERENCES

- [1] A. Sohga and P. Bigoniya, A Review on Epidemiology and Etiology of Renal Stone, *Am. J. Drug Discov. Dev.*, vol. 7, no. 2, pp. 5462, 2017.
- [2] W. Wang et al., Prevalence of kidney stones in mainland China: A systematic review, *Sci. Rep.*, vol. 7, pp. 19, 2017.
- [3] I. Introduction, Distinguishing Staghorn and Struvite kidney stones using GLCM and Pixel Intensity Matrix Parameters, vol. 4, pp. 25, 2017.
- [4] W. Brisbane, M. R. Bailey, and M. D. Sorensen, An overview of kidney stone imaging techniques, *Nat. Rev. Urol.*, vol. 13, no. 11, pp. 654662, 2016.
- [5] Y. Andrabi, M. Patino, C. J. Das, B. Eisner, D. V. Sahani, and A. Kambadakone, Advances in CT imaging for urolithiasis., *Indian J. Urol.*, vol. 31, no. 3, pp. 18593, 2015.
- [6] G. Chevreau et al., Estimation of urinary stone composition by automated processing of CT images ., pp. 111.
- [7] N. Kidney, U. Diseases, and I. Clearinghouse, Kidney Stones in Adults, *NIH Publ.*, vol. 132495, no. February 2013, pp. 112, 2012.
- [8] W. Zhu, N. Zeng, and N. Wang, Sensitivity, specificity, accuracy, associated confidence interval and ROC analysis with practical SAS implementations., *Northeast SAS Users Gr. 2010 Heal. Care Life Sci.*, pp. 19, 2010.