Automatic Region of Interest Generation for Kidney Ultrasound Images

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Abstract: - Ultrasound scanning of the kidney is performed to assess kidney size, shape and location as well as to detect any abnormalities in kidney like cysts and stones. Since ultrasound image contains speckle noise, performing the segmentation methods for the kidney images has always been a very challenging task. For further segmentation purpose, deleting and removing the complicated background not only speeds up the segmentation process, but also increases accuracy. However, in previous studies, the ROI of the kidney is manually cropped. Therefore, this study proposed an automatic region of interest (ROI) generation for kidney ultrasound images. The methods consist of the speckle noise reduction using Gaussian low-pass filter, texture analysis by calculating the local entropy of the image, threshold selection, morphological operations, object windowing, determination of seed point and last but not least the ROI generation. This algorithm has been tested to more than 200 kidney ultrasound images. As the result, for longitudinal kidney images, out of 120 images, 109 images generate true ROI (91%) and another 11 images generate false ROI (9%). For transverse kidney images, out of 100 images, 89 images generate true ROI (89%) and 11 images generate false ROI (11%). To conclude, the method in this study can be practically used for automatic generation of US kidney ROI.

Key-Words: - kidney ultrasound, region of interest, seed point, texture analysis, morphological operation

1 Introduction

The kidneys are retroperitoneal organs protected by the lower ribs where the kidney can be found just below the liver on the right, and just below the spleen on the left. During the scanning session, if the kidney were scanned in longitudinal view, the kidney will appear football-shaped, and C-shaped in transverse view.

The normal kidney has a bright area around it, made up of perinephric fat and Gerota's fascia. The kidney periphery parts appear grainy gray, consists of renal cortex and pyramids while the central area of the kidney, the renal sinus, will appear bright (echogenic), consists of renal sinus fat, calyces, as well as renal pelvis.

Since some other organs lie close to the kidney which may give effect to the performance of other image processing methods, finding a region of interest (ROI) for kidney is quite helpful. Besides, this ROI will improve the speed and accuracy of further segmentation process. Furthermore, many existing kidney ultrasound image processing methods, including enhancement and segmentation techniques have been developed based on a manually selected ROI, not on the whole image [1-4].

Some researchers define ROI as the rough contour or initial contour of the interest object, while the other defines ROI as a rectangular region containing both the interest object kidney and some background information. For this study, a rectangular ROI will be automatically generated and any further operation will be conducted only in that rectangular ROI.

For further segmentation purpose, deleting and removing the complicated background not only speeds up the segmentation process, but also increases accuracy. Therefore, this ROI generation method can be used by any other segmentation method as a preprocessing step since it only cuts the background outside the rectangular ROI while keeping the interest object (kidney) and nearby surrounding tissues untouched.

Automatic ROI has been proposed by other researchers but they were not using the kidney ultrasound images. Yap et al. for example has successfully developed an algorithm to automate the manual process of region of interest (ROI) labeling in computer-aided diagnosis (CAD) for breast lesions [5, 6]. There were other researchers who also focusing on automatically detection lesions in breast ultrasound images [7-9].

However, ROI generation of lesion in breast ultrasound image is not as complicated as in ROI generation of kidney ultrasound image. In breast images, the shape of the lesion can be seen easily thus, the seed point for generating the ROI is more obvious. For kidney ultrasound image, in order to generate ROI for the whole kidney image for both longitudinal and transverse view, selection of seed point is quite troublesome.

Thus, in this study, we proposed the development of an automatic ROI generation method that facilitates full automation of kidney ultrasound image segmentation. Therefore, we conducted a texture analysis to the kidney images. As the result, the renal sinus, the central area of the kidney appeared brighter compared to the other part of the images, and in the texture analysis, it also appear as the most common region detected in kidney images. So, by using this finding, we have developed an algorithm for automatic ROI generation of ultrasound kidney images.

The rest of this paper is organized as follows. In section 2, we describe on the materials and the methods applied for generating ROI of the kidney in ultrasound images. The results are shown in Section 3, and Section 4 shows the conclusion.

2 Materials and Methods

For this study, longitudinal and transverse view of ultrasound kidney images were taken from volunteers from Universiti Teknologi Malaysia Johor Bahru (UTM) by using TOSHIBA *AplioMX* ultrasound machine with 3.5MHz transducer. The kidneys were scanned in supine position and with inspiration of the subjects. Then, MATLAB programming was used to develop the system for generating the kidney ultrasound region of interest automatically.

Fig. 1 shows the longitudinal section of the original ultrasound kidney image while Fig. 2 shows the transverse section of the image.

Fig. 1: Longitudinal section of original ultrasound kidney image

Fig. 2: Transverse section of original ultrasound kidney image

For this study, an automatic defined rectangular ROI will be generated and this ROI generation can be used as a preprocessing step for any other segmentation method since it only cuts the redundant background while keeping the lesion and nearby surrounding tissues untouched. Fig. 3 shows the block diagram of the steps for ROI generation.

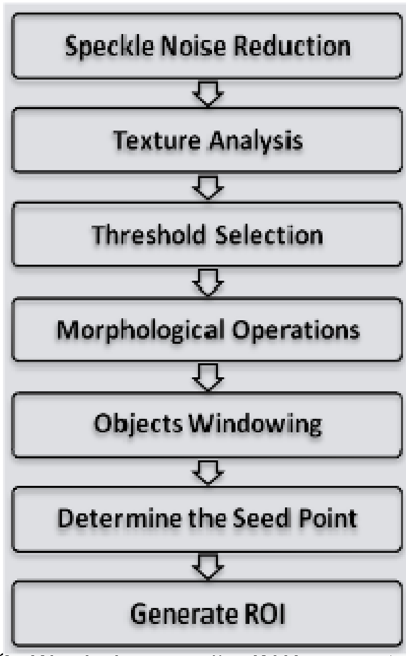

Fig. 3: Block diagram for ROI generation

Firstly, the Gaussian low-pass filter will be used for speckle noise reduction and smoothing. Then texture analysis is implemented for creating texture image and based on the threshold value selected, morphological operation is used for removing unwanted regions. After that, the remaining objects will be windowed so that only one object is choosed as the seed point. Lastly, the ROI is generated according to the seed values.

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2.1 Gaussian Low-pass Filtering

Gaussian Low-pass filtering has been used in previous researches for removing the speckle noise in US images [10, 11]. Besides, low-pass filter based on Gaussian function is also common in frequency domain filtering, since both the forward and the inverse Fourier transforms of a Gaussian are the real Gaussian functions [4].

The equation for Gaussian filter is:

$$g(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-x^2}{2\sigma^2}} \quad (1)$$

σ in the equation (1) is the standard deviation of the distribution, and also the degree of smoothing. The larger the value of σ, the filtered image is smoother. In order to be accurate, if larger value of σ is used, larger convolution kernel need to be used.

2.2 Texture Analysis

Texture analysis is important in characterizing regions in an image by their texture content and it is helpful when objects in an image are more characterized by their texture than by intensity, and traditional thresholding techniques cannot be used effectively. When certain values either range, standard deviation or entropy of the image are calculated, they will provide information about the local variability of the intensity values of pixels in the image, thus the texture can be characterized.

For this study, entropy, a statistical measure of randomness, is calculated. Then, threshold value is set to segment the textures. Threshold value of 0.7 is selected because it is roughly the intensity value of pixels along the boundary between the textures in US kidney images.

2.3 Morphological Operations

After image binarization, morphological operations were performed to remove the unwanted regions. Morphological filters are based on two main operations, which are dilation and erosion [12]. In order to extract useful information in images, a small pattern called structuring element is translated over the image [13]. Small objects were removed, and holes were filled using erosion and dilation operations.

Since there were possibilities that not all the unwanted regions were removed, the image is windowed again using a center window with 80x80 of height and width, assuming all the kidney images were taken with the kidney is almost at the center of the image. Only the regions that intersect with this window will be remained as seed point candidates, and the rest will be deleted.

2.4 Determine the Seed Point

The left regions will undergo another selection steps to determine which is the correct seed point. The algorithm for seed point selection is as in Fig. 4.

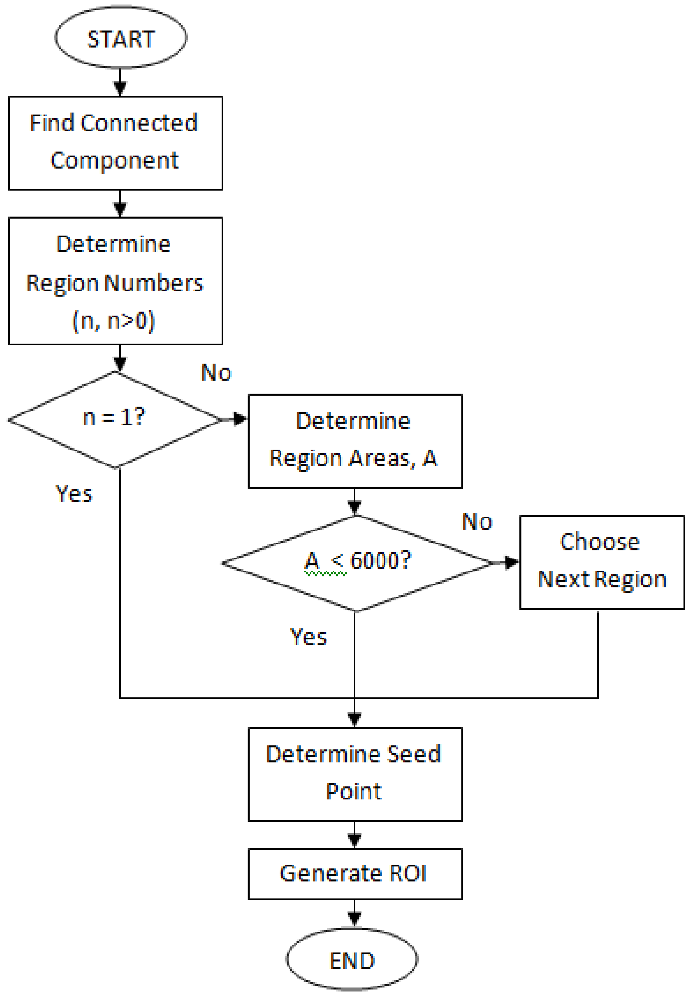

Fig. 4: Algorithm for seed point detection

For seed point detection, firstly, the number of connected components (region), n needs to be determined so that we can know how many regions left in the image. If there is only one region left, it is automatically considered as the seed point. If not, the region areas (pixel), A also needs to be determined. We set the threshold pixel areas as 6000. If A is less than 6000, that region is selected as the seed point. If not, the other region will be selected.

Then, the center pixel value (x,y) of the winning region is determined and based on the value, a rectangular window is defined to generate

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longitudinal and cross section ROI of kidney. For longitudinal kidney image, a window of 400x200 is defined and for transverse kidney image, a window of 240x240 is defined.

The algorithm was tested for more than 200 images and the results were displayed and discussed in the next section.

3 Results and Analysis

Fig. 5 shows the result of the images before and after using Gaussian low-pass filter. As can be seen, the image after being filtered by using Gaussian low-pass filter is smoothed.

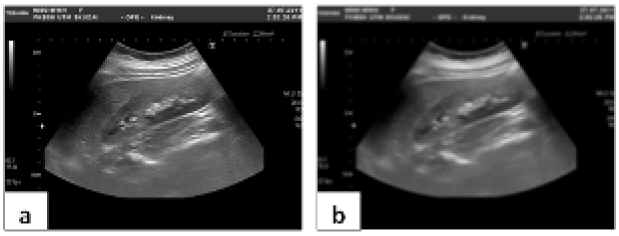

Fig. 5: US kidney image (a) before and (b) after Gaussian low-pass filter

Then, texture analysis is implemented and the result is changed to binary by setting the threshold value at 0.7 (Fig. 6(a) and (b)). After that, morphological operation is performed (Fig. 6(c)) and the result is windowed by using a center window with 80x80 height and width. If the result in Fig. 6(d) has more than one region, algorithm as in Fig. 4 will be implemented for selection of a correct seed point.

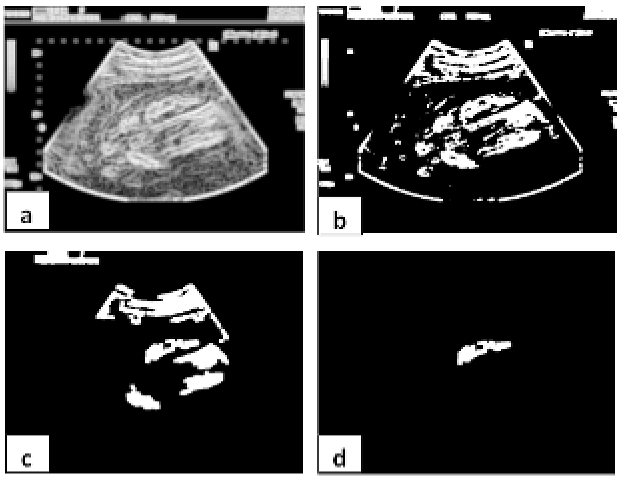

Fig. 6: US kidney image, (a) after texture analysis, (b) binary image with threshold value 0.7, (c) after morphological operations, (d) after windowing.

After selecting the seed point, the center pixel value of the region is determined. A rectangular window of 400x200 is defined for longitudinal kidney image and 240x240 is defined for transverse kidney image. The result can be seen in Fig. 7 (a) and (b).

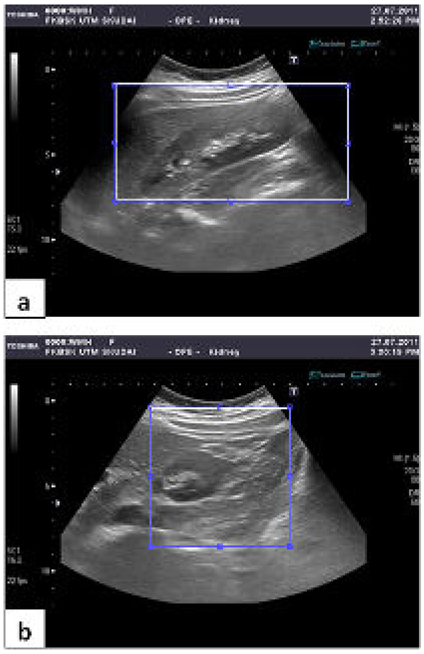

Fig. 7: Automatic ROI generation for (a) longitudinal kidney image, (b) transverse kidney image

The experiment has been done for this study using more than 200 US kidney images for both longitudinal and cross section. For longitudinal kidney images, out of 120 images, 109 images generate true ROI (91%) and another 11 images generate false ROI (9%). For transverse kidney images, out of 100 images, 89 images generate true ROI (89%) and 11 images generate false ROI (11%). The results can be seen in Fig. 8 and Fig. 9.

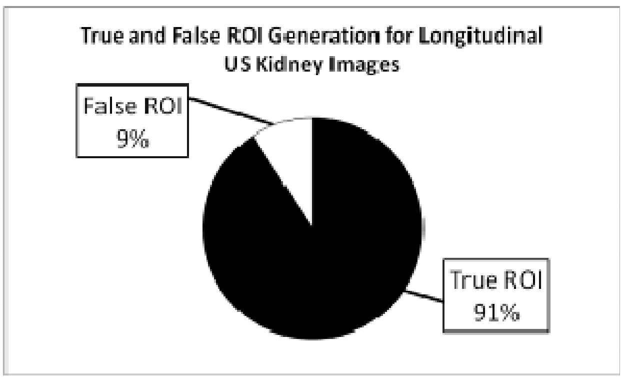

Fig. 8: ROI generation for longitudinal US kidney images

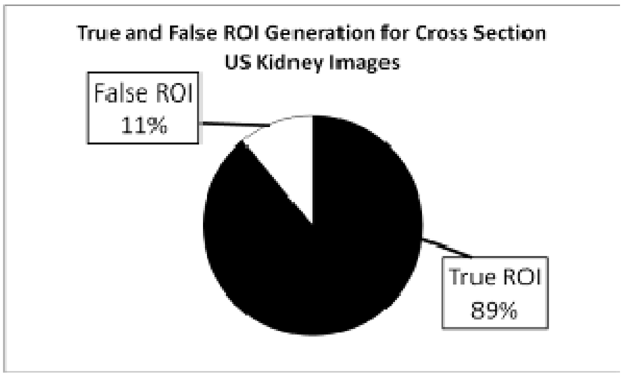

Fig. 9: ROI generation for cross section (transverse) US kidney images

The false ROI in certain images maybe caused by the noise in kidney US image. Besides, the position of the kidney also plays an important role in generating a true ROI, as in this study, assumption have been made that the kidney is located at the center of the images. That is probably why the algorithm for image processing was failed to generate a true ROI in some images. Nevertheless, about 89% true ROI have been generated for both longitudinal and transverse ultrasound kidney images. Therefore, the method in this study is reliable for automatic generation of US kidney ROI.

4 Conclusion

From the results, it was proved that this study can be used to automatically detect the seed point of the kidney and successfully generate true kidney ROI until 89%. The generation of true ROI can be used as the preprocessing methods for any other segmentation techniques. This ROI generation can make the next image processing methods is faster as some part of the original image has been cropped. For further research, improvement can be made by comparing some filters for speckle noise reduction instead of straight away using Gaussian low-pass filter. Other filter might give a better result in generating true ROI for both longitudinal and cross section US kidney images.

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