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BOUNDARY DETECTION OF KIDNEY ULTRASOUND IMAGE BASED ON VECTOR GRAPHIC APPROACH

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ABSTRACT

This paper presents a new approach for boundary detection of kidney from three-dimensional ultrasound images. The technique proposed here is based on vector graphic image formation. Before converting the ultrasound image into vector graphic image, the region of interest (ROI) of the kidney for each slice was generated automatically. Some images also needed to be rotated to zero degree depending on the position of the kidney in the images. After the vector graphic formation, the boundary points of the kidney were identified. The error points were removed and the interpolation was then performed for contouring the kidney from its background. Experiments had been carried out step by step for validation purposes. Test result based on 30 kidney ultrasound image slices showed that the developed algorithms were able to detect 86.67% true ROIs. When compared to manual contouring, the sensitivity of this boundary detection technique was in between 94.95% to 97.75% and the specificity was in between 99.26% to 99.92%. Based on the results, it can be concluded that this new semi-automatic technique is reliable to be used for contouring the kidney from three-dimensional ultrasound images.

Keywords: ultrasound image processing, kidney segmentation, vector graphic image.

INTRODUCTION

Kidney volume is a more sensitive means of detecting renal abnormalities and correlates well with renal mass compared to other single linear measurements (Yong *et al.*, 2007). Traditionally, most medical doctors will measure the length and width of the kidney as they are easier to be identified and measured. With an additional measurement which is the thickness of the kidney (which can be obtained by 90 degrees rotation of transducer from the angle of transducer during measurement of length and width), the volume can be calculated by using ellipsoid formula (*length* × *width* × *thickness* × *π/6*) (Breau *et al.*, 2013). However, it has been experimentally tested that the use of ellipsoid formula consistently and significantly underestimates the true kidney volume (Cheong *et al.*, 2007), and it is as well not appropriate for accurate and reproducible of calculating kidney volume as the volume was underestimated about 25%.

The determination of kidney size is important in clinical field and it is frequently repeated as it can facilitate in making decisions for the management strategy, and kidney length and volume are also important for evaluating and following-up of patients especially for patients with kidney transplants. Therefore, other than choosing an imaging modality which is more affordable, safer and more convenient to both operator and patient, it is also important that the method of measuring the kidney is accurate and precise. Development in imaging techniques has led to a better way of volume estimation as medical imaging modalities started to evolve from two-dimensional to three-dimensional reconstruction images. Volume estimation based on three-dimensional reconstruction was a convenient and accurate method for volume determination and assessments have been made by using images from computed tomography (CT) and magnetic resonance imaging (MRI) (Breau *et al.*, 2013). Furthermore, Mahmud and Supriyanto (2014) in their study concluded that for kidney volume measurement, area-based (using 3D reconstruction) is more accurate compared to length-based (using ellipsoid formula), but an automatic technique for contour detection need to be developed for repeatability usage of the methods.

Therefore, in order to clinically implement the use of 3D reconstruction for volume estimation, a good contour detection technique needs to be used so that results can be obtained with least manual interaction and within short time periods, especially when dealing with ultrasound (US) image, which is known as image with poor signal-to-noise ratio. Previous boundary detection techniques were studied to gather information on possible techniques that could be used for better segmentation of kidney boundary. Besides, in order to develop a model that can be easily repeated, possible automatic detection techniques were also studied.

Kidney segmentation techniques

The most challenging task when dealing with ultrasound images is finding the right method or technique for segmenting the region of interest of organs as those images are characterized by weak edge information, thus leading to difficulties in locating the organ's contour. It is also difficult to automatically segment these images to detect interesting objects in the correct position and orientation since these images contain strong speckle noise (Shrimali *et al*., 2009). Many approaches had been done in segmenting ultrasound images as had been further discussed in Shrimali *et al.* (2009), and Saini *et al*. (2010). Some of the common methods are edge based, region based, texture based, shape based, etc.

For segmenting kidney ultrasound image, some approaches can be seen in Kop and Hegadi (2010), Jeyakumar and Hasmi (2013), and Prevost *et al*. (2014). Kop and Hegadi (2010), proposed a method of segmenting kidney from an Ultrasound image using the snakes model which help to deform the initial contour towards the possible edge of the kidney in ultrasound images. Jeyakumar and Hasmi (2013) on the other hand proposed a framework for evaluating ultrasound kidney image segmentation using various algorithms like edge detection, watershed segmentation, region based segmentation and clustering method, and the conclude that the K-means clustering gives better result for kidney image segmentation. Prevost *et al* (2014) performed study on kidney segmentation methods in 3D contrast-enhanced US (CEUS) images, by presenting a generic and fast two-step approach to locate and segment the kidney automatically, as well as developing a co-segmentation framework that generalizes the aforementioned method and allows the simultaneous use of multiple images (CEUS and US images) to improve the segmentation result.

Automatic approach of kidney region of interest

Since some other organs lie close to the kidney, finding a region of interest (ROI) for kidney is quite helpful as this ROI can improve the speed and accuracy of further segmentation process. 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 (Hafizah *et al.*, 2011). In order to reduce, or if possible, avoid any human error which may lead to wrong interpretation of patients' condition, an automatic approach should be taken into consideration. There were some approaches on automatic kidney segmentation but they did not use ultrasound images. Freiman *et al*. (2010) in their experiments used CT images and Tang *et al*. (2010) used MR urography. For ultrasound images, automatic kidney segmentation, however, remains a challenge due to the speckle noise and various other artifacts inherent to US (Tamilselvi *et al*., 2010).

Kidney contour detection

For further image analysis, especially for volume estimation using 3D-reconstruction method, identifying and contouring the boundary of the organ are important. Performing edge detection method that can distinguish between regions effectively in the presence of noise as been experimented in Suhaila *et al*. (2013) is quite useful when dealing with ultrasound images. Other researches on the edge detection have been performed previously with the implementation of different techniques for different ultrasound images such as for cardiac images, breast tumours, ovary follicles prostate volume and kidney. Since manual contour detection is very time consuming, the automatic approach is much more preferred but thorough investigation still needs to be done as it is very difficult to develop an edge detection technique that can be used in all ultrasound images.

Thus, this paper proposes a kidney boundary detection method based on vector graphic images. A vector graphics image contains one or more connected as well as not connected polygons. During the vector graphic transform, the images are broken into small, non-overlapping patches, and the images are then manipulated in this vector graphic image. Vector-based method is useful for stitching small overlapping patches of the input texture and this method has dominated the texture synthesis field in several years since its publication (Efros *et al*., 2001; Liang *et al*., 2001). A similar approach was performed for class-based edge detection (Borenstein *et al*., 2002) and for super-resolution (Freeman *et al.*, 2002). As an extension to the success of this vector-based method, it has also been implemented for image completion (Drori *et al*., 2003) and image denoising (Awate *et al*., 2004). Besides that, these methods have shown a promising result in object recognition (Ullman *et al*., 2000).

MATERIAL AND METHODS

The contour detection model designed consists of few major steps which are the ultrasound image acquisition, automatic ROI generation, image rotation to zero degree, kidney contour detection, kidney boundary point's detection and lastly kidney interpolation as can be seen in Figure-1 below. The detail of each process is elaborated in the next sections below.

VOL. 10, NO 19, OCTOBER, 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

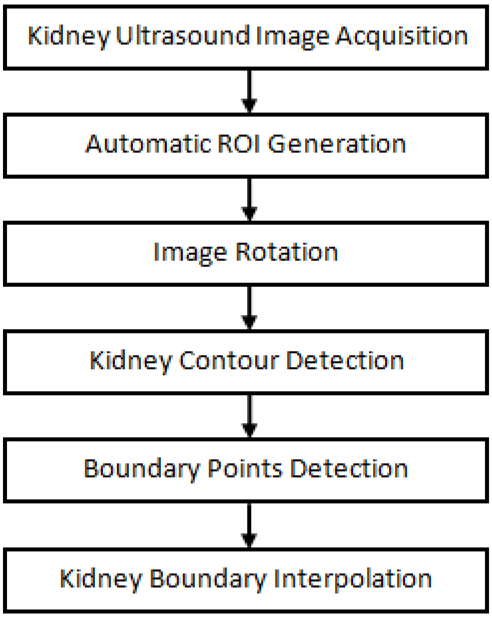

Figure-1. Block diagram showing the process for kidney contour detection.

Kidney ultrasound image acquisition

For this study, 30 longitudinal view of ultrasound kidney image slices were taken from a healthy male volunteer with the age of 22 years from Universiti Teknologi Malaysia Johor Bahru (UTM) by using TOSHIBA Apliomx ultrasound machine with 3.5MHz transducer. The kidneys were scanned in supine position where the subjects were lying down with the face upward and with inspiration of the subject. Then, MATLAB programming was used to develop the whole steps of kidney contour detection. Figure-2 shows a sample of longitudinal section of the original ultrasound kidney image.

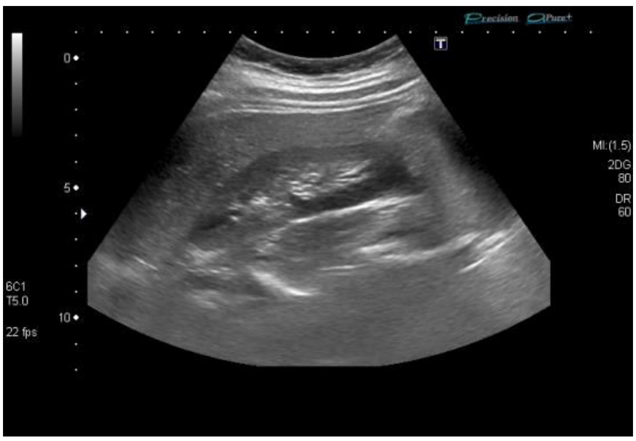

Figure-2. Longitudinal section of original ultrasound kidney image.

Automatic region of interest (ROI) generation

In ROI generation, the input image, $f(x,y)$ will first undergo the smoothing process where in frequency domain, it can be achieved by using low pass filter as it dropped out every components located in high frequency. The general model for filtering is:

$$G(u,v) = H(u,v)F(u,v) \tag{1}$$

$H(u,v)$ = Transfer function of the filter
$F(u,v)$ = Fourier transform of the image

Gaussian low pass filter transfer function is as below:

$$H(u,v) = e^{-D^2(u,v)/2{D_0}^2} \tag{2}$$

σ = standard deviation
D_0 = cut-off frequency of the filter

The output image, $I(x,y)$ can be expressed as follows:

$$I(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{3}$$

After that, the texture of the image is analyzed. Texture analysis is important in characterizing regions in an image by their texture content. 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. Each output pixel in image $I_{entropy}$ contains the entropy value of the 9-by-9 neighborhood around the corresponding pixel in the input image I. Then, threshold value, T_T is set for segmenting the textures. The threshold value can be set between 0 and 1 and default value is 0.5. In output image I_T, all pixels of input image is replaced with the value 1 if it is less and equal to T_T, and value 0 for other pixels. In this experiment, threshold value of 0.7 is selected because it is the optimum value for selection of seed point region of the kidney. If threshold is set below than 0.7, the seed point region detected attached together with the region outside the kidney boundary and if threshold is set above 0.7, the seed point region is failed to detect.

After image binarization, morphological operations were performed to remove the unwanted regions. 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 80-by-80, assuming all the kidney images were taken with the kidney is almost at the center of the

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image. As S is the size of the image, the height, h_1 and width, w_1 of the defined window is calculated as follows:

$$\frac{S_x}{2} - p : h_1 : \frac{S_x}{2} + p \quad (4)$$

$$\frac{S_y}{2} - p : w_1 : \frac{S_y}{2} + p \quad (5)$$

S_x = size of image in x-direction
S_y = size of image in y-direction
P = 40

Only the regions that intersect with this window will be remained as seed point candidates, and the rest will be deleted. Then, the remaining regions will undergo another selection steps to determine which one is the true seed point, SP. For seed point detection, firstly, the number of connected components (region), n needs to be determined so that the number of remaining region in the image is known. 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. The threshold pixel areas, T_A was set as 6000. If A is less than T_A, that region is registered as true SP and is selected as the seed point. If not, it is registered as false SP and the other region will be selected. Then, the center pixel value (x_c, y_c) of the true SP is determined and based on the value, a rectangular window is defined to generate ROI of kidney. For this study, a rectangle of size 400-by-200 is defined where 400 is the width, w_2 and 200 is the height, h_2 of the rectangular ROI. As additional size factor, q = 100, the rectangular ROI can be calculated as follows;

$$x_c - q : h_2 : y_c + q \quad (6)$$

$$x_c - 2q : w_2 : y_c + 2q \quad (7)$$

The previous steps for generating the ROI of kidney can be done automatically without manual selection of certain feature such as points, regions, lines or others. The ROI generated then can be used as input image to next steps of the model designed.

Image rotation to zero degree

For implementing further steps, the image contains the seed region need to be rotated to zero degree. The angle position of the true SP, θ_{SP} of kidney in US image can be calculated based on the value of Y_{min}, Y_{max}, X_{min} and X_{max}. In order to perform this calculation, the SP of the image I_{SP} is set as 0 while the background of the image I_{SP} is set as 1. For i = 1: S_x-1, and j = 1: S_y-1 the value of Y_{min} and Y_{max} can be calculated by implementing these below equations:

$$Y_{mins} = j + 1, \quad if\ I_{SP}(i,j) > I_{SP}(i,j+1) \quad (8)$$

$$Y_{maxs} = j, \quad if\ I_{SP}(i,j) < I_{SP}(i,j+1) \quad (9)$$

Y_{mins} and Y_{maxs} are the new matrices created which consist of possible values of Y_{min} and Y_{max}. Y_{min} can be obtained by finding the minimum value in Y_{mins} and Y_{max} can be identified by finding the maximum value in Y_{maxs}. To calculate the x-coordinates, X_{min} and X_{max} of each Y_{mins} and Y_{max}, the equation below is used:

$$X_{min} = \frac{(X_{min1} - X_{min2})}{2} + X_{min2} \quad (10)$$

$$X_{max} = \frac{(X_{max1} - X_{max2})}{2} + X_{max2} \quad (11)$$

$$X_{min1} = i + 1, \quad if\ I_{SP}(i, Y_{min}) > I_{SP}(i+1, Y_{min})$$
$$X_{min2} = i, \quad if\ I_{SP}(i, Y_{min}) < I_{SP}(i+1, Y_{min})$$
$$X_{max1} = i + 1, \quad if\ I_{SP}(i, Y_{max}) > I_{SP}(i+1, Y_{max})$$
$$X_{max2} = i, \quad if\ I_{SP}(i, Y_{max}) < I_{SP}(i+1, Y_{max})$$

Kidney contour detection

The original image, f is cropped based on the ROI that has been automatically generated earlier, and after obtaining the angle position, θ_{SP} the image, I_{ROI} is then rotated to 0^o before the image being converted to vector graphic image which composed of one or more polygons defined by the vertices' coordinates. The vector image can be created using:

$$I_{patch} = patch(P, T, C) \quad (12)$$

P, T = specify the vertices of a polygon
C = determines the color of the vector

The steps for converting into vector image are as follows. First, the number of colors to be used in vector image is set. In this paper, the number of colors, N_{color} is set at 15 as based on the experiment; it can detect the kidney edges better. Then, the image is separated into white and black mask layers, before being stored in a cell array. For i = 1: N_{color}, the layered image can be obtained by:

$$I_{layered}(i) = \{I_{wf}(EQ(I_{ROI} + 1, i))\} \quad (13)$$

I_{wf} = output image after being filtered using Wiener

EQ is the equality test between (I_{ROI} + 1) and i where it compares elements, e in array (I_{ROI} + 1) with e in array i, and returns an array with e = 1 if (I_{ROI} + 1) and i are equal, or e = 0 if they are not equal. For i = 1: N_{color} also, any holes in $I_{layered}$ were filled and edges were traced. Then, the number of shapes, N_{shape} in each layer will be calculated by using:

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ARPN Journal of Engineering and Applied Sciences

$$N_{shape} = size(I_{layered}\{i\}, 1) \quad (14)$$

Lastly, for i = 1: N_{color} and for k = 1: N_{shape}, the shapes were plotted as polygons using vector as in previous equation, using C = 1 by implementing P and T as below:

$$P = I_{layered}\{i\}\{k\}(:,2) \quad (15)$$

$$T = -I_{layered}\{i\}\{k\}(:,1) \quad (16)$$

Boundary points detection

Since N_{color} = 15, the output image of I_{vector} will also have 15 colors with 15 pixel intensity values varies from 0 to 255. Therefore, to simplify the next step, I_{vector} is then change to black and white image by defining certain threshold values. A matrix consist of 15 pixel values will be created and is filtered so that only values more than 100 is remain as those values were the best values for detecting the kidney contour. After being converted back to matrix image, I_m, the new black and white image, I_{new} can be created. By assuming $[S_m,S_n]$= $size(I_m)$, and for i =1: S_m, for j =1: S_n, I_{new} is as follows:

$$I_{new}(i,j) = \begin{cases} 0 \ \text{if}\ (i,j) < PixelList(1) \ \&\ (i,j) > PixelList(n) \\ 1 \ \text{if}\ PixelList(1) \le (i,j) \le PixelList(n) \end{cases} \quad (17)$$

n = maximum number of pixel values in *PixelList*

By using the same equation as in (4) and (5), I_{new} is then windowed using a center window with 80-by-80. Then, detection of true initial mask, *IM* was performed. However, due to the position of the true *IM* detected is not exactly in the middle of the kidney, the size of *IM* need to be corrected. Based on the size of *IM* bounding box, B_{IM} = (B_y, B_x, w_3, h_3), where B_x,B_y is the coordinate of the most upper left box point, h_3 is the height of B_{IM} and w_3 is the weight of B_{IM}, the *IM* size can be corrected using:

$$B_{IM\_x1} = B_x - 15 \quad (18)$$

$$B_{IM\_x2} = B_x + h_3 + 15 \quad (19)$$

$$B_{IM\_y1} = B_y - 15 \quad (20)$$

$$B_{IM\_y1} = B_y + w_3 + 15 \quad (21)$$

By implementing the $IM(x,y)$ with x = B_{IM_x1}: B_{IM_x2} and y = B_{IM_y1}: B_{IM_y2} in I_{new}, a set of X and Y coordinates of kidney border points can be detected and created. Then, cubic spline interpolation is performed to connect the entire boundary points detected.

RESULTS AND DISCUSSIONS

For ROI generation, the experiment has been done by implementing the steps proposed to 30 kidney US image slices. The output example for ROI detection is as in Figure-3. As a result as in Table-1, out of 30 images, 26 images generate true ROI (86.67%) and another 4 images generate false ROI (13.33%) due to wrong detection of seed point region.

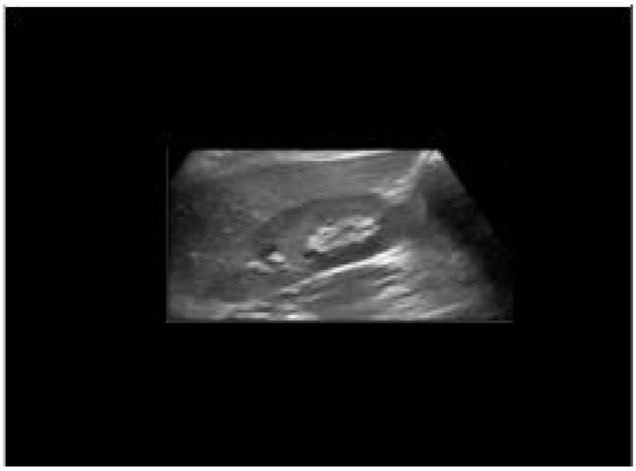

Figure-3. Kidney US image with rectangular ROI.

Table-1. Performance testing for rectangular ROI generation of kidney ultrasound image slices.

Number of image slices	True ROI generation	False ROI generation	Percentage
30	26	4	86.67%

After the rectangular ROI of kidney US image was rotated to zero degree position, conversion to graphic image is done by using the vector where the user needs to set the input color first. This setting will determine the result of the graphic image later. In the conversion process, the image is separated into layers and is stored in cell arrays. The layers depend on number of colors that we set. For this experiment, as we set N_{color} = 15, the image will then have 15 layers.

After calculation of number of shape in image for each layer, the shape is plotted by using vector polygons. Then, simplification is made. Example of vector image is as in Figure-4. Figure-4(a) shows the ultrasound image and Figure-4(b) shows the vector image as well as the part (red box) that have been zoomed. Based on the images, it can be seen see that the kidney boundary for vector image has sharper edge compared to the kidney boundary for ultrasound image. This is important for the next step, which was detection of the x and y coordinates of kidney boundary.

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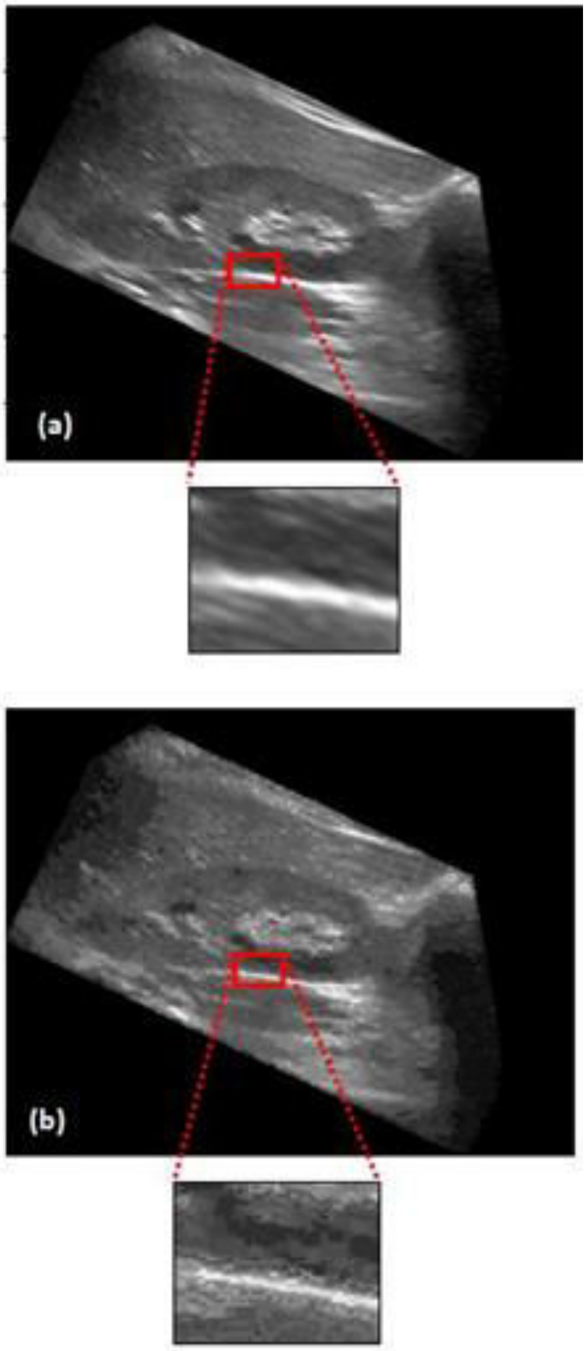

Figure-4. Kidney boundary for (a) ultrasound image, and (b) vector graphic image.

Further evaluation of the output of this proposed method has been made by comparing the result to the manual contour of the original image. The sample result is as in Figure 5, where the red contour is the manual contour by experts and the blue contour is the contour detected using proposed method. Sensitivity and specificity test have been performed with respect to manual contour (ground truth) for all 30 image slices. Sensitivity is a true positive measure in that it refers to the proportion of images that contain kidney which have been classified correctly as in equation (22). Specificity is a true negative measure that refers to the proportion of images containing kidney that have been incorrectly classified as in equation (23).

$$Sensitivity, y = \frac{N_{TP}}{N_{TP}+N_{FN}} \tag{22}$$

$$Specificity, y = \frac{N_{TN}}{N_{TN}+N_{FP}} \tag{23}$$

N_{TP} = true positive
N_{TN} = true negative
N_{FP} = false positive
N_{FN} = false negative

As the result in Table-2, the sensitivity of model developed is around 94.95% to 97.75% and the specificity is around 99.26% to 99.92%.

Table-2. Evaluation of proposed method.

Evaluation index	Min value (%)	Max value (%)
Sensitivity	94.95	97.75
Specificity	99.26	99.92

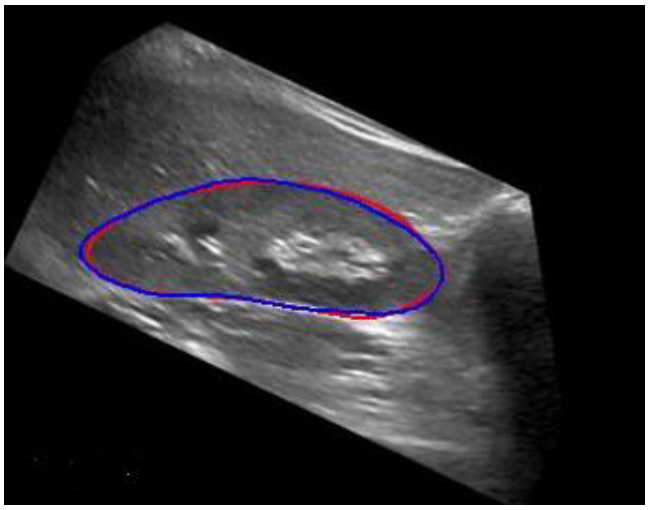

Figure-5. Output of few kidney images ( ) is the manual contour made by user and ( ) is the contour detected using model designed

Based on the results obtained in the experiments, this new contour detection technique developed can be used as one of the alternative for segmenting the kidney in ultrasound images. The model designed starting with the region of interest generation for the kidney, rotation to zero degree, kidneys' contour detection by converting US images to vector graphic images, and interpolation of boundary points can be performed automatically. Manual interrupt is done only for removing errors in boundary points' detection (if there were points that are out of segmentation value range).

CONCLUSIONS

Accurate detection of kidney boundary is necessary for improvement of diagnosis and monitoring of kidneys' condition as voxel count method for kidney volume estimation can be performed only after all slices of 2D kidney ultrasound images being segmented. Therefore, a new segmentation technique for kidney ultrasound images has been developed.

Two main ideas proposed in this paper are the automatic detection and generation of kidney region of interest and also the boundary detection of the kidney by converting to vector graphic images. Most of previous techniques used for kidney segmentation will do manual tracking of the seed point. This paper proposed a new algorithm for automatic detection of seed point region as well as region of interest in kidney ultrasound images. This proposed algorithm is based mainly on texture analysis of kidney ultrasound image itself along with the smoothing process, threshold selection and morphological operations. Conversion to vector graphic image based on number of color defined by user gave a new way of detecting the boundary of kidney. Since this vector graphic image only contain the pixel value based on number of color, it is easier to manipulate the image and detect the points (x and y coordinates) at the boundary of the kidney. Based on the segmentation result presented in this paper, together with the sensitivity and specificity test with respect to manual contour by user, it can be conclude that this research enables us to move forward in the area of kidney ultrasound segmentation. For further research, extended research could be preformed for validating the use of this segmentation model developed for volume calculation of the kidney.

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