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I. Introduction

One of the most common problems that occur in the human urinary system is renal calculi, which is often called as kidney stones or urinary stones [1]. Normally, any person affected by these kidney stone diseases will suffer from considerable pain which leads to abnormal kidney function, and also the mechanism for this disease is poorly understood so far [2]. Kidney is the most salient organ in the urinary system, which not only produce urine but also helpful in purifying the blood.

The two important functions of kidney: (i) Removing harmful substances from the blood, and (ii) Keeping the useful components in proper balance. Kidney stones appear in diverse varieties, among which the four basic types that found more often are Calcium-containing stones, Uric acid stones, Struvite or infected stones and Cystine stones [8].

Normally the kidney diseases are classified as hereditary, congenital or acquired [14]. The detection of calcifications inside the body is a large field of study including several dynamic areas of research, which is mainly useful for diagnosing the kidney stone diseases. The actual kidney stones may be rough non-spherical in shape, but the dominant effects that are used to find the fracture in actual kidney stones, are based on the reverberation time across the length of the stone [16].

Due to the presence of powerful speckle noise and attenuated artifacts in abdominal ultrasound images, the segmentation of stones from these images is very complex and challenging [12]. Hence, this task is performed by the use of much prior information such as texture, shape, spatial location of organs and so on. Several automatic and semiautomatic methods have been proposed. Even though the performance such methods are better when the contrast-to-noise ratio is high, it deteriorates quickly when the structures are inadequately defined and have low contrast like the neuroanatomic structures, such as thalamus, globus pallidus, putamen, etc. [4]. The X-ray, positron emission tomography (PET), computer tomography (CT), Ultrasound (US) and magnetic resonance imaging (MRI) are the widely available different medical imaging modalities which are broadly employed in regular clinical practice [6]. As compared to other medical imaging modalities such as computed tomography (CT) and magnetic resonance imaging (MRI), the US is particularly difficult to segment because the quality of the image is almost low than the CT and MRI [3]. Ultrasound (US) image segmentation is greatly depends on the quality of data [7]. Moreover, it is complex to extract the features that represent the kidney tissues by segmenting the kidney region [14]. Although, ultrasound imaging is widely utilized in the medical field [13]

Ultrasound imaging is popular in the field of medicine not only due to its economical cost and non-invasive nature, but also it is a radiation-free imaging technique [12]. US imaging is economical and simple to use and also provides a faster and more exact procedures due to its real time capabilities. In numerous applications, an important role is played by the precise identification of organs or objects that are present in US

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images [3]. Resolutions required by murine imaging could be achieved in ultrasonic imaging which already has a broad variety of clinical applications for human imaging, if higher frequencies (20 – 50 MHz) are used instead of the normally used frequencies (3 – 15 MHz) [5]. Speckle is a multiplicative noise, which is an important performance limiting factor in visual perception of US imaging that makes the signal or lesion complicated to identify [9, 10]. Numerous research papers have been presented on segmentation of renal calculi in US images by using diverse techniques. Since US kidney images are noisy and contain poor signal-to-noise ratio, an alternative effective techniques employing a-priori information may be utilized for compensating such problems [11]. The segmentation of renal calculi using renal images is a difficult task. Lots of researches have been performed for the successful segmentation of renal calculi using ultra sound images. A few recent related works in the literature are reviewed in the following section.

II. Related Work

Benoit *et al.* [15] have proposed a region growing algorithm for segmentation of kidney stones on ureteroscopic images. Using real video images, the ground truth has been computed and the segmentation has been compared with reference segmentation. Then for comparison with ground truth, they have calculated statistics on diverse image metrics, namely Precision, Recall, and Yasnoff Measure.

Sridhar *et al.* [16] have constructed a framework for the identification of renal calculi. Normally, the kidney stones are formed by the abnormal collection of some specific chemicals such as oxalate, phosphate and uric acid. These stones can be found in the kidney, ureter or urinary bladder. Performance analysis has been performed to a set of five known algorithms by using the parameters namely success rate in calculi detection, border error metric and time. Then the best algorithm has been chosen from this performance analysis and the framework has been constructed by using this algorithm. Moreover, a procedure has been given to validate the detected calculi using the shadow that appear in ultrasound images. The algorithm has been tested by using the ultrasound images of 37 patients. The detected calculi based on the framework match those determined by professional clinicians in more than 95% of the cases.

Sridhar *et al.* [17] have developed an automated system to detect the renal calculi based on its physical characteristics. Due to the anomalous collection of certain chemicals like oxalate, phosphate and uric acid, the calculi are formed in the kidney, ureter or in urinary bladder. An algorithm has been employed to identify the calculus using its shadow. The properties of calculi such as size, shape and location have also been extracted by their proposed system, which are crucial for reliable diagnosis. Their technique has been implemented in the MATLAB/IDL platform and a substantial success rate has been obtained.

Tamilselvi *et al.* [18] have proposed an improved seeded region growing based method which performs both segmentation and classification of kidney images with stone sizes using ultrasound kidney image for the diagnosis of stone and its early identification. The images are classified as normal, stone and early stone stage by recognizing multiple classes via intensity threshold variation diagnosis on segmented region of the images. Homogeneous region are relied on the image granularity features in the enhanced semiautomatic SRG based image segmentation process, in which the pertinent structures with dimensions similar to the speckle size extracted. The shape and size of the growing regions have relied on this look up table entries. The high frequency artifacts are also being reduced by performing region merging after the region growing. By employing the intensity threshold variation acquired for the segmented parts of the image, the diagnosis process is being performed. They have compared the size of the segmented parts of the image with the standard stone sizes i.e., if the size is below 2 mm, it is considered as absence of stone, between 2-4 mm indicates early stone stage, and 5mm & above indicates presence of kidney stones.

Tamilselvi *et al.* [19] have suggested a segmentation method for an exact segmentation of renal calculi. Classification and segmentation are the two important steps in their proposed approach. In the preprocessing stage, the image contrast improvement is being carried out by using histogram equalization and the reference pixel are selected via GA techniques before classifying a given image either as normal or stone image. The training and the classification process of diverse US images is performed by using an ANFIS system. Moreover, the same procedure is followed for the testing process of classification approach and several US images are utilized for the analysis of the precision of preprocessing classification. Subsequently, in the calculi recognition process, ANFIS is trained by using the renal calculi images having manually segmented stone regions. Several region parameters are determined and the calculi detection training process is performed by giving the result values to the ANFIS. During the testing process, the reference and testing images are compared and morphological dilation operation is applied in the calculi regions. An accurate renal calculi region was found from the result of the testing process. The experimental results have shown that their proposed segmentation method has found the accurate renal calculi from US images. They have also analyzed the performance of the proposed method by comparing it with the existing Neural Network

(NN) and SVM classifier.

The existing segmentation method has performed the calculi segmentation by region indicators and modified watershed algorithms. But in this method, the calculi detection accuracy is not satisfactory and it has produced high complexity in the calculi detection process. To avoid this drawback, we proposed a Region Indicator with Contour Segmentation (RICS) method. The outline of the paper is as follows: Section 3 briefly explains the proposed RICS segmentation process. In section 3.1, the region indictor process is explained and in section 3.2, the region parameters are computed. The contrast enhancement and most fascinated pixels by k-means clustering are explained in section 3.3 and 3.4. In section 3.5, the Contour based regions selection process is described. The experimental result and the conclusion of this paper are given in Section 4 and 5 respectively.

III. Proposed Renal Calculi Segmentation Technique

The proposed renal calculi segmentation method consists of five major steps namely, (i) Determining inner region indicators (ii) Determining the region parameters (iii) Enhancing the contrast of the image using Histogram Equalization (iv) Finding most fascinated Pixels by K-means clustering and (v) Contour based Region selection process. The proposed renal calculi segmentation training and testing procedure is shown in Figure 1.

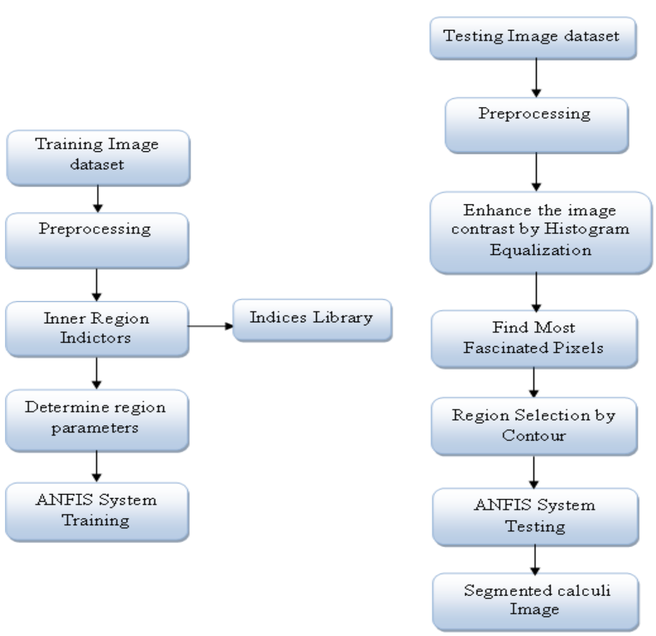


Fig.1. Proposed RICS segmentation training and testing procedure

a) Preprocessing

In this preprocessing phase, principal component analysis with local pixel grouping (LPG-PCA) based image denoising algorithm is used to remove the noise from the US renal calculi images.

b) Determining Inner Region Indicators

Let D represents the renal calculi image training dataset, which contains renal calculi images $D=\{I_1, I_2, \cdots I_n\}; n=1\cdots N$, where N is the number of the renal calculi images in the given dataset D. To determine the inner region indicators, firstly, the regions representing kidney are manually marked in the known training data set ultrasound images. Then the whole image is divided into L number of blocks and for every block, an index value, which can be represented as $B=\{I_i\}: i=1\cdots L$, is allocated. Then, each block included in B is checked to find the edge pixels present in the kidney. If any block is found to be containing edge pixels of the kidney, then the index value of the corresponding block is kept as $K=\{I_l\}:$ $l \in L$. Hence, K which can also be called as indices library, contains the indices of blocks of all the known images.

c) Determine Region Parameters

Using the renal calculi images in D, the calculi and non calculi regions are extracted. The extracted regions from the renal calculi images are $R=\{r_1, r_2, \cdots r_m\}, m=1\cdots M$, where M represents the total number of extracted regions. Next we find the centroids values for all the renal part of images in D, that is $C(x,y)=\{c_1^{I_1}(x,y), c_2^{I_2}(x,y), \cdots c_n^{I_n}(x,y)\}$, where $c_1^{I_1}(x,y)$ is a centroid value of image I_1. Then, we determine the region parameters for the extracted regions from R by utilizing MATLAB function. The region parameters determined for each region are (i) Area (ii) Centroid (iii) Orientation and (iv) Bounding Box. This region parameter values are given to the ANFIS system for training process. In training process, the normal and calculi area is identified by the threshold values t_1 and t_2. The ANFIS system result value is represented as χ. The final decision is defined by

$$\chi = \begin{cases} t_1 == \text{normal} \\ t_2 == \text{calculi} \end{cases} \qquad (1)$$

d) Contrast Enhancement using Histogram Equalization

In contrast to the following enhancement process [19], initially we have converted given ultrasound image I_n^t into a grayscale image G_n^t, as histogram equalization process can be used only on grayscale images. Histogram equalization make some enhancements to the contrast of the given gray scale ultra sound image. In histogram equalization all pixel values in gray scale image are adjusted to maximum intensity values of the image. The image that is obtained after the histogram equalization process is denoted as $G_n^{t'}$.

e) Find Most Fascinated Pixels by K-means clustering

Mostly required pixels are computed from the image G_n^t by utilizing the k-means clustering method. K-means clustering [22] is a method of cluster analysis which aims on partition of observations into number of clusters in which each observation belongs to the cluster with the nearest mean [21]. The steps involved in the K-means clustering used in our method are described as following:-

(i) Partition of the gray scale data points to A arbitrary centroids, one for each cluster.
(ii) To determine new cluster centroid by calculating the mean values of all the cluster elements.
(iii) Determining distance between the cluster centroid and the cluster elements and obtain new clusters.
(v) Repeat process from step (i) till a defined number of iterations are performed.

The k-means algorithm aims at minimizing an objective function

$$H = \sum_{a=1}^{A} \sum_{g=1}^{G} \left\| d_g^a - C_a \right\|^2 \qquad (2)$$

In eqn (2) d_g^a represents data points and C_a means center of the cluster. The resultant of the k-means clustering process has a number of clusters, which forms a cluster-enabled image I_A . Here we can select the cluster, with maximum white color pixel values, and is applied to the newly created mask I'.

f) Contour based Region Selection Process

Region selection process performed using renal calculi images are taken from the testing image dataset $D^t = \{I_1^t, I_2^t, \cdots I_n^t\}; n = 1 \cdots N^t$, where N represents the total number of renal calculi images in the dataset D^t. The dataset D^t contains the images that are in the dimension of $P \times Q$; $1 \le p \le P, 1 \le q \le Q$. To accomplish the region selection process, a contour extraction process is utilized.
The procedure for contour based region extraction Process is as follows

Step 1

Initially the contour plot of the given gray scale image G_n^t is extracted. The contour function is described in the following equation 6. 3.

$$G_n^{tc} = (G_n^t, k) \qquad (6.3)$$

G_n^t is an input renal calculi gray scale image

- k is the number of evenly spaced contour levels in the plot
- In order to find the contour plot, the axis and their orientation and aspect ratio are defined.
- Where, G_n^{tc} represents the result of the extracted contours of renal calculi gray scale image

Step 2

After that, the final group values from the contour result image G_n^{tc} is selected. This group values contains some regions, then calculates the region parameters for that regions and the region parameters values are given to the ANFIS system that are referred in section 6.3.3.

Step 3

Then choose numbers of regions from the image G_n^{tc} which are greater than the threshold value t_1 and this selected region values are given to the empty mask S.

Step 4

The mask S contains m^s number of regions, which is represented as

$$R^s = \{r_1^s, r_2^s, \cdots r_{m^s}^s\}, m^s = 1 \cdots M^s.$$

Next, compute the centroid values for the regions R^s in the mask S, it is represented as

$$C^s(x,y) = \{c_1^s(x,y), c_2^s(x,y), \cdots c_{m^s}^s(x,y)\}.$$

Step 5

There are m^s number of regions in the mask S, these mask regions are not optimal to find the exact calculi from the images. So find the optimal regions among the available regions in S by exploiting Squared Euclidean Distance (SED) between the regions.

Step 6

SED is computed between the x coordinates regions centroid values $C^s(x,y)$ and training images centroid values $C(x, y)$ and y coordinates regions centroid values $C^S(x, y)$ and training images centroid values $C(x, y)$ values individually.

Step 7

The SED difference process is described in the following equ.2&3 for both x and y coordinates values.

$$\varphi(x) = (c_1^{I_1}(x) - c_1^S(x))^2 + (c_2^{I_2}(x) - c_2^S(x))^2 + \cdots (c_n^{I_n}(x) - c_{m^S}^S(x))^2 \qquad (2)$$

$$\varphi(y) = (c_1^{I_1}(y) - c_1^S(y))^2 + (c_2^{I_2}(y) - c_2^S(y))^2 + \cdots (c_n^{I_n}(y) - c_{m^S}^S(y))^2 \qquad (3)$$

The values $\varphi(x)$ and $\varphi(y)$ are compared with the threshold value t_3. If any one of the result values $\varphi(x)$ or $\varphi(y)$ are greater than the given threshold value t_3, that corresponding region are selected.

Step 8

Then, the last group values are selected from the contour method result image G_n^{tc} and have placed these values into the newly created mask M. After getting the result from contour process, the pixel matching and Multidirectional traversal operation is performed.

Pixels Matching: Here, first step is to divide the mask image M into m number of blocks and the index values $I^X = \{I_m^X\}$ are allocated. Then $I^X = \{I_m^X\}$ is compared against K by using the following conditions

(i) Retain the pixel values in the block $m \in M$; if an index value $I_m^X = I_L$, then.

(ii) Change the block $m \in M$ pixel values into *0*; or else

And hence M' is generated. Over M' and I' an AND operation is performed followed by a morphological dilation operation and hence the resultant image U is obtained.

Multidirectional Traversal: Here we have proposed two major traversals called bottom-up traversal and top-down traversal. In each of the traversal, a left-right traversal is applied. The traversals are applied over U, which is binary. At the time of two major traversals, once the pixel with '1' is obtained, then left-right traversal is enabled so that all the regions in the same axis and the region of the first obtained pixel are removed from the mask. The survived pixel values are marked into the original test image and it is subjected to the consequent process of Thresholding.

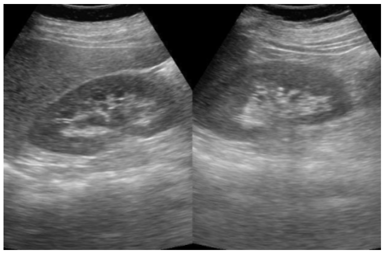
Thresholding: Here, a chain of thresholding process is performed in the original image.

- Firstly, the pixel values that are marked by using the previous process are compared against a defined threshold value t_3. The pixel values those are greater than t_3 are stored in a newly created mask U_S.
- The region parameters are determined for the regions in the mask U_S and the computed region parameters are given to the ANFIS to obtain the ANFIS score. If the ANFIS score is greater as compared to t_4, then the selection of regions is performed.
- Then, we count the number of neighbor pixel values around the selected regions which are greater than the threshold value t_5, and the number of count value of each region is compared with the threshold value t_6. If the count value is greater than the threshold value t_6, then the regions are selected.
- The selected regions from the previous thresholding process are involved in the morphological dilation operation. After the morphological operation, count the number of regions that are presented in the image. The region count value is compared with two threshold values t_7 and t_8.
- If the count value is greater than t_7, then perform the traversing down operation once, and if the count value is greater than t_8, then perform traversing down operation in multiple times.
- In the final thresholding process, each regions area value is calculated and it is compared with the threshold values t_9 and t_{10}. The regions that are less than t_9 and greater than t_{10} are selected. The selected regions are then placed into the original testing image I_n^t.

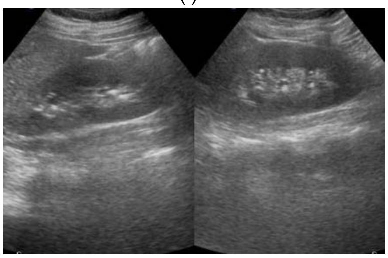
By performing all the above described process in various renal calculi kidney images, the calculi region is segmented.

IV. Results and Discussion

The proposed RIC segmentation technique is implemented in MATLAB platform (version 7.10) and the performance of the proposed RIC segmentation method is evaluated using 50 images. In the proposed RICS segmentation method, five major steps are performed over these training and testing renal calculi and renal ultra sound images. The sample input normal and calculi images are shown in figure 2.



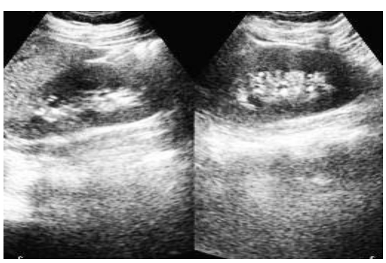
(i)



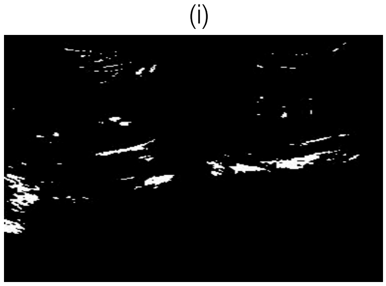
(ii)

Figure 2: Sample Input Renal Images (i) Normal Renal Image (ii) Renal Image with Calculi

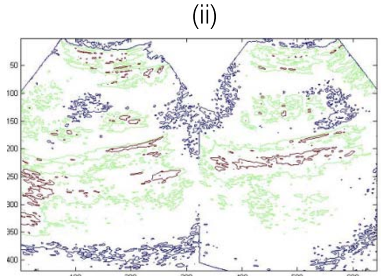
The region parameter values are computed for the 110 training images and these parameters result values are given to the ANFIS system to perform the training process. The region parameter values are well trained in the ANFIS system and this performance is evaluated with testing renal calculi images. 50 testing images are involved in the testing process. Figure 3 shows the result of the histogram equalization, k-means clustering and contour method.



(i)



(ii)



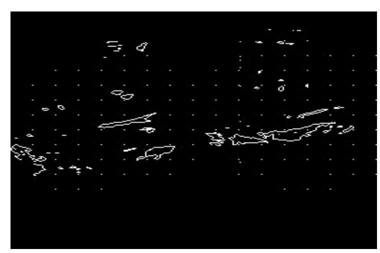
(iii)

Figure 3: Result images are obtained from (i) Histogram Equalization (ii) K-Means clustering (iii) Contour Method

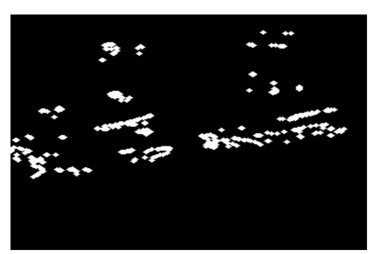
The histogram equalized image contrast is enhanced when compared to the original input image shown in Fig 2 (i). In Fig. 3 (ii), the same pixel values are grouped into number of clusters values and this can be used to find the most interested pixel values. The result images in fig 3 (iii) shows that the contour method has divided the testing image pixels into three groups by representing three different colors. The selected group value from the contour method result is shown in figure 4.

Figure 4 : Selected Group Value Result from the Contour Method

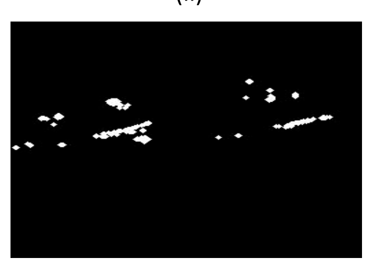
After the contour process, the chain of dilation and traversing operation are performed in the processed renal calculi image results that are shown in figure 5. The traversing operations eliminate the most unwanted regions from the renal calculi images, so as to easily find the calculi from the image. Subsequently, the thresholding process intermediate results are shown in the figure 6.



(i)



(ii)



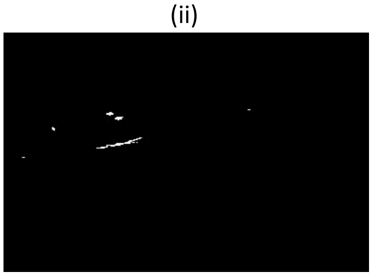
(iii)

(iv)

Figure 5: Result Images from (i) Pixel Matching (ii) Morphological Dilation (iii) Traversing up and (iv) Traversing down

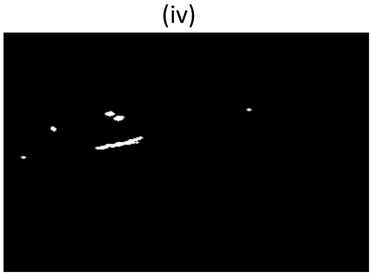
(i)

(ii)



(iii)

(iv)



(v)

Figure 6 : Thresholding Process Results

Finally, the selected regions from the thresholding process are given to the original image that is demonstrated in the following figure 7. In figure 7, the calculi regions are exactly marked in red color. The result image has shown that the proposed RIC segmentation method has exactly found the calculi region from the renal calculi images. The performance of proposed RIC segmentation method is analyzed with different images and it is described in the following section.

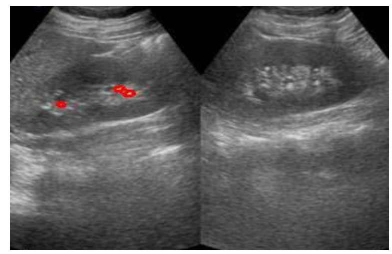


Figure 7 : Proposed RIC Segmentation Result Image

a) Performance Analysis

The performance of the RICS segmentation method by using four testing images is given in table 1. This performance analysis exploits statistical measures [20], to compute the accuracy of calculi segmentation done by the RIC segmentation method.The performance of the RIC segmentation analysis is shown in the below Table 1.

ID No	Se	Sp	Acc	FPR
1	93.33	99.93	99.92	0.07
2	89.06	100	99.98	0
3	100	100	100	0
4	100	100	100	0
Average	95.60	99.98	99.98	0.02

ID No	PPV	NPV	FDR	MCC
1	59.96	99.99	40.04	74.77
2	100	99.98	0	94.36
3	100	100	0	100
4	100	100	0	100
Average	89.99	99.99	10.01	92.28

Table 1: Statistical performance measures for four different US renal calculi

In Table 1, we have achieved high sensitivity, specificity and accuracy level in 1 sec computational time. The segmented stone area by RICS segmentation method is compared with previous IORM segmentation method and conventional segmentation algorithms. A relative error is calculated between the segmented stone area marked by the expert radiologist and the proposed method. The formula for the calculation of relative error is described below,

$$\nu = \left| \frac{E - P}{E} \right| \times 100 \qquad (4)$$

Where, ν - Relative Error

E - Stone area marked by Expert radiologist

P - Stone area marked by the proposed RIC segmentation method

The stone area marked by the expert radiologist, the RICS segmentation method and its relative error are given in Table 2.

Expert radiologist (mm^2)	Stone area (mm^2)	Relative error of RICS method
88.4	88.3	0.113
61.5	61.6	0.163
64.0	64.0	0.000
91.9	90.3	1.741
72.4	72.4	0.000
25.0	24.9	0.400
121.7	121.1	0.493
36.0	36.0	0.000

Table 2 : RICS segmentation relative error performance

The computational time of RICS method is obtained from the calculi detection process. The average Computational time of the system is shown in the Table 3 for four renal calculi images. The computational time of RICS method is very low .

Systems	Images	Computational Time(sec)
RICS	1	1.455874
	2	1.572855
	3	1.807253
	4	1.685209
	Average	1.630298

Table 3 : Computational time of the RICS Methods

V. Conclusion

In this paper, a RICS segmentation method to segment the calculi from the renal calculi images was proposed. The proposed method was implemented and set of renal calculi images were utilized to evaluate the proposed RICS segmentation method. The proposed method has exactly detected the calculi and produced a high segmentation accuracy result. The performance of RIC segmentation method was analyzed has produced less relative error. Moreover, our proposed RICS segmentation method has produced 99.98% of accuracy, 95.60% sensitivity and 99.98 % specificity values.

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