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Automated Kidney Stone Segmentation by Seed Pixel Region Growing Approach: Initial Implementation and Results

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Abstract

This research develop a computer aided diagnosis prototype for early detection of kidney stone. Once a kidney stone is diagnosed accurately, this will be useful for the patients to change their diet condition. The proposed approach is based on five stages which includes kidney image acquisition, pre-processing, segmentation, feature extraction and classification. The enhanced seed region growing segmentation depends on the extracted feature granularities. Noise may be visible and more prevalent in certain dimensions of an image, where this particular specific portion will be extracted. The segmentation process is based on the thresholds of the identified renal stone regions. The segmented stone size portion is classified based on rules; if the size is greater than 2mm, then the stone is at benign stage; if the size is greater than 5mm, then it is in malignant stage; if the size is lesser than 2mm, then this leads to absence of stone. The proposed work is implemented in MATLAB with the development of an initial prototype with the detection of stone accuracy of 92%. Based on the experimental analysis, texture feature, threshold intensity values and stone sizes are evaluated. This study will help the urologist to take decision whether there is a presence or absence of stone in early stage diagnosis and clinical decision-making.

Keywords: *Kidney Stone; Seed Pixel Region Growing and Segmentation.*

1. Introduction

Kidney diseases have increased rapidly among the global population due to food habits, less water consumption and lack of exercise. The major renal disease is kidney stone, which occurs commonly among all ages. If the renal stone is not properly treated or diagnosed, this will lead to serious health issues and cause damages in kidney function. One of the major kidney diseases occurs among the men and women are the presence of renal calculi or kidney stone. Kidney stone problems are very common in the Malaysian region due to changes in food habits and lack of water in the body. The formation of kidney stone is due to the present of mineral particles in the urine, which appears in the form of nidus with higher sedimentation. These sediment particles form the kidney stone. The stone or calculi will be found in the kidney or urinary bladder, which is an abnormal collection of chemical substances that includes uric acid and phosphates. The stone size varied from small, medium or larger size. If the stone is not diagnosed in early stages, then the growth of the stone will be larger like a golf ball and produce more pain in the lower abdomen of the body. This can lead to urine block and bleeding. The anatomy of the urinary tract consists of two kidneys, two ureter and a bladder. The shape of the kidney is in the form of double bean shaped organ, which can process 200 quarts of blood and produces 2 quarters of urine that consists of waste particle and water. The flow of urine from the kidney to the bladder is through the ureter tubes. The bladder stores urine and releases when the human body produces urination. Stones are formed in the urinary bladder, ureter or kidney due to the collection of chemical substances like calcium deposits, oxalates and phosphates. Early diagnosis of stone will prevent the formation of stone in the kidney. To diagnose the kidney stone in early stages, the Ultrasound Screening (US) is the initial and effective screening method to measure the size, portion and kidney growth. Most of the previous research on detection of renal calculi identifies the presence or absence of the stone based on the screening procedure. The developed CAD systems for kidney stone have a difficulty in detecting the smaller stones which are lesser than 2mm in size. In this paper, the enhanced computer vision algorithm based on Seed Region Growing Segmentation is proposed to diagnose the acquired ultrasound kidney images which can improve the classification accuracy of detecting the stone.

Current research is the extension of the previous proposed study of the kidney stone section in conceptual level and it is extended to implementation and testing [1]. The scope of the research is to develop a prototype for detecting renal stones from the ultrasound kidney images, the focus is carried out on the image processing approach which includes pre-processing, segmentation, feature extraction and classification.

In the first stage, image acquisition is based on ultrasound screening procedure. The patients are requested to carry out a long breath, so that the kidney can show some movements. There will be amplitude variations based on specific centimeters and further observation are carried on the movement. The outcome from these screening procedures is the renal images resulting in increased noise and low quality of image. Another constraint is the stone with various chemical substances will have a different set of shapes, colours and texture features, causing some difficulties in the classification process. The classification process is critical

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prior to classify the features and confirm the presence or absence of a stone. These two constraints are considered as effective research challenges; therefore, the proposed study is designed to overcome the two main challenges identified in the research. The proposed algorithm will effectively enhance the quality of the images after the acquisition from the ultrasound screening. More expertise and radiologist are needed to read the image and interpret the presence of stones; there is a variation in each interpretation by the experts in manual basis, which leads to more time and poor accuracy [1].

The main aim of this paper is to design a prototype for the automated segmentation of renal calculi and classify the size of calculi for ultrasound kidney images by using the Enhanced Seed Region Growing Segmentation approach. The organization of the paper is as follows: Section 2 describes the related works on kidney stone segmentation and classification. Section 3 explains the proposed methodology on the segmentation of kidney stone object from US images. Section 4 presents the results of various kidney stone datasets and classification outcomes based on the size of renal calculi from the images. Finally, the conclusion and future works are explained in section 5.

2. Literature Review

Several research studies were conducted on medical imaging domains, which improve the accuracy rate of diagnosis for research study and commercial applications through CAD development. Numerous approaches were identified and applied to a different set of medical images acquired through X-rays, MRI, Ultrasound, and CT SCAN etc. CAD application is to read the image and detect the suspicious regions in the image. Once the suspicious regions are identified, then the image segmentation process is the next critical step to segment the different anatomies based on image analysis. In previous research on ultrasound kidney image segmentation, the constraint addressed is to segment the abdomen based on similar soft tissues to resemble the texture features [2, 3]. Researchers also have proposed a method called statistical texture analysis to label the regions according to texture variance. In another work, texture information which consists of various extracted low-level features that are homogenous in nature and consistent when divided into multi slices for that specific organ. Therefore, an automated image analysis was proposed to improve the accuracy. Among several research works, researchers have proposed a fundamental seed pixel region growing segmentation which is considered as fast and robust in detecting the stone. The working procedure proposed by the author is based on identifying the seed pixel, scan the rows and column of neighboring pixels if they are similar merged together and connected for segmentation [4]. As part of the research, locating the seed pixels, identifying threshold value in maximum and minimum range and measuring the similarity are performed through manual and partial approach. Current proposed will overcome the manual or partial process replaced by automated approach.

There were several existing segmentation approaches for medical image datasets, but region-based approaches have increased the attention to be applied as part of segmentation techniques for complex images. The region-based segmentation procedure starts with classification pixels based on the presence of objects, which has its gray scale value representation in independent context. Therefore, isolated points are considered as object pixel region representations and are being connected based on neighborhood pixel similarities. For this purpose, original images are not used, only images with features are applied for segmentation. Feature representation is not depending on single pixels, but on its neighboring pixels with mask size operations. At each object edge, the mask will have pixels for foreground and background, features that are related to object pixels will be computed or else there is no feature computation for unwanted pixels. This work procedure of region growing segmentation can limit the size of the mask at the edges or background. The similar concept is applied for kidney stone segmentation in previous research works [5] in which seed pixels are located and start finding out the neighboring pixels of stone located regions which has a variation in texture features, only similar pixels within the threshold are detected, remaining pixels are not connected and condition is terminated [6]. CAD systems for medical imaging have limitations due to various format of image data and noise in the image, there is another research on focal liver tumor detection which has higher complexity in reading the image, the work focus on wavelet based segmentation and classification of tumor based on texture analysis and extraction to achieve 85% of accuracy in detecting the liver tumor [7]. Based on various research works, there is a need to handle noises in images, which are acquired from ultrasound. Quantitative evaluation by applying partial automated segmentation or manual segmentation on ultrasound images is not considered as direct work, but semi segmentation results are good and measurements are consistent for certain studies [8]. Another research carried out on watershed segmentation in which watershed line is treated as dividing the two-catchment basis, which is bounded by the valleys. In [9] described a watershed algorithm to detect tumors in kidney based on sober operator. Another research method based on immersion simulation algorithm is applied on renal images to identify the abnormalities in surface level of each region, gradient local values are determined based on the level of water with different parameters in abdominal regions. Local minima are computed for overlapped 3x3 block regions and objects are segmented [10, 11]. The authors have used three different sets of neural network classifier algorithm to detect and classify the kidney stone, there were comparison studies made with other works on accuracy and time to train and test the data and achieved a result of 89 [12]. Kidney stone classification research is not much experimented with hybrid classifiers and different models of ANN classifiers to detect the stone in an accurate manner, now the researchers have started experimenting with more data sets to achieve accurate results [13-15]. As per research studies on different format of data to analyze and detect the abnormalities, there were very limited research on CAD systems for medical video images which are not discussed in this section. In this proposed work, initial automated segmentation and classification prototype is developed for detection of kidney stone with various sizes and it is tested with various datasets.

3. Methodology

We proposed a CAD based kidney stone detection and classification scheme by using a method called 'enhanced seed pixel region growing segmentation'. The proposed approach does not lie on the shape and intensity values of kidney stone in the US image. There were different types of calculi observed through US image but our focus of research at the initial stage is calcium deposit stone formation, not on the other stone formation which different in texture feature and size. The detection of calcium stone in the US image is a very complicated task at early lab diagnosis process, sonographer or radiologist read the location of stone through normal eyes, there may be a higher possibility of false positive, to reduce the false positive, CAD systems are proposed. The reason why it is hard to detect the calcium stones is due to the hidden complex features which are present anywhere in the urinary tract, shape of boundaries are smoother, it is subtle as per observation, it is of various shapes which includes circumscribed, crystal like particles or golf shape ball. Reading or interpreting the US image of kidney stone is a complex task. The judgement results of the US are based on training, experience in reading with different interpretations and certain criteria. Figure 1 illustrates a simple image processing approach for detecting and segmenting the kidney stone from a US image.

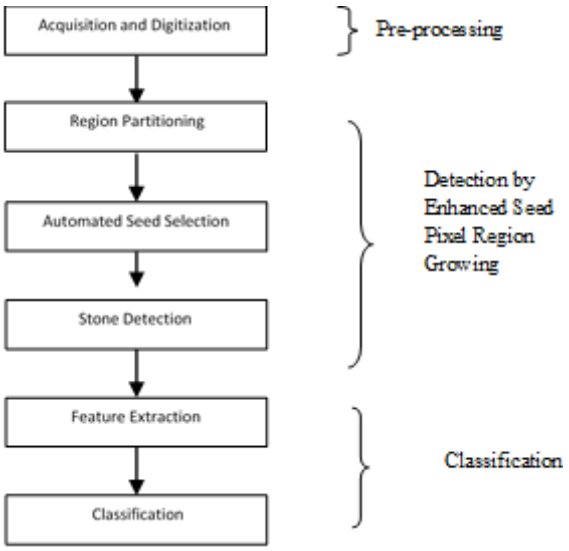


Fig. 1: Illustration of the methodology of kidney stone segmentation and classification method.

The proposed CAD methodology is composed of four stages which includes: a) Image Acquisition and Digitization, b) Preprocessing and Segmentation, c) Feature Extraction, and d) Classification.

3.1. Image Acquisition and Digitization

In the first stage, the Ultrasound Images (US) are acquired from the clinical research center. Ultrasound screening is a non-invasive procedure compared to other image screening modalities with minimum cost, less time, flexible process and low exposure to radiation. The methodology applied here is from the modification of previous work of mammogram segmentation [16, 17]. Once the image is acquired, it is digitized with high quality image resolution of 200 × 200 μm2 and use laser digitizer with a received output of 12 bits per pixel in the image. For more quality digitization in commercial applications, the digitizer is performed with 500 × 500 mm 2 by averaging 4 × 4 pixels into one pixel in which computation time can be saved. The procedure of digitization and decimation process leads to the next level of enhancing the image to observe the presence of stone for recognition and detection.
After the process of digitization and decimation on US images, kidney bladder portion is closely read in the presence or absence of calcium stone. As per medical studies, calcium deposits are present anywhere near to the location of the kidney. Automated segmentation and classification of kidney stone is based on the extracted features from the US image and produce the kidney stone results.
Second stage, from the acquired digitized image, boundary of kidney location is marked as Kr after the decimation process. Only the bladder region will be considered. The non-bladder region is ignored due to its low intensity values and it has a maximum peak level from the histogram computation. Threshold limit is set to mark the boundary of the bladder region from maximum to minimum level. The value of threshold Kt nis is computed using equation (1):

$$K_t = I_{\max} + 2.5\sigma_{bg} \tag{1}$$

Derived equation will calculate the threshold limit of the kidney bladder boundary; in which $I_{\max}$ is the maximum intensity pixels based on computation of decimated image histogram calculation. σ_{bg} is the standard deviation computation for all the pixels present in the image. The pixel values of σ_{bg} is lower than the value of $I_{\max}$; the background of the computed image with histogram has a Gaussian distribution centered with value of $I_{\max}$, it is considered as assumption. The automated improved seed region growing segmentation consists of three stages which includes region partitioning, seed selection and region growing segmentation process. Before applying the proposed approach, a kidney region represented by Kr is decomposed into three specific regions which includes a) distal region, b) center region, and c) proximal region. The proposed improved seed pixel selection and segmentation are applied to all the partitioned regions. Based on the proposed algorithm, abnormal regions are segmented and classified from the image.

3.2. Region Partitioning

Region partitioning is required to decompose the images in distinct regions, which have the same properties. In each partitioned region, various thresholds are applied. Therefore, the process of region partitioning is focused on identifying the kidney bladder region. To implement the process, OTSU approach of region partitioning is applied for extracting the portion of the kidney bladder region before detecting the stone.
The process starts with identifying the pixels of x(i, j) on the image I with a position of (i, j) coordinates, gray scale image values range from 0 to N – 1; the value of the threshold is represented by t, image is divided into R_0 and R_1 , if the threshold value is greater than the pixels of the image, then it will produce the first region partition else second region partition. Equations are derived as follow.

That is if x (i, j) <= t, then (i, j) = R_0 , otherwise, (i, j) Є R_1 . Probability functions of regions R_0 and R_1 . With respect to a given threshold t is given respectively as follows:

$$W_0(t) = \sum_{x=o}^{t} p(x) \tag{2}$$

$$W_1(t) = \sum_{x=t+1}^{L-1} p(x) \tag{3}$$

In which p(x) denotes the probability of gray level x in the image I. Gray level of the image, means and variances of region R_0 and R_1 is calculated based on Equation (4)-(7):

$$\mu_0(t) = \sum_{x=0}^{t} xp(x)/W_0(t) \tag{4}$$

$$\mu_1(t) = \sum_{x=t+1}^{L-1} xp(x)/W_1(t) \tag{5}$$

$$\sigma_0^2(t) = \sum_{x=0}^{t} (x-\mu_0(t))^2\, p(x)/w_0(t) \tag{6}$$

$$\sigma_1^2(t) = \sum_{x=t+1}^{L-1} (x-\mu_1(t))^2\, p(x)/w_1(t) \tag{7}$$

$\sigma_w^2(t)$ is represented by in-class variance and $\sigma_b^2(t)$ class variance of these regions with a difference are computed by deriving Equation (8) and (9).

$$\sigma_w^2(t) = W_0(t)\sigma_0^2(t) + W_1(t)\sigma_1^2(t) \quad (8)$$

$$\sigma_b^2(t) = W_0(t)W_1(t)(\mu_0(t) - \mu_1(t))^2 \quad (9)$$

By combining the computed class variances, it will determine the subjective function and maximize the threshold value to have an optimized result. This procedure is implemented in region partitioning of bladder region. The region partition works as follows: First the kidney bladder region Kr is divided into two specific regions with low intensity region R_0 with gray level [O, T_1-1] and the higher intensity region R_1 with gray level [T_1, L-1]. The value of T_1 is determined from extracted bladder region Kr which has obtained maximum threshold ranges. The partitioning is performed in a recursive manner in the higher intensity region, in which regions are separated based on distal to proximal regions. Regions are merged easier when they are closer to each neighbouring regions. After the pixels in the image has been partitioned as x(i, j), it needs to normalize for every partitioned region before proceeding to the next stage of operation.

3.3. Seed Pixel Selection

Seed is the main pre-requirement so that the automatic selection of seed pixels can be applied. The seed can grow from one neighbour to another to identify the reasonable pixels, but the threshold values need to be fixed. In this proposed work, selecting seed pixel is a major process which dominate the next stage of segmentation quality. If there is a selection in one specific point, it will allow one region to grow. If the selection is multiple points, then it will allow the growing of multiple regions. The measured parameter for seed selection is carried out through local variance and mean ratio of the granularity in kidney image. Our focus is on the bladder background; therefore, seed point selection is identified in the specific part of the background or in the location of the bladder. Selection of seed point is automatic in which local variance to mean ratio is higher than that of speckle, then the pixel can have selected as resolvable item or it belongs to homogenous region. The shape of the speckle can be varied in different locations in the image; to smooth the speckle region growing procedure is applied without any shape constraints and fit to the homogenous regions.

In detail, the automated seed selection process is as follows: The bladder region is partitioned into three sets of regions, which has been allocated with three sets of seed pixels that are selected from partitioned regions. Seed selection parameters are selected based on calculating the local variance, contrast but also local maximum intensity values and mean ratio between each seed pixel and neighbours. Considered an ascending path P of length l between two normalized pixels U_s and U_e in a partitioned region, which is a sequence of eight-neighbour connected pixels, is applied. Each set of pixel value U_{pk} which is assumed as the largest pixel within a 3 × 3 window centered at U_{pk-1} for 1< k <= l.

Every partitioned region which has a pixel becomes an initial pixel U_s of a path and the termination pixel U_e, which is the largest value pixel in its eight neighbour connectivity. In order to determine a local contrast at the end pixel U_e and intensity difference U_e is measured as the difference between the initial pixels U_s and the termination pixel U_e are determined in below equation (10):

$$D(U_s U_e) = U_e - Us \quad (10)$$

At the termination pixel U_e which may have greater than one intensity difference $D(U_s, U_e)$ due to there are many initial pixels U_s where its ascending paths will have the same termination pixel U_e. The value of seed contrast associated with U_e is determined by considering the maximum value among all values of $D(U_{s,} U_e)$ are determined using equation (11).

$$S(U_e) = \max[\, D(U_s Ue) \quad (11)$$

Selection of seed pixel is normalized and smoothened through region growing process, which selects the termination pixels U_e with consideration of normalized mean value, local variance and contrast values. While selecting the seed pixels automatically in partitioned regions, for each set, threshold values are assigned.

3.4. Improved Seed Pixel Region Growing

The choice of smoothening the speckle in the kidney image is through region growing process of seed pixel segmentation in the ultrasonic renal image. The region growing process is based on look up entities, which has computed values of local statistics. The objective of applying the region-growing process is to filter the homogenous seed points from the filtered digitized US image. When the image has more noise, then region growing is the best choice to apply it. Similarly, when there is an irregular boundary or more speckle, then the region growing is best choice in kidney stone image. In region growing, homogeneity plays an important role for processing the segmentation; homogeneity includes gray scale values, shapes and models. The major requirement of region growing is identifying the similarity in regions to segment the kidney stone.

The working process is as follows: First, a window sized at center is selected for calculating the seed pixel region. Once the region is selected which has the highest gray value compared to other regions within the boundary. The proposed approach use texture features as parameters, calculation of texture feature is based on statistical measures on each slice of partitioned kidney image. The selected seed pixel region starts growing, and its gray level mapping is applied in which the local valleys at the boundary of the two neighbouring pixels are compared and the information on that visited pixels is then stored. The local peak followed by the local valley is determined based on the gray level mapping, which leads to the changes in the pixel absorption from one boundary of the current region and neighbouring region pixels. Growing regions at each seed points are processed and compared with statistical similarity conditions. The conditions are as follows: a) when a region is growing, the size of the region is equal to or greater than the minimum region size with a termination condition which has speckle noise or overlapping with previous regions, adjacent regions, limitation in contrast of the region, when there is an occurrence of above characteristics, termination condition is applied, then the process seed pixel region growing is applied for segmentation.

The implementation process of the proposed approach on seed pixel region growing is designed as follows: To start with, the image which has the pixels, will be considered as unvisited. When a seed point is determined, then the image will be marked as visited and it will be taken as initial item or center point where the growth is being started and it will have a lookup entry or a growth list. The core part of the algorithms is summarized below:

a) Select the top item or higher entity pixel from the growth list
b) Selected pixel is marked as output image – it is considered as part of region
c) Each pixel in grown region which is the neighbouring pixel is checked based on similarity criteria, whether the pixel is visited or not visited and added it into the growth list for future analysis
d) Visit back to step 1, i.e. (a) and iterate till all the items are visited until there are no items in the growth list and it is connected based on merging the neighbouring region based on rules with seed regions, each portion of visit is updated on the segmented part which is called segmented output of kidney stone.

3.5. Feature Extraction and Classification

Image diagnosis depends on the calculation of features on segmented images and compared with texture values of benchmarked kidney image data. The next step after the segmentation is extracting the properties of segmented object. In real segmentation, extracted features are based on shape, density, margin and texture. Features were determined based on the first order statistic approach, spatial gray level dependency and spatial frequency content. There are two sets of features for this proposed approach, i.e. statistical and spatial frequency based feature sets. To calculate the optimal subset of features, combining the two sets of features with third sets will lead to a total of 14 features determined as part of feature extraction for segmented kidney portion. Calculated features have different physical characteristics and there will be unique differences in the variance. Therefore, it requires a normalization prior to the selection of features. Each of the features are scaled to mean value of zero and variance. The subsequent analysis is performed for all set of features. Selection of extracted features are feed into the proposed classifier known as Artificial Neural Network (ANN) classifier. The selected ANN classifier will act as feed forward multilayer perceptron with various hidden nodes. The proposed ANN classifier is designed with single hidden layer with 15 sigmoid nodes, output layer with single sigmoid node which predicts the level of stone size. Before feeding the extracted features, optimal features must be feed into ANN. For the process of selecting the features, the Principle Component Analysis (PCA) is proposed in which the size of the input feature vectors are reduced. The reduced feature vector in PCA is consists of seven features from the selected 14 features for the classification. Based on reduction of feature sets, classification performance is improved. PCA feature selection ignores more than 5% of original feature set which are having variation or redundancy based on normalization to zero mean or variance as mentioned earlier. In ANN architecture, gradient and back propagation training procedure are applied to improve the classification ability. The training procedure of the classifier is terminated based on achieving a training error, if it is less than 20 or 1000 iterations are conducted. The training error is determined based on the mean square error. The mean square error is the average square error between the output of the network and target output based on all the training behaviours (evaluation). The method applied to assess the performance of kidney stone detection is based on two-fold cross validation procedure. The performance assessment of renal calculi classification is based on evaluating the Receiver Operating Characteristic Curve (ROC) analysis. In this research study, to evaluate the efficiency of each feature subsets, ROC and FROC analysis are performed.

Kidney stone detection based on improved seed pixel region growing approach has correctly identified the presence or absence of kidney stone in the images and provides higher classification accuracy. The segmentation and classification accuracy of renal calculi or kidney stone at initial stages are promising.

4. Materials and Methods

Ultrasound kidney images with normal or abnormal, which as the presence of stones, are acquired from the clinical research center. The acquired images from scanner are digitized and processed using higher intensity features. The presence of stones with their edges will be observed through the segmented portion of the kidney image, in which the classification rule is applied to classify the stone size. The segmented images will be processed to calculate the average, mean, median values of pixel intensity in the image. The seed acts as a starting point for growth of the region, locations of the seed are determined inside or outside the boundary of the US kidney image. The image segmented will be a representation of binary, similarity conditions will be applied on the region growing process to calculate the difference from the center to remaining portion of the image. Similarity condition will provide a score or rank to represent the region, which has been visited and not visited based on the set of pixels. The termination condition is applied based on the similarity condition and the result is segmented; it is considered as threshold value. The current experiment for this proposed kidney stone segmentation is conducted at initial stage with 50 images. The results are accurate for the current availability of datasets; there is a modification in the algorithm once the defined parameters are not adjusting to the classification accuracy. The results are compared with manual biopsy reports in early stages and the variation of results is observed. The proposed CAD system for kidney stone is accurate for less image datasets where 92% accuracy is achieved after certain variations in parameters and noise preprocessing steps.

5. Results and discussion

Currently the work is at a fundamental stage and has been implemented in MATLAB. There were 50 image datasets, out of that, 35 images were used for training and 15 images were used for testing, the renal images were acquired for the early stages are from Calvin College free medical data set. In the 15 image datasets, 5 normal and 10 abnormal were chosen for experimentation. The stone size classification is as follows: if the size in lesser than 2mm, then it is considered as normal; if the size is greater than 5mm, then it is considered as abnormal. The results are shown in Figures 2-6 for kidney stone segmentation and classification. Table 1 shows the extracted features for normal, abnormal and detected stone image datasets.

Step 1: The US renal image after the scanning process

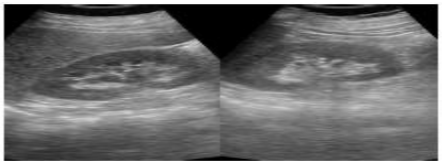


Fig. 2: Illustration of the input US renal image

Step 2: Acquired images after enhancement by filtering the noise

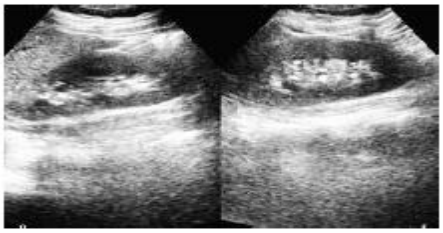


Fig. 3: Illustration of the pre-processing

Step 3: Kidney bladder images are partitioned into three set of regions

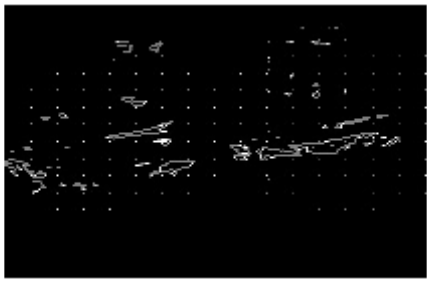


Fig. 4: Illustration of the region partitioning based on group of pixels

Step 4: Selection of seed point from the centered region



Fig. 5: Illustration of the seed pixel identification

Step 5: Computation of homogeneity and similarity rules are applied in the grown regions to get connected

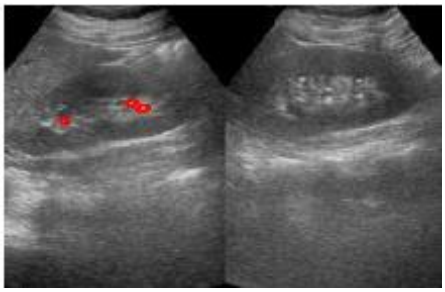


Fig. 6: Illustration of the kidney stone segmentation

Table 1: The feature extraction of kidney stone

Kidney Datasets	Mean	Standard Deviation	Variance	Entropy
NormaliImages	15	6	2	20
Kidney stone images	22	9	4	32
Stone detected Images	20	7	3	21

6. Conclusion

The work presented in this paper is on kidney stone or renal calculi segmentation based on enhanced seed pixel region growing segmentation method. The strength of this algorithm is based on automatic selection of seed pixels in which threshold values are minimized for selected partitioned regions. The proposed methodology has determined local contrast, mean, variance standard deviation, entropy as features to detect the stone. When a threshold value is set higher than the value of 12, segmentation of stone and size are diagnosed to categorize the presence, absence or early stage of stone. The paper is at conceptual level and have shown basic implementation with limited 50 datasets, detection rate is 92% and shown promising results at early stage of kidney tone detection. The results achieved were tested with limited datasets, within the testing datasets, results were effective and shown that extracted texture features were feed for classifying accurately the kidney stone. Current work is a partial prototype, when it is fully developed based on urologist input, it will be a greater impact for CAD application. In future research, the methodology will be applied for larger data sets and applied in different medical imaging applications.

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