IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 9, Issue 3, March 2021

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 7.488

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 7.488 |

|| Volume 9, Issue 3, March 2021 ||

| DOI: 10.15680/IJIRCCE.2021.0903035 |

Kidney Stone Detection using MRI

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ABSTRACT: Currently, kidney stone and tumor removal can be done without surgery. For this purpose, it is required imaging modalities that able to visualize kidney accurately. In order to improve the accuracy of kidney visualization in a short time, an automatic kidney centroid detection is required. This project developed a software to automatically detect the centroid of human kidney. The software was developed using MATLAB with smoothing filter, texture filter and morphological operators. They were used for image segmentation in order to extract important features. Test result shows the software achieve until 96.43% of accuracy in detecting the centroid. The detected centroid can be used as initial point to create ellipse model, which can be used to detect kidney's contour in further research. This software can be implemented in the most US machine that will be used as segmentation tool to reduce human errors and time. Then texture analysis was performed by calculating the local entropy of the image, continued with the threshold selection, morphological operations, object windowing, determination of seed point and ROI generation. This method was performed to several kidney ultrasound images with different speckle noise reduction techniques and different threshold value selection. Based on the result, it shows that for median filter, threshold value of 0.6 gave the highest TRUE ROIs which were 70%. For Wiener filter, threshold value of 0.8 gave highest TRUE ROIs which were 80% and for Gaussian low-pass filter, threshold value of 0.7 gave highest TRUE ROIs which were 100%. By using the previous methods result, this method has been tested also to more than 200 kidney stone ultrasound images.

I. INTRODUCTION

Nowadays, kidney stone has become a major problem and if not detected at an early stage then it may cause complications and sometimes surgery is also needed to remove the stone. So, to detect the stone and that too precisely paves the way to image processing because through image processing there is a tendency to get the precise results and it is an automatic method of detecting the stone. Doctor generally uses the manual method to detect the stone from the Computed Tomography image but our technique is fully automated so it is advantageous as the time is reduced and with that the chances of error also reduces.

Kidney stone disease is one of the major life threatening ailments persisting worldwide. The stone diseases remain unnoticed in the initial stage, which in turn damages the kidney as they develop. A majority of people are affected by kidney failure due to diabetes mellitus, hypertension, glomerulonephritis, and so forth. Since kidney malfunctioning can be menacing, diagnosis of the problem in the initial stages is advisable. Ultrasound (US) image is one of the currently available methods with noninvasive low cost and widely used imaging techniques for analyzing kidney diseases [1]. Shock wave lithotripsy (SWL), percutaneous nephrolithotomy (PCNL), and relative super saturation (RSS) are the available practices to test urine. The Robertson Risk Factor Algorithms (RRFA) are open and are used for laparoscopic surgery; these algorithms are assigned for exceptional [2] special cases. Hyaluronan is a large (>106 Da) linear glycosaminoglycan composed of repeating units of glucuronic acid (GlcUA) and N-acetyl glucosamine (GlcNAc) disaccharides [3]. It has a significant role in a number of processes that can eventually lead to renal stone disease, including urine concentration, uric acid, salt form crystal, crystallization inhibition, crystal retention, magnesium ammonium phosphate, and amino acid.

II. LITERATURE SURVEY

A REVIEW OF SEGMENTATION METHODS IN SHORT AXIS CARDIAC MR IMAGES

This paper is a review of fully and semi-automated methods performing segmentation in short axis images using a cardiac cine MRI sequence. We will review automatic and semi-automatic segmentation methods of cine MR images of the cardiac ventricles, using the short-axis view. The wide variety of image-driven approaches using weak or no prior have been proposed to tackle the ventricle segmentation in cardiac MRI. Almost all of these methods require either minimal or great user intervention. If image based and pixel classification-based approaches offer a limited framework for incorporating strong prior, straightforward extensions of deformable models in this sense have been extensively

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studied. In the next section are presented Methods relying on strong prior for heart segmentation. It can be generated by manually segmenting an image or by integrating information from multiple segmented images from different individuals. Strong prior based methods can overcome the previously defined segmentation problems. This paper has been presenting segmentation methods in cardiac MRI. We have proposed a categorization for these methods, highlighting the key role of the type of prior information used during segmentation, and has distinguished three levels of information:

(i) No information is used, but our study shows that min this case user interaction is required
(ii) Weak prior, that is, low level information such as geometrical assumptions on the ventricle shape, often combined to low-level user interaction,
(iii) Strong prior such as statistical models, constructed or learned from a large number of manually segmented images, not requiring user interaction.

Our image segmentation categorization includes on the one hand image-driven and pixel classification based approaches, and deformable models, making use of weak or no prior.

III. PROJECT ANALYSIS

3.1 PROBLEM IDENTIFICATION

- In the scheme does not permit the direct derivation of deformation parameters.
- Detection accuracy is low
- This particularly complex segmentation task, prior knowledge is required.
- Major challenges linked to this segmentation task.

3.2 EXISTING SYSTEM:

- In existing studies suggest neuro imaging may become a valuable tool in the early diagnosis of neurodegenerative diseases by extracting anatomical patterns and revealing hidden relations from structural magnetic resonance (MR) images.
- At analyzing structural brain MR images, a main aim is to find anatomical changes, either local or global, related to functional disturbances.
- In particular, radiologists examine images by looking at distinctively regions and compare them by searching differences.
- The most popular technique has been by far the support vector machine (SVM), which has been applied to classifying individuals with several neurological disorders.
- In this Methods that face the problem of high-dimensionality are the ones that perform image synthesis

3.3 PROPOSED METHOD:

The proposed method is based on a two-phase PSO model that combines bottom-up and top-down approaches to achieve accurate classification of brain MR images as normal controls or probable AD subjects. K-means with PSO based on clustering which is used to classify the problem. In the proposed approach, the pre-defined kernels convert the input image into individual feature saliency maps, whose pso correspond to dimensions of the kmeans space. Most brain lesion segmentation methods based on outlier detection, the proposed method is generic. It does not consider single voxels independently and makes no assumption about shape or intensity profile of the abnormality.

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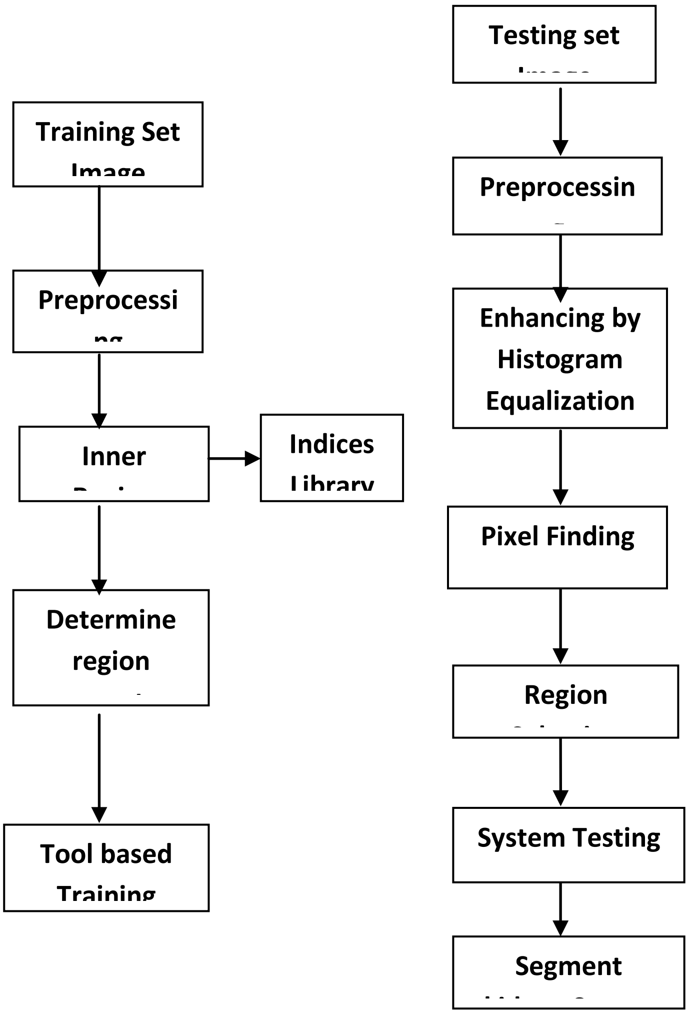
3.4 KIDNEY DATA FLOW DIAGRAM



IV. SYSTEM IMPLEMENTATION

Modules

The proposed renal kidney stone 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 [7] and
- **(v)** Contour based Region selection process

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.

Determining Inner Region Indicators

Let D represents the renal calculi image training dataset, which contains renal calculi images D = {I1, I2 ,…In};n = 1…N, where N is the number of the renal calculi images in the given dataset D . To determine the inner region indicators, Then the whole image is divided into L number of blocks and for every block, an index value, firstly, the regions representing kidney are manually marked in the known training data set ultrasound images.

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Determine Region Parameter

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 = {r1, r2 ,….rm},m = 1…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 , where is a centroid value of image I1. 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 t1 and t2.

Contrast Enhancement using Histogram Equalization

In contrast to the following enhancement process, initially we have converted given ultrasound image tn I into a grayscale image G t' n, 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 mage that is obtained after the histogram equalization process is denoted as G t' n .

Find Most Fascinated Pixels by K-means clustering

Mostly required pixels are computed from the image G t' n by utilizing the k-means clustering method. K-means clustering 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. 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.
(iv) Repeat process from step

V. CONCLUSION AND SCOPE FOR FUTURE WORK

To sum up, through power law transformation kidney area is enhanced properly. In the original image the gray level of thoracic cage, vertebral column and lesion part is same. Hence, to separate the anatomical part, preprocessing and segmentation is done. Also, thresholding technique is very simple and accurate to do segmentation.

The ANN is trained with normal kidney image and classified image input for normal or abnormal conditions by considering extracted energy levels from wavelets filters. The developed system is examined for different kidney images from the database and the results are effective in classifying the types of stone successfully with the accuracy of 98.8% [23]. Thus this system can be readily utilized in the hospitals for patients with abnormality in kidney. This work proves that the combination of level set segmentation, lifting scheme wavelet filters, and multilayer perceptron with back propagation means a better approach for the detection of stones in the kidney. In the future work, the system will be designed for real time implementation by placing biomedical sensors in the abdomen region to capture kidney portion. The captured kidney image is subjected to the proposed algorithm to process and detect stone on FPGA using hardware description language (HDL). The identified kidney stone in the image is displayed with colour for easy identification and visibility of stone in monitor.

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