Detection of Kidney Stone in MRI Images Using Ideal Filter

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Abstract:
A Filter method is introduced in this paper for efficient speckle suppression and detection of calculi in sonographic images of the kidney. Wavelets are developed in applied mathematics for the analysis of multiscale image structures. The aim of this project is to analyze and provide the most significant content descriptive parameters to identify and classify the kidney stones with ultrasound scan. Speckle filtering is a critical preprocessing step. Ideal Filter provides an appropriate basis for separating the speckle noise from an image. Filtering is used for unsupervised image segmentation. The statistical features are extracted by decomposing the kidney stone images into different frequency sub-bands using wavelet transform.

Keywords: Renal Calculi, Kidney Stones, MSE (Mean Square Error), PSNR (Peak Signal to Noise Ratio).

I. INTRODUCTION
Kidneys are retroperitoneal organs, located near the middle of the back, just below the rib cage, one on each side of the spine. Every year in both developed and developing countries, many people affected by chronic kidney failure due to diabetes mellitus and hypertension, glomerulonephritis etc. Worldwide research indicates that one out of 10 adults had kidney problems and by 2015 it is estimated that about 36 premature deaths due to kidney disease will happen [2]. Since kidney function impairment can be life threatening, diagnosis of the disorders and diseases in the early stages is crucial. Ultrasound is one of the non-invasive low cost widely used imaging techniques for diagnosing kidney diseases.

Though ultrasound image is adaptable, transferable and comparatively safe, but this type of image often full of acoustic interferences (speckle noise) and artifacts. Speckle is a complex phenomenon, which degrades detectability of target organ and reduces the contrast, resolutions with back-scattered wave appearance which originates from many microscopic diffused reflections. It affects the human ability to identify normal and pathological tissue. Hence, the automatic segmentation of anatomical structures like kidney in ultrasound imagery is a real challenge.

Ultrasound has been a welcome tool for many years to break up kidney stones, but finding the stones still requires radiograph or CT imaging. The accurate diagnosis of a renal stone is dependent on many factors, including the clinical history, the nature of the imaging findings, the experience of the radiologist, and the quality of the examination. A high-quality imaging examination, which is under the control of the radiologist, is essential. We present our technique in the performance of US imaging for the evaluation of kidney stone range and acknowledge that other protocols work equally well. It is expected that these protocols will be modified over time as new equipment becomes available. Ultrasound has been shown to be relatively safe but no imaging method which deposits additional energy into the body should be considered entirely risk free. When the decision to make a diagnostic
image is made, the physician should always make a conscious judgment about whether the potential benefits of the imaging procedure are greater than any potential risk. In recent years a great effort of the research in field of medical imaging was focused on kidney stone, renal cavity segmentation. The automatic segmentation has great potential in clinical medicine by freeing physicians from the burden of manual labeling; whereas only a quantitative measurement allows to track and modeling precisely the kidney disease. Despite the undisputed The rest of the paper is organized as follows. Literature Survey describe in this section. Section II outlines the complete design of the proposed Filtering Technique. Measured and simulated results of the kidney stone are discussed in Section III. The conclusions are given in Section IV.

II. Literature Survey

[1] In this paper, authors reduce speckle noise and smooth resultant image using Gabor filter. Histogram equalization is used to enhance the image quality. Two segmentation techniques were chosen to be compared consist of cell segmentation and region based segmentation. In this paper, author focused on ultrasound images.

[2] In this paper, author gives the clear indication of difference in the energy levels compared to that of normal kidney image if there is stone. The ANN trained with normal kidney image and classified image input into normal or abnormal by considering extracted energy levels from wavelets filters. The energy level gives an indication about presence of stone in that particular location which significantly vary from that of normal energy level. These energy levels are trained by Multilayer Perception (MLP) and Back Propagation (BP) ANN to identify the type of stone with an accuracy of 98.8%.

[3] In this paper, author proposed an approach to automatically detect and segment kidneys in 3-D abdominal ultrasound images. Our proposed kidney detection and segmentation methods are based on the probabilistic kidney shape model. We utilized 4 manually segmented kidneys to create the probabilistic kidney shape model. The proposed segmentation results confirm the superiority of our proposed method, compared to MRF-AC.

[4] In this paper, author represent two methods for enhancement. First one is ESWL & another one is PCNL used for less than 10mm stone detection & more than 10mm stone detection respectively. Children with staghorn calculi, stones in lower poles, and stones in a solitary kidney are among the most challenging cases in end urology. Uninephric children with renal stones of <10mm are usually successfully treated with ESWL; larger stones, especially within the lower pole, are more efficiently treated by PCNL.

[5] In this paper, author represent, the measurement method presented here is a convenient method to analyze the fragmentation level during an ESWL treatment. In this study we propose that such two dimensional images can assemble three-dimensional images acquired along the duration of the treatment and apply Grey-Level Co-occurrence Matrix (GLCM) texture measurements to produce a fragmentation level measurement. Measurements with phantoms and simulated stone models were used to demonstrate the effectiveness of the proposed method.

[6] In this paper, author tells about wavelet based method. A wavelet-based method is introduced in this paper for efficient speckle suppression and detection of calculi in sonographic images of the kidney. Wavelets are developed in applied mathematics for the analysis of multiscale image structures.

[7] In this paper, a method for segmentation and identification of renal calculi is proposed. Preprocessing involves the two types of filters namely median and wiener filters to de speckle the ultrasound images of kidney. The
segmentation results with regions then region properties are extracted for those regions. Time required for entire process is calculated for each kidney images. The average accuracy of the proposed method for both normal and calculi images are as 95% and 90%. Our segmentation method is easier and the time taken to process the image is comparatively low than other methods described in literature.

[8] In this paper, some techniques of speckle noise reduction were implemented consist of median filter, Wiener filter and Gaussian low-pass filter. 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.

[9] In this paper, CANR has produced 91.80% accuracy in predicting an US image of Kidney with the presence or absence of Calculi. Extracting Kidney region from the US image is very challenging due to its complex anatomical structure. An accurate algorithm is necessary for segmenting kidney region from medically scanned images. A new approach of differentiating artifacts from calculi can solve the problem of wrong diagnosis in medical Ultra sound Kidney images. Methods vary in advantages and disadvantages, and the choice of which algorithm to use depends on the requirements posed by the application at hand.

III. Ideal Filter Technique :-
Simply cut off all high frequency components that are a specified distance $D_0$ from the origin of the transform changing the distance changes the behaviour of the filter.

IV. Performance Parameter
The analysis is done on the basis of various performance metrics like PSNR (Peak Signal to Noise Ratio), MSE (Mean Square Error) and SSIM(Structural Similarity Index for Measuring Image). These are explain below as

1. PSNR :-
The Peak Signal to Noise Ratio (PSNR) is the ratio between maximum possible power and corrupting noise that affect representation of image. PSNR is usually expressed as decibel scale. The PSNR is commonly used as measure of quality reconstruction of image.

$$MSE = \frac{1}{MN} \sum_{m=1}^{M} \sum_{n=1}^{N} [f(m/n) - \hat{f}(m/n)]$$
2. Mean Square Error
Mean Square Error can be estimated in one of many ways to quantify the difference between values implied by an estimate and the true quality being certificated. MSE is a risk function corresponding to the expected value of squared error. The MSE is the second moment of error and thus incorporates both the variance of the estimate and its bias. The MSE of an estimate and is defined as

\[
\text{MSE} = \frac{1}{MN} \sum_{m=1}^{M} \sum_{n=1}^{N} [f(m/n) - f'(m/n)]^2
\]

3. SNR :-
Shot noise is used to measure the amount of noise present in any image acquisition as it takes into account all the different sources of noise present in the image. Shot Noise is defined as:

\[
\text{Shot Noise} = \frac{N}{\sqrt{N}} = \sqrt{N}
\]

Where \( N \) is the total amount of signal measured.

To find the total signal then, we need to find the amount of signal contributed by noise. By squaring the value of the noise, we arrive at the signal value.

Signal due to Noise = \( \text{Noise}^2 \)

To find the total amount of signal being measured we need to account for the signal generated by read noise and dark current.

Total Signal = \( \text{Actual Signal} + \text{Read Noise}^2 + \text{Dark Current Noise}^2 \)

By calculating the shot noise of the total signal, you arrive at the value of total noise present in our acquisition.

\[
\text{Total} = \sqrt{\text{Total Signal}}
\]

From here, we can calculate your SNR.

\[
\text{SNR} = \frac{\text{Actual Signal}}{\text{Total Noise}}
\]

By using these measurements, you can ensure that your image acquisitions are at an acceptable signal-to-noise ratio, allowing for cleaner, crisper images.

IV. Conclusion
After analyzing, it is found that ideal filter has high value of PSNR with low MSE and Simulated PSNR is 76.80767 with MSE 0.001086 db. These results show that Ideal filter is best filtering method for enhancement of kidney stone image.

References


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