Enhancement of Kidney Stone Images using different Filtering Technique

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Abstract :-
Kidney-Urine-Belly computed tomography (KUB CT) analysis is an imaging modality that has the potential to enhance kidney stone screening and diagnosis. This study explored the development of a semi-automated program that used image processing techniques and geometry principles to define the boundary, and segmentation of the kidney area, and to enhance kidney stone detection. This can be done by different filtering technique. In our work, we have present ideal, median and Butterworth filter. The performance of these filter is analyzed on the basis of MSE, PSNR,SNR. After analyzing all the parameter it is conclude that Median filters are best fitted for enhancement of kidney stone Images.

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

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 delectability 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

DOI: 10.18535/ijsrm/v4i8.12

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. 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.

Filter Techniques :-

Ideal Filter :-

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 .The transfer function for the ideal low pass filter can be given as:

$$H(u,v) = \begin{cases} 1 & if\ D(u,v) \le D_0 \\ 0 & if\ D(u,v) > D_0 \end{cases}$$

where *D(u,v)* is given as:

$$D(u,v) = \left[(U - \tfrac{M}{2})^2 + \left(V - \tfrac{N}{2}\right)^2 \right]^{1/2}$$

The ideal filtered image with different frequency range as shown in fig 1.

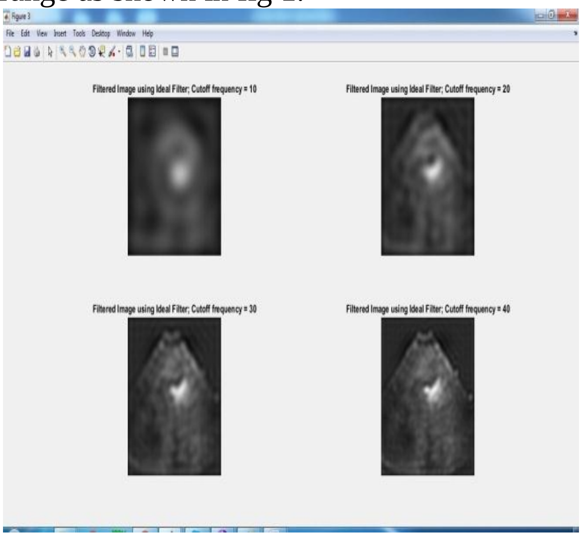

Fig 1. Filtered Image using Ideal Filter with different cutoff Frequency

Median Filter :-

Median filtering is a nonlinear method used to remove noise from images. It is widely used as it is very effective at removing noise while preserving edges. It is particularly effective at removing 'salt and pepper' type noise. The median filter works by moving through the image pixel by pixel, replacing each value with the median value of neighbouring pixels. The pattern of neighbors is called the "window", which slides, pixel by pixel over the entire image 2 pixel, over the entire image. The median is calculated by first sorting all the pixel values from the window into numerical order, and then replacing the pixel being considered with the middle (median) pixel value.
The median filtered image with different window techniques as shown in fig 2.

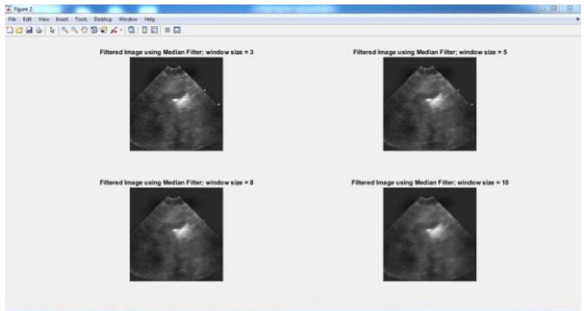

Fig 2. Filtered Image using Median Filter with different Window Size.

Butterworth Filter :-

The butterworth filter has a maximally flat response, i.e., no pass band ripple and roll-off of minus 20db per pole. Another name for it is "flat maximally magnitude" filters at the frequency of Ω = 0, as the first 2N - 1 derivatives of the transfer function when Ω = 0 are equal to zero. [4]. The Butterworth filters achieve its flatness at the expense of a relatively wide transition region from passband to stopband with average transient characteristics. This filter is completely defined mathematically by two parameters i.e. cut off frequency and number of poles. Compared to chebyshev filter, the phase linearity of buttorworth filter is better. In other words, the group delay (derivative of phase with respect to frequency) is more constant with respect to frequency. This means that the waveform distortion of the butterworth filter is lower. This Butterworth filters have the following characteristics

i)The magnitude response is nearly constant (equal to 1) at lower frequencies. That means pass band is maximally flat .

DOI: 10.18535/ijsrm/v4i8.12

ii)The response is monotonically decreasing from the specified cut off frequencies. The maximum gain occurs at $\Omega = 0$ and it is $|H(0)| = 1$. iii)Half power frequency, or 3db down frequency, that corresponds to the specified cut off frequencies.
The butterworth filtered image with different frequency range as shown in fig 1.

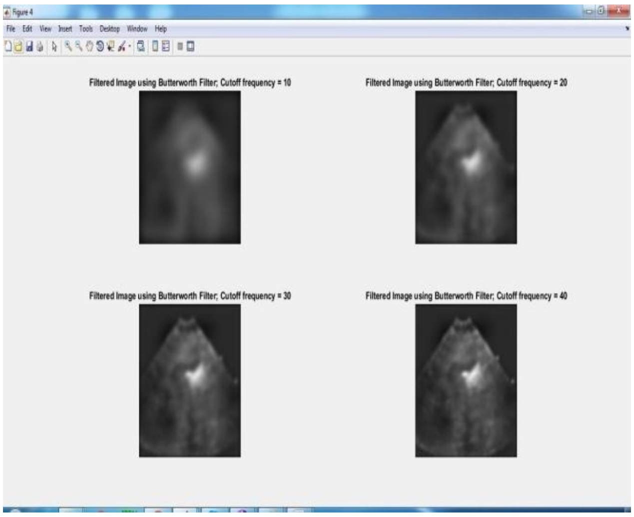

Fig 3. Filtered Image using Butterworth Filter with different Frequency.

III. Performance Parameter

There are three performance parameter to measure restored image. Image restoration research aims to restored image to from a blurred and noisy image. A widely used measure of reconstructed image fidelity for an N * *M* size image is the mean square error (MSE) and is given by

$$\mathrm{MSE} = \frac{1}{MN}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}\left|f(i,j)-\hat{f}(i,j)\right|^2$$

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{255}{MSE}\right)$$

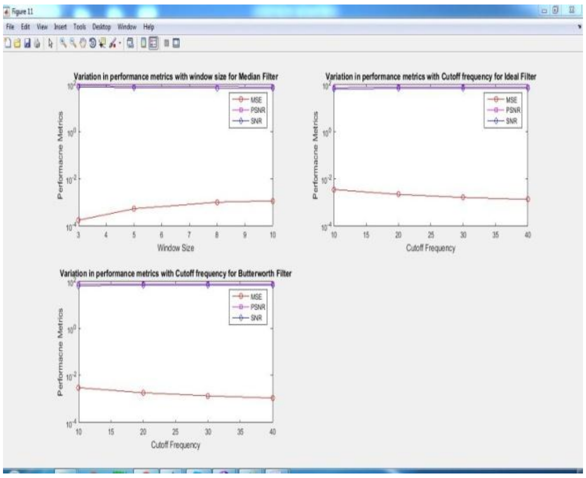

Fig 4. Performance Metrics of different Filters

Comparative Analysis

In this section, comparative of three filtering technique is shown in tabular form. Return loss and bandwidth is compared in table 1.

Sr. No	Parameter	Cut-off Frequency	MSE	PSNR	SNR
1.	Ideal Filter	10	0.00339	72.82892	63.44691
2.		20	0.00211	74.88745	65.50545
3.		30	0.00153	76.19105	66.80905
4.		40	0.001289	77.02801	67.64601
5.	Median Filter	3	0.00017	85.82815	76.44614
6.		5	0.00052	80.96916	71.58715
7.		8	0.000984	78.20292	68.82091
8.		10	0.001123	77.62873	68.24673
9.	Butterworth Filter	10	0.003016	73.33667	63.95466
10.		20	0.001825	75.51922	66.13722
11.		30	0.001356	76.80767	67.42567
12		40	0.001086	77.77396	68.39195

Table 1.Comparative analysis of different Filter.

IV. Conclusion

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

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