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Liver Ultrasound Image Enhancement Using Bilateral Filter

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***Abstract*— Medical image processing is used for the diagnosis of diseases by the physicians or radiologists. Noise is introduced to the medical images due to various factors in medical imaging. Noise corrupts the medical images and the quality of the images degrades. This degradation includes suppression of edges, structural details, blurring boundaries etc. To diagnosticate liver diseases edge and details salvation are very significant. Medical image denoising can help the physicians to diagnose the diseases. Medical images include MRI, CT scan, x-ray images, ultrasound images etc. In this paper we implemented bilateral filtering for medical image denoising. Its formulation & implementation are easy but the performance of bilateral filter depends upon its parameter. Therefore for obtaining the optimum result parameter must be estimated. We have applied bilateral filtering on medical images which are corrupted by additive white Gaussian noise with different values of variances. It is a nonlinear and local technique that preserves the features while smoothing the images. It removes the additive white Gaussian noise effectively but its performance is poor in removing salt and pepper noise.**

***Index Terms*— Liver disease, Ultrasound image, contrast enhancement, 3D Discrete Wavelet Transform, Wavelet Thresholding, Image Denoising, Bilateral Filter.**

I. INTRODUCTION

Ultrasound imaging, also called sonography, is a medical imaging modality which uses high-frequency sound waves to produce pictures of the inside of the body (see Fig 1.1). Ultrasound imaging uses a transducer, which is placed directly on the skin. Ultrasound waves are transmitted from the transducer into the body. At interfaces between different structures the waves are bounced back to the transducer. The transducer collects these waves to create an image. Ultrasound imaging does not use ionizing radiation, and is principally harmless [3]. Depending on probe type, ultrasound imaging can be 2D or 3D and can be acquired in real-time.

Therefore, this modality can show not only structure but also movement of the internal organs of the body. Beside the normal mode, called B mode, Doppler mode is a special ultrasound technique that permits clinicians to investigate and evaluate blood flow through vessels of the liver as well as other body organs such as the kidneys and the heart. Compared Medical imaging is the technique and process used to create images of the human body for clinical purposes or medical science. In the last few years, huge parts of research have been carried out on the image Processing and analysis such as magnetic resonance image (MRI), ultrasonography, computed tomography (CT) [4].

and nuclear medicine which can be used to assist doctors in diagnosis, treatment, and research. It is very important to produce a common standard tool, which is able to perform diagnosis with same ground criteria uniformly everywhere. Ultrasound is an impactful technique for imaging the internal anatomy (e.g., abdomen, breast, liver, kidney, and musculoskeletal).

It is relatively economical, noninvasive, benign for the human body, and portable, but it suffers from a main downside, i.e., contamination by speckle noise. Speckle noise significantly devalues the image quality and tangles diagnostic decisions for discriminating fine details in ultrasound images. Many techniques have been proposed to reduce this noise. Prior methods use various spatial filters such as median, average, and Wiener filter Contrast Limited Adaptive Histogram Equalization (CLAHE), spatial filter, however, each usually do not accurately preserve all the useful information such as anatomical boundaries in the image [1]. For removing such noise and to improve the interpretability or perception of information in images, we need to have efficient enhancement techniques like Bilateral Filter [2].

Figure 1: A US image of a necrotic liver tumor (arrow)

II. PRELIMINARIES

In this section, some related scheme are reviewed for the Liver Ultrasound Image Enhancement.

SPATIAL FILTER

Spatial filters are employed to remove noise from image data. Spatial filtering term is the filtering operations which performed directly on the pixels of an image. Spatial filters are used to produce smoothing effect, spatial mask are used for it

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[5] [12]. Spatial mask is nothing but a kind of finite impulse response filter (FIR filter), usually has small support 2x2, 3x3, 5x5, 7x7, this mask is convolved with the image. The result is the sum of products of the mask coefficients with the corresponding pixels directly under the mask as shown in figure (1) and we get the filtered image [11]. If the operation is linear, the filter is said to be a linear spatial filter. Consider an image f of size M ×N with a filter mask of size m× n, the expression for linear filtering is given as in equation (1).

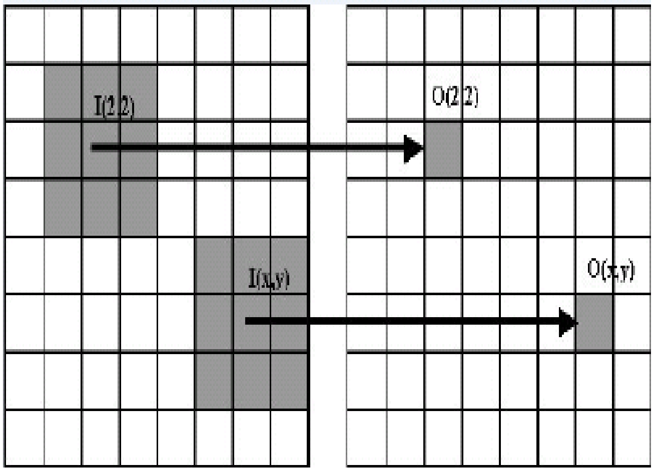

Figure 2: Masking Block

$$g(x,y) = \sum_{s=-a}^{a} \sum_{s=-b}^{b} w(s,t) f(x+s, y+t) \quad (1)$$

Where a and b are nonnegative integer. The Spatial filter method applied by using two type of filter, Low Pass Filter (LPF) and High Pass Filter (HPF).This applying to choose the best guesses for enhancement image. We get different filtered output, based on the type of spatial filter used. The normal, benign malignant Ultrasound images are used as test images to evaluate the efficiency of the developed algorithm.

SHOCK FILTER

Shock filter is used for de-blurring signals and images by creates shocks at inflection points. Shock filters satisfy a maximum-minimum principle gives that the range of the filtered image remains within the range of the original image. Shock filters [8] apply either erosion or dilation process. The concept is that the dilation process is used near a maximum and an erosion process around a minimum. The decision between dilation and erosion is based on the signum function s in set {-1, 0, +1} based on the Laplace operator (Kramer-Bruckner, 1975). This process is iterated by using a Partial Differential Equation (PDE) according to a small time increment d_t, which a continuous image f(x, y), then a class of filtered images

{u(x, y, t) t|≤ 0} of f(x, y) may be generated by evolving f under the process. The Kramer and Bruckner definition can produces a sharp discontinuity called shock at the borderline between two influence zones and finally we get deblurred output. For better understanding, let us consider be expressed using the following PDE as [7] is given in equation

$$u_t = -\text{sign}\, \Delta u\, |\nabla u| \quad (2)$$

Where subscripts denote partial derivatives, and $\nabla u = (u_x, u_y)^T$ is the gradient of u as given in

$$u(x,y,0) = f(x,y) \quad (3)$$

Above initial condition gives that the process starts at time zero with the original image. Let us assume that some pixels are in the influence zone of a maximum (negative Laplacian) i.e.

$$\nabla u = u_{xx} + u_{yy} \quad (4)$$

is negative. Then a dilation given by equation (3) is

$$u_{t=|\nabla u|} \quad (5)$$

For positive Laplacian, pixels belong to the influence zone of a minimum, with $\nabla u < 0$, then (2) can be reduced to an erosion equation i.e.

$$u_t = -|\nabla u| \quad (6)$$

These two cases show that for increasing time, (1) increases the radius of the structuring element until it reaches a zero-crossing of u. Then a shock is produced due to meeting of the influence zones of a maximum and a minimum, which separates adjacent segments. Thus, the zero-crossings of the Laplacian serve as an edge detector [8],[9]. Basically the result is enhancement/sharpening of the input image.

CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION (CLAHE)

Contrast Limited Adaptive Histogram Equalization (CLAHE) is a generalization of Adaptive Histogram Equalization and used to prevent the problem of noise amplification. In the case of CLAHE, the contrast limiting procedure is applied for each neighborhood from which a transformation function is derived. This is achieved by limiting the contrast enhancement of AHE [6], [10]. One advantage is that the part of histogram which exceeds the clip limit is not discarded but redistributed equally among all histogram bins. The method has three parameters:

Block size: It is the size of the local region around a pixel for which the histogram is equalized.
Histogram bins: It is the number of histogram bins used for histogram equalization process. It should be smaller than the number of pixels in a block.
Max slope: It limits the contrast stretch in the intensity transfer function. Very large values will result in maximal local contrast.

The method takes in one additional parameter 'clip level' - which varies between 0 and 1. The method computes the histogram for each and every pixel and then does a equalization operation on the window or block size. After the pdf's for the bins are calculated, each one of them is checked if it is above the given clip level. If yes then the extra amount (pdf- cliplevel) is accumulated. After all the pdf's have been checked, the accumulated extra amount is uniformly distributed among all the bins. Thus when the pdf values are modified, they add to a cumulative distribution function (cdf). The cdf value is then mapped to an output intensity value (between 0 - 255). While in the case of AHE, pixels lying outside the image domain are padded with 0's.

III. PROPOSED WORK

In this section, some related steps for the proposed image ultrasound scheme are reviewed.

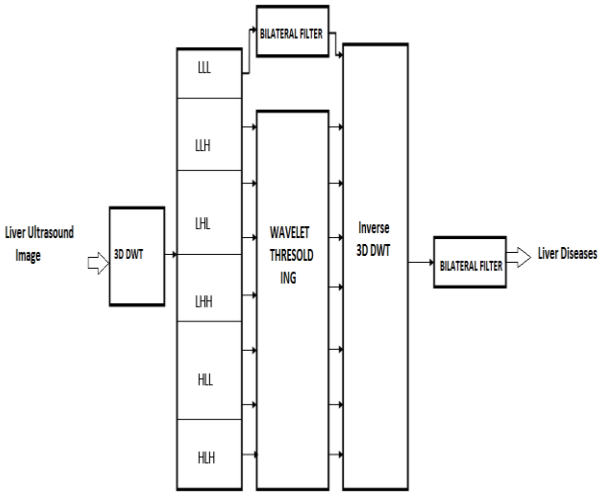

Figure 3: Block Diagram of Proposed Architecture

IV. 3D DISCRETE WAVELET TRANSFORM (3D DWT)

Medical data needs a true 3-D transform for compression and transmission. DWT considers correlation of images, which translates to better compression. According to Lee, et al., the 3-D DCT is more efficient than the 2-D DCT for x-ray CT [13]. Likewise, one would expect the 3-D DWT to outperform the 2-D DWT for MRI. Wang and Huang showed the 3-D DWT to outperform the 2-D DWT by 40-90% [14].
The 3-DWT is like a 1-D DWT in three directions. Refer to fig.1. First, the process transforms the data in the x-direction. Next, the low and high pass outputs both feed to other filter pairs, which transforms the data in the y direction. These four output streams go to four more filter pairs, performing the final transform in the z-direction. The process results in 8 data streams. The approximate signal, resulting from scaling operations only, goes to the next octave of the 3-D transform. It has roughly 90% of the total energy. Meanwhile, the 7 other streams contain the detail signals. Note that the conceptual drawing of the 3-D WT for one octave has 7 filter pairs, though this does not mean that the process needs 7 physical pairs.

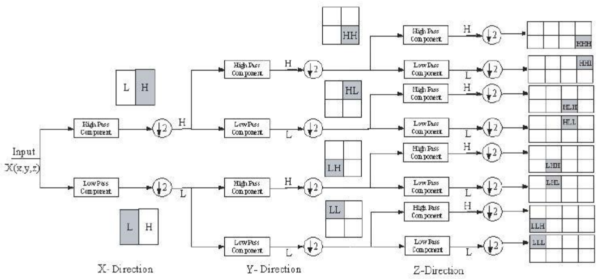

Figure 4: 3D-DWT in X, Y and Z directions

V. WAVELET THRESHOLDING

An image is often corrupted by noise in its acquisition and transmission. Image de-noising is used to remove the additive noise while retaining as much as possible the important signal features. In the recent years there has been a fair amount of research on wavelet thresholding and threshold selection for signal de-noising [15], [16]-[25], because wavelet provides an appropriate basis for separating noisy signal from the image signal. The motivation is that as the wavelet transform is good at energy compaction, the small coefficient are more likely due to noise and large coefficient due to important signal features.[23] These small coefficients can be thresholded without affecting the significant features of the image. Thresholding is a simple non-linear technique, which operates on one wavelet coefficient at a time. In its most basic form, each coefficient is thresholded by comparing against threshold, if the coefficient is smaller than threshold, set to zero; otherwise it is kept or modified. Replacing the small noisy coefficients by zero and inverse wavelet transform on the result may lead to reconstruction with the essential signal characteristics and with less noise. Since the work of Donoho & Johnstone [15], [17], [24], [25], there has been much research on finding thresholds, however few are specifically designed for images.
Let f = $\{f_{ij}$, i, j = 1,2 …M$\}$ denote the M × M matrix of the original image to be recovered and M is some integer power of 2. During transmission the signal f is corrupted by independent and identically distributed (i.i.d) zero mean, white Gaussian Noise n_{ij} with standard deviation σ i.e. $n_{ij} \sim N(0, \sigma^2)$ and at the receiver end, the noisy observations $g_{ij} = f_{ij} + \sigma n_{ij}$ is obtained. The goal is to estimate the signal f from noisy observations g_{ij} such that Mean Squared error (MSE) is minimum. Let W and W^{-1} denote the two dimensional orthogonal discrete wavelet transform (DWT) matrix and its inverse respectively. Then Y = W_g represents the matrix of wavelet coefficients of g having four subbands (LL, LH, HL and HH. The sub-bands HHk, HLk, LHk are called details, where k is the scale varying from 1, 2 …… J and J is the total number of decompositions. The size of the sub-band at scale k is $N/2^k \times N/2^k$. The subband LL_j is the low-resolution residue. The wavelet thresholding denoising method processes each coefficient of Y from the detail sub-bands with a soft threshold function to obtain $\hat{X}$. The de-noised estimate is inverse transformed to $\hat{f} = W^{-1}\hat{X}$. In the experiments, soft thresholding has been used over hard thresholding because it gives more visually pleasant images as compared to hard thresholding, reason being the latter is discontinuous and yields abrupt artifacts in the recovered images especially when the noise energy is significant.

BILATERAL FILTER

Bilateral filtering is a technique to smooth images while preserving edges. The use of bilateral filtering has grown rapidly and is now it is used in image processing applications such as image denoising, image enhancement etc [30]. Several qualities of bilateral filter are enlisted below which explains its success:
• It is simple to formulate it. Each pixel is replaced by a weighted average of its neighbors.
• It depends only on two parameters that indicate the size and contrast of the features to preserve.
• It is a non-iterative method. This makes the parameters easy to set since their effect is not cumulative over several iterations [31].
However, the bilateral filter is not parameter-free. The set of the bilateral filter parameters has an important influence on its behavior and performance. The parameters are window size w, standard deviation σd and σr. In the case of noise removal; the

parameters have to be adapted to the noise level, while the bilateral filter adapts itself to the image details content.
The drawback of this filter is that it cannot remove salt and pepper noise [32] also it causes propagation of noise in medical images [31]. Another drawback of bilateral filter is that it is single resolution in nature that means it cannot access to the different frequency components of the image It is efficient to remove the noise in high frequency area but gives poor performance to remove noise to low frequency area.
Bilateral filter is firstly presented by Tomasi and Manduchi in 1998. The concept of the bilateral filter was also presented in as the SUSAN filter and in as the neighborhood filter. It is mentionable that the Beltrami flow algorithm is considered as the theoretical origin of the bilateral filter which produces a spectrum of image enhancing algorithms ranging from the 2 L linear diffusion to the 1 L non-linear flows. The bilateral filter takes a weighted sum of the pixels in a local neighborhood; the weights depend on both the spatial distance and the intensity distance. In this way, edges are preserved well while noise is averaged out.

$$\hat{I}(X) = \frac{1}{C}\sum_{y\in N(x)} e^{\frac{-\|y-x\|^2}{2\sigma_d^2}}\, e^{-\frac{|I(y)-I(x)|^2}{2\sigma_r^2}} \quad (7)$$

IMPLEMENTATION OF BILETERAL FILTER

Bilateral Filtering is achieved by the combinations of two Gaussian filters [30]. One filter works in spatial domain and second filter works in intensity domain. This filter applies spatially weighted averaging smoothing edges. In traditional low pass filtering [31] it is assumed that the pixel of any point is similar to that of the nearby points:

$$h(x) = k_d^{-1}(x) \iint_{-\infty}^{\infty} f(\xi)\, c(\xi, x)\, d\xi \quad (8)$$

where c (ξ, x) measures the geometric closeness between the neighborhood cener x and a nearby point ξ.
Both input (f) and output (h) images may be multi-band.

$$k_d(x) = \iint_{-\infty}^{\infty} c(\xi, x)\, d\xi \quad (9)$$

$$h(x) = k_r^{-1}(x) \iint_{\infty}^{-\infty} f(\xi)\, s\big(f(\xi), f(x)\big)\, d\xi \quad (10)$$

where s (f (ξ), f(x)) measures the photographic similarity between the pixel at the neighborhood center x and that of nearby point ξ.
In this case, the kernel measures the photometric similarity between pixels. The normalization constant in this case is

$$K_r(x) = \iint_{-\infty}^{\infty} s\big(f(\xi), f(x)\big)\, d\xi \quad (11)$$

We can combine equation (10) and (11) which describes the bilateral filtering as follows:

$$h(x) = k^{-1}(x) \iint_{\infty}^{-\infty} f(\xi)\, c(\xi, x)\, s\big(f(\xi), f(x)\big)\, d\xi \quad (12)$$

$$k(x) = \iint_{\infty}^{-\infty} c(\xi, x)\, f\big(f(\xi), f(x)\big)\, d\xi \quad (13)$$

Combined domain and range filtering will be denoted as bilateral filtering. It replaces the pixel value at x with an average of similar and nearby pixel values. In smooth regions, pixel values in a small neighborhood are similar to each other, and the bilateral filter acts essentially as a standard domain filter, averaging away the small, weakly correlated differences between pixel values caused by noise. Bilateral filtering is a non-iterative method. Unlike traditional filters it removes the noise and preserves the edge information. But the optimal performance of the bilateral filter depends upon the parameters of the filter.

VI. RESULTS

Bilateral filtering is applied in the different liver ultrasound images as shown below. In the first denoising experiment firstly different liver ultrasound images are corrupted by additive speckle noise then bilateral filtering is applied. The parameters of bilateral filter can be tuned to find the optimal performance. The following figure 6 has been taken to test the system.

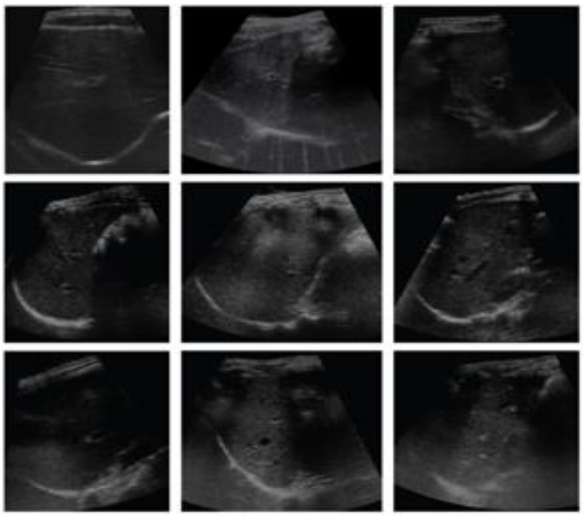

Figure 5 Experimental Dataset

We have presented a comparative study of various enhancement techniques for Ultrasound image in terms of PSNR and MSE. All the simulations are done using MATLAB tool. The images taken as input shown in figure (6), to figure (16) and corresponding comparison tables (1), table (2) and table (3) are given below.

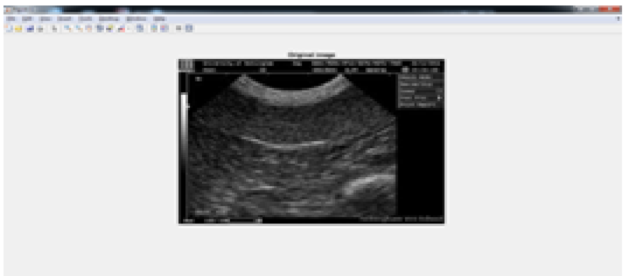

Figure 6 Normal Ultrasound Image

Figure 7 Denoised Image using shock filter

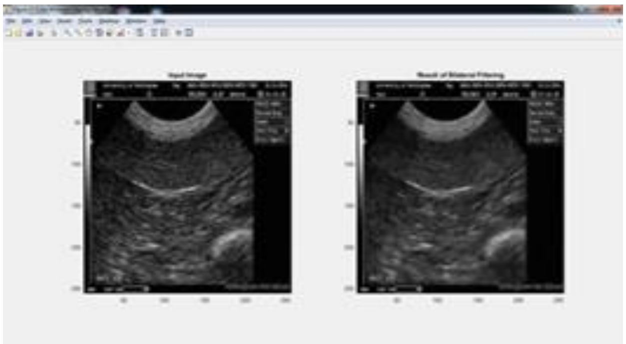

Figure 8 Input Image and Result of Bilateral Filter

Figure 9 Source Image in(RGB)

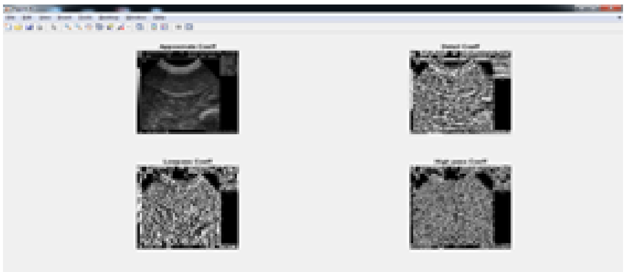

Figure 10 Approximate coeff.,detail coeff., Low-pass coeff., High-pass coeff. For Input image

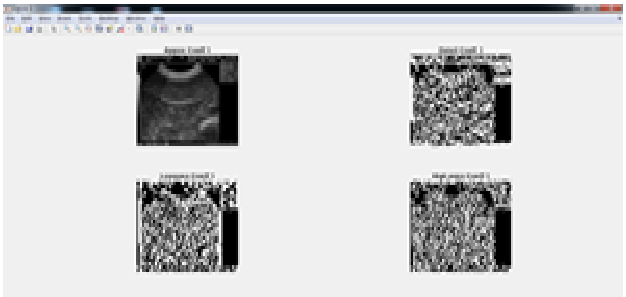

Figure 11 Approximate coeff.,detail coeff., Low-pass coeff., High-pass coeff. For filtrerd image

Figure 12 1st level IDWT

Figure 13 2nd level IDWT

Figure 14 Histogram Equalization for Bilateral Filter Image

Figure 15 Noising Image

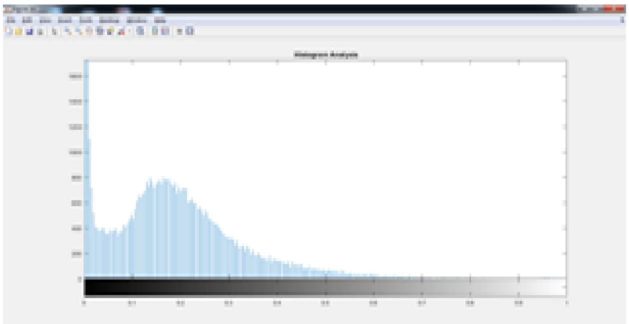

Figure 16 Histogram Analysis

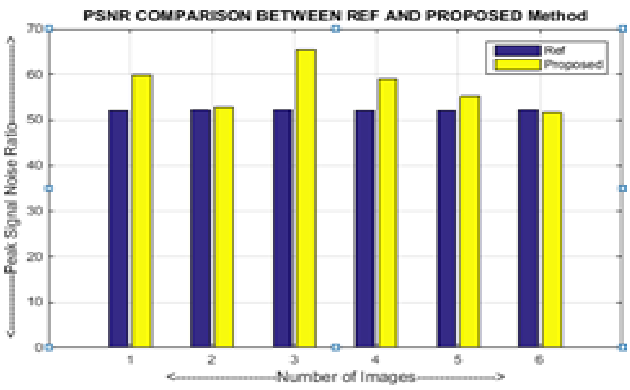

Figure 17 PSNR comparisons between Ref and Proposed method

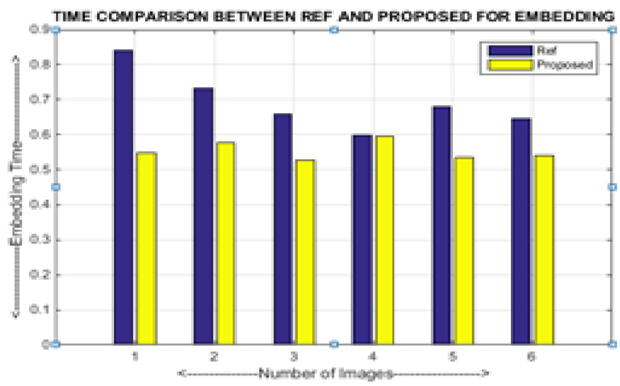

Figure 18 Time comparison between Ref and

Input Image	Enhancement Technique	Parameter	
		MSE	PSNR
Liver ultrasound image	Shock Filter	1.8178e+04	5.5354
	Bilateral Filter	86.585	28.7564

Table 1: Performance of Enhancement Techniques for Normal Liver image

Input Image	Enhancement Technique	Parameter		
		Structural Content	Maximum difference	Normalized Absolute Error
Noised Liver Image	Shock filter	0.2083	190.0039	2.9106
	Bilateral filter	1.0194	74	0.1434

Table 2: Performance of Enhancement Techniques for Noised Liver Image

Input Image	Enhancement Technique	Parameter	
		Normalized Cross relation	Average difference
Liver Ultrasound Image (in RGB)	Shock filter	0.2378	120.4184
	Bilateral filter	0.9771	-0.5122

Table 3: Performance of Enhancement Techniques for Liver Image (in RGB)

The purpose of calculating the performance of the image and after that comparison between ref and proposed methods will show which method is better for ultrasound image. Such method is mainly due to highly accurate detection with various attacks. The (Peak signal to noise ratio) PSNR, (Signal to noise ratio) SNR is high; (mean squared error) MSE is low. This proposed method is a fast method for ultrasound image.

VII. CONCLUSION

Here we describe the procedure of bilateral filter to de-noise the medical images. Its performance is improved than that of linear filters such as Wiener filter, mean filters etc. It gives better performance to remove the noise in high frequency area but it fails to remove noise to low frequency area. However its performance is not satisfactory to remove the noise from the image. The drawback of this filter is that it cannot remove salt and pepper noise. Also it gives poor performance to remove speckle noise from the ultrasound images. To upgrade the efficiency of bilateral filter to eliminate speckle multiplicative noise modal can be transmitted into an preservative one by taking logarithm of the debased image.

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