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Research Article

An Image Denoising Framework with Multi-resolution Bilateral Filtering and Normal Shrink Approach

Shivani Sharma and Gursharanjeet Singh Kalra
Lovely Professional University, Punjab, India

Abstract: In this study, an image denoising algorithm is presented, which takes into account wavelet thresholding and bilateral filtering in transform domain. The proposed algorithm gives an extension of the bilateral filter i.e., multiresolution bilateral filter, in which bilateral filtering is applied to the approximation sub bands and normal shrink is used for thresholding the wavelet coefficients of the detail sub bands of an image decomposed using a wavelet filter bank up to 2-level of decomposition. The algorithm is tested against ultrasound image of gall bladder corrupted by different types of noise namely, gaussian, speckle, poisson and impulse. The result shows that with increase in decomposition levels the proposed method is effective in eliminating noise but gives overly smoothed image. The algorithm outperforms with speckle and poisson noise at 2- level decomposition in terms of PSNR.

Keywords: Bilateral filter, MBF, MSE, NormalShrink, PSNR, wavelet thresholding

INTRODUCTION

The applications like video broadcasting, satellite imaging, medical imaging or research in telescope imaging totally depend on the quality of the digital images for their success. There are different sources of noise that may contaminate any digital image and degrade the quality. The overall noise characteristics in an image depend on many factors like, pixel dimensions, temperature, exposure time and type of sensor (Ming and Bahadir, 2008). Among the noise sources, dark current noise is due to the thermally generated electron at the sensor sites. It is proportional to the exposure time and highly dependent on the sensor temperature. Shot noise has the characteristics of Poisson distribution and is generated due to the quantum uncertainty in the generation of photoelectron. Amplifier noise and quantization noise occur during the conversion of number of electrons to pixel intensities (Ming and Bahadir, 2008). Images are often corrupted by noise usually modelled as Gaussian type during acquisition and transmission. Additive noise removal from a given signal is an important problem in signal and image processing (Michael, 2002). In medical imaging applications especially considering ultrasound imaging suffer from speckle noise. Speckle is a random multiplicative noise which obscures the perception and extraction of fine details in ultrasound image and despeckling is necessary for better diagnosis of the images (Vanithamani and Umamaheswari, 2011). Impulse noise generates a pixel with gray value, which is not correlated with their local neighborhood. It appears as a sprinkle of both light and dark or only light or only dark spot in image by replacing a portion of image's pixel value with random value in the dynamic range [0,255] while leaving the remainder unchanged (Kumar, 2010). Many imaging modalities such as PET, SPECT and fluorescent confocal microscopy imaging results in poisson noise, is a basic form of uncertainty associated with the measurement of light, inherent to the quantized nature of light and the independence of photon detections. Its expected magnitude is signal dependent and constitutes the dominant source of image noise except in low-light conditions Noise removal may help to improve the performances for many signal processing algorithms, such as compression, detection, enhancement, recognition and more. Noise is also color or channel dependent. Typically, green channel is the least noisy where as blue channel is the noisiest. Noise in a digital image has low frequency (coarse-grain) and high frequency (fine-grain) components. The high-frequency components are typically easier to remove but it is difficult to distinguish between real signal and low- frequency noise (Ming and Bahadir, 2008). Most of the natural images are assumed to have additive random noise which is modelled as Gaussian type. This denoising is often an essential and the first step to be considered before the image data is analysed. The goal of denoising is to remove the noise while preserving the important image features as much as possible and to achieve this goal many denoising methods have been proposed over the years. Filtering is the most fundamental operation of image processing. In the broadest sense of the term "filtering", the value of the filtered image at a given location is a function of the values of the input image in a small neighbourhood of

Corresponding Author: Shivani Sharma, Lovely Professional University, Punjab, India

the same location. There are two types of filtering techniques namely linear filtering techniques and non-linear filtering techniques. Linear filtering techniques are optimal but result in problems like blurring sharp edges, destroying lines and other fine image details. Mean filtering and Gaussian filtering are the examples of linear filtering techniques. On the other hand, non-linear filtering techniques avoid the limitations of linear filtering techniques and hence preserve edges and other fine details of the image. Median filtering, anisotropic filtering and bilateral filtering are the examples of non-linear filtering (Ming and Bahadir, 2008).

Among the various method of denoising, wavelet thresholding has been reported to be a highly successful method. In this wavelet thresholding technique, a signal is decomposed into approximation (low-frequency) and detail (high-frequency) subband and the coefficients of the detail subband are processed via hard or soft thresholding. The hard thresholding eliminates those coefficients that are smaller than the threshold value while the soft thresholding shrinks the coefficients that are larger than the threshold. The performance of denoising depends on the selected threshold so threshold selection is the most critical task of the wavelet thresholding process. For the threshold selection, there are various shrink functions developed (Rohit *et al*., 2011). Various threshold selection strategies have been proposed, such as VishuShrink, SUREShrink, NormalShrink and BayesShrink etc (Rohit *et al*., 2011). But the limitation of wavelet thresholding is that it results in smoothing of edges (Sudipta *et al*., 2012). The bilateral filter was proposed in Tomasi and Manduchi (1998) as an alternative to wavelet thresholding and is a very popular non-linear denoising method. Bilateral filter is a combination of two Gaussian filters; one works in spatial domain, the other filter works in intensity domain. The bilateral filter takes a weighted sum of the pixels in a local neighbourhood; the weights depend on both the spatial distance and the intensity distance. In this way, edges are preserved well while noise is averaged out. Noise may have low frequency and high frequency fluctuations. It is easier to remove high frequency but it is difficult to distinguish between real signal and low frequency noise. The limitation of bilateral filter is its single resolution nature. Although bilateral filter is effective in removing high frequency noise but fails to remove low frequency noise (Ming and Bahadir, 2008). This limitation of bilateral filter can be avoided by using bilateral filter in multiresolution framework. As it is seen that low frequency noise becomes high frequency noise as the image is decomposed into subbands further and possible to get rid of it at lower level (Ming and Bahadir, 2008). So in this proposed work, bilateral filter is used in multiresolution framework along with wavelet thresholding technique so as to remove low frequency noise from the image. This approach exploits the capabilities of both bilateral filter and wavelet thresholding using NormalShrink function for threshold selection. While bilateral filter works in approximation subbands, wavelet thresholding is to be applied in the detail subbands, where some noise components can be identified and hence can be removed effectively. The proposed work is tested on ultrasound images corrupted by poisson, gaussian and speckle and impulse noise.

LITERATURE REVIEW

The de-noising is a challenging task in the field of signal and image processing. There are two types of denoising approaches, one is wavelet approaches and the other is non-wavelet approaches. Wavelet shrinkage is a wavelet approach and the selection of threshold plays an essential role in wavelet denoising. The first category of threshold selection uses universal threshold method, in which the threshold is common for all the wavelet coefficients of the noisy image. The second category is subband adaptive in which the threshold value is estimated for each subband separately. VishuShrink (Donoho and Johnstone, 2002) uses universal threshold that results in overly smoothed images. SUREShrink (Donoho and Johnstone, 1995) uses independently chosen thresholds for each subband through the minimization of the Stein's unbiased Risk Estimate. SUREShrink performs better than VishuShrink. In BayesShrink (Chang *et al*., 2000) the threshold is determined for each subband by modelling the wavelet coefficients within each subband as random variables with Generalized Gaussian Distribution (GGD). The NeighShrink thresholds the wavelet coefficients according to the magnitude of the square sum of all the wavelet coefficients within the neighbourhood pixels. But the average elapsed time by Neigh Shrink for coiflet wavelet bases in a single test is much more than the Bayes Shrink and Normal Shrink method (Rohit *et al*., 2011). The result shows that the Neigh Shrink gives the better result than the Bayes and Normal Shrink in terms of PSNR. However, in terms of the processing time, the Normal Shrink is faster than the remaining both (Rohit *et al*., 2011).

A major strength of the wavelet thresholding which is a wavelet approach is its ability to treat different frequency components of an image separately, which is important, because noise in real scenarios may be frequency dependent. But, in wavelet thresholding the problem experienced is generally smoothening of edges. Bilateral filtering is a technique to smooth images while preserving edges. It can be traced back to 1995 with the work of Aurich and Weule (1995) on nonlinear Gaussian filters. It was later rediscovered by Smith and Brady (1997) as part of their SUSAN framework and Tomasi and Manduchi (1998) who gave it its current name. Since then, the use of bilateral filtering has grown rapidly. Although the bilateral filter was first proposed as an intuitive tool, it shows some connections with some well established techniques. It is shown that the bilateral filter is identical to the first iteration of the Jacobi algorithm (diagonal normalized steepest descent) with a specific cost function (Michael, 2002). The bilateral filter is also related with the anisotropic diffusion. The bilateral filter can also be viewed as a Euclidean approximation of the Beltrami flow, which produces a spectrum of image enhancement algorithms ranging from the L_2 linear diffusion to the L_1 nonlinear flows. In nonlocal means filter, where similarity of local patches is used in determining the pixel weights. When the patch size is reduced to one pixel, the nonlocal means filter becomes equivalent to the bilateral filter (Ming and Bahadir, 2008). Multi-resolution analysis has been proven to be an important tool for eliminating noise in signals, it is possible to distinguish between noise and image information better at one resolution level than another (Ming and Bahadir, 2008). So in my proposed work, bilateral filter is used in multi-resolution framework so as to remove low frequency noise as it is difficult to remove it at single resolution. Also, NormalShrink wavelet thresholding is used in detail subbands as it requires less processing time.

THE PROPOSED SCHEME

Assume a color image say $g(x,y)$ of size $M \times N \times 3$ and convert it into gray scale image say $f(x,y)$ of size $M \times N \times 1$. For the implementation, $g(x,y)$ or $f(x,y)$ should be a double precision matrix. Adding noise into the gray scale image for generating a noisy image for study purpose

The noisy image signal so obtained is decomposed into its frequency subband with wavelet-decomposition. As image is a two-dimensional entity so after wavelet decomposition it gets decomposed into approximate subband and detail subband. The detail subband comprises of horizontal, vertical and diagonal detail. The coarse-grain noise at the original level is difficult to identify and eliminate so the noise becomes fine grain as the image is decomposed and can be eliminated more easily. In two dimensions, a two-dimensional scaling function, $\varphi(x,y)$ *and* three two- dimensional wavelets, $\psi^H(x,y)$, $\psi^V(x,y)$ and, $\psi^D(x,y)$ are required. Each is the product of two one-dimensional functions. Excluding one dimensional results like $\varphi(x)\psi(x)$, the four remaining products produce the separable scaling function:

$$\varphi(x,y) = \varphi(x)\varphi(y) \tag{1}$$

and separable, directionally sensitive wavelets:

$$\psi^H(x,y) = \psi(x)\varphi(y) \tag{2}$$

$$\psi^V(x,y) = \varphi(x)\psi(y) \tag{3}$$

$$\psi^D(x,y)=\psi(x)\psi(y) \tag{4}$$

where, ψ^H measures intensity variations along columns, ψ^V measures intensity variations along rows, ψ^D measures intensity variations along diagonals. The scaled and translated basis functions are given in Eq. (5) and (6):

$$\varphi_{j,m,n}(x,y) = 2^{\frac{j}{2}}\varphi(2^j x - m, 2^j y - n) \tag{5}$$

$$\psi^i{}_{j,m,n}(x,y) = 2^{\frac{j}{2}}\psi^i(2^j x - m, 2^j y - n), \tag{6}$$

$$i = \{H,V,D\}$$

where, index i identifies the directional wavelets in Eq. (2) to (4). The discrete wavelet transform of noisy image $f^{'}(x,y)$ of size $M \times N \times 1$ is then given by:

$$W_\varphi(j_0,m,n) = \frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f'(x,y)\ \varphi_{j_0,m,n}(x,y) \tag{7}$$

$$W^i{}_\psi(j,m,n) = \frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f'(x,y)\psi^i{}_{j,m,n}(x,y), \tag{8}$$

$i = \{H,V,D\}$, j_0 is an arbitrary starting scale and the $W_\varphi(j_0,m,n)$ coefficients define an approximation of $f'(x,y)$ at scale j_0.

The $W^i{}_\psi(j,m,n)$ coefficients add horizontal, vertical and diagonal details for scales $j \leq j_0$, we normally let j_0=0 and select N =M = 2^J so that j = 0, 1, 2…J−1 and m = n = 0, 1, 2….$2^j - 1$.

Applying bilateral filtering to the approximate subband $W_\varphi(j_0,m,n)$. Mathematically, at a pixel location x, the output of the bilateral filter is calculated as follows:

$$\widetilde{I(x)} = \frac{1}{C}\sum_{y \in N(x)} e^{\frac{-||y-x||^2}{2\sigma_d^2}} e^{\frac{-|I(y)-I(x)|^2}{2\sigma_r^2}} I(y) \tag{9}$$

where σ_d and σ_r are parameters controlling the fall-off of the weights in spatial and intensity domains, respectively N(x) is a spatial neighborhood of x and C is the normalization constant that assures that the filter preserves average gray value in constant areas of the image, respectively:

$$C = \sum_{y \in N(x)} e^{\frac{-||y-x||^2}{2\sigma_d^2}} e^{\frac{-|I(y)-I(x)|^2}{2\sigma_r^2}} \tag{10}$$

Equation (9) performs bilateral filtering combining domain and range filtering based on geometric closeness and photometric similarity between the neighbourhood centre and nearby point.

Now, applying Normal Shrink thresholding technique to the detail subband $W^i{}_\psi(j,m,n)$. In the

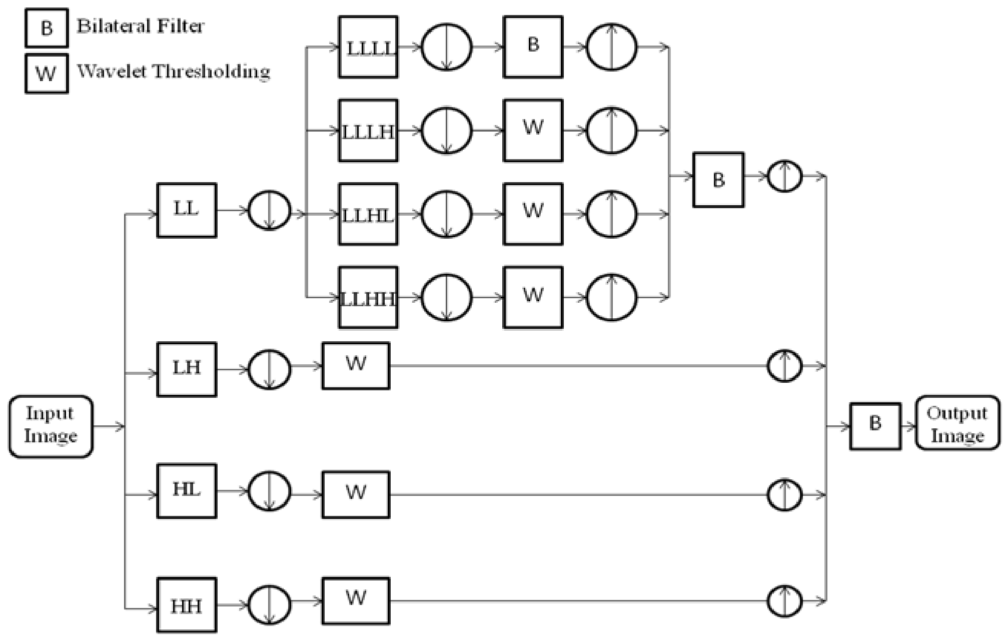


Fig. 1: Flowchart of the proposed work for 2 decomposition level

proposed work, NormalShrink approach is used for thresholding, various parameters are used to calculate the threshold value (T_N), which is adaptive to different subband characteristics:

$$T_N = \frac{\beta\hat{\sigma}^2}{\widehat{\sigma_y}} \tag{11}$$

where, the scale parameter β is computed once for each scale using the following equation:

$$\beta = \sqrt{\log\left(\frac{L_k}{J}\right)} \tag{12}$$

L_k = The length of the subband at k^{th} scale.
$\hat{\sigma}^2$ = The noise variance, which is estimated from the subband HH1, using the formula

$$\hat{\sigma}^2 = \left[\frac{median(|Y_{ij}|)}{0.6745}\right]^2 \tag{13}$$

and $\hat{\sigma}_y$ is the standard deviation of the subband. This is the way to compute the estimation parameter of NormalShrink approach. Applying this thresholding approach on the horizontal, vertical and diagonal details, where some noise components can be identified and removed effectively.

The image signal is reconstructed back using inverse wavelet transform. The original image $f(x, y)$ is obtained via inverse discrete wavelet transform, using Eq. (7) and (8), is given by:

$$f(x,y) = \frac{1}{\sqrt{MN}}\sum_m\sum_n W_\varphi\left(j_0,m,n\right)\ \varphi_{j_0,m,n}(x,y) + \frac{1}{\sqrt{MN}}\sum_{i=H,V,D}\sum_{j=j_0}^{\infty}\sum_m\sum_n W^i{}_\psi\left(j,m,n\right)\ \psi^i{}_{j,m,n}(x,y) \tag{14}$$

Once the image signal is recovered back then again bilateral filtering is to be applied on it. The Fig. 1 shows the flowchart of the proposed work for 2- level of decomposition.

PERFORMANCE EVALUATION

In order to measure the performance of the proposed denoising method several parameters are available for comparison. Among the various parameters, Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE) are calculated as the performance measurement criteria in this proposed work. The PSNR is defined as:

$$\text{PSNR (dB)} = 10\log_{10}\left(\frac{255\times255}{MSE}\right) \tag{15}$$

where, MSE is the mean square error between the denoised and original image. It is calculated by taking the difference between two images say g_i and f_i pixel by pixel, square the result and finally average the results. MSE may be defined as:

$$\text{MSE} = \frac{1}{M}\sum_1^M(gi - fi)^2 \tag{16}$$

Higher value of PSNR of denoised and original image implies that the performance of the denoising method is good and hence better image quality.

RESULTS AND DISCUSSION

Some experiments were conducted using ultrasound medical images that include gall bladder, among others, corrupted by different types of noise namely Gaussian, speckle, poisson and impulse noise with a noise of variance 0.02. These noisy images were denoised using proposed method and the PSNR results were calculated. Table 1 gives the PSNR comparison between the proposed method (multiresolution bilateral filtering with NormalShrink) and multiresolution bilateral filtering in combination with the BayesShrink thresholding for 1- level and 2- level of decomposition.

At a noise variance of 0.02 and at 1- level decomposition, the proposed method gives 0.02 dB better result for ultrasound image corrupted by poisson noise than that of the multiresolution bilateral filtering with Bayes Shrink approach. However, for the case of impulse noise both the methods shows unsatisfactory results and also for the case of ultrasound image corrupted by Gaussian noise and speckle noise the multiresolution bilateral filtering with BayesShrink thresholding shows better results than the proposed method. On comparing the PSNR values at 1-level and 2-level of decomposition for the same two methods discussed above at a noise variance of 0.02, the proposed method shows improved results that means with increase in decomposition levels the proposed method is effective in eliminating noise but gives overly smoothed images as shown in Fig. 2. At 2- level of decomposition, proposed method shows good results with speckle i.e., 2.15 dB increases in PSNR value by the proposed method than that with multiresolution bilateral filtering with BayesShrink and the proposed method outperforms for poisson noise with 3.48 dB increase in PSNR values. But on increasing the noise variance to 0.04, the proposed method gives better result at 2-level of decomposition with the speckle and poisson noise. For speckle noise, there is 2.01 dB increases in PSNR value and 6.21 dB increase for the case of poisson noise but results in overly smoothed images due to the application of bilateral filter.

Table 2 shows the PSNR comparison of different methods for different types of ultrasound noisy images with a noise of variance 0.02 and the corresponding results were displayed in Fig. 3. Observation of the result reveals that the multiresolution bilateral filter with BayesShrink thresholding gives better result for ultrasound image corrupted by Gaussian noise.

If we take only the multiresolution characteristic into account than it was observed that multiresolution filter (BayesShrink) and the proposed method both outperforms than the single resolution bilateral filter.

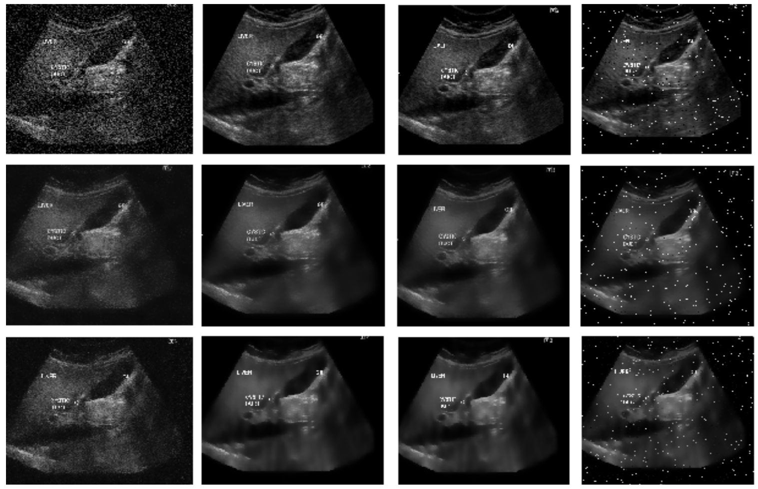
Both multiresolution filter (BayesShrink) and the proposed method give 3.36 dB and 1.86 dB better results than the single resolution nature of bilateral filter for Gaussian noisy ultrasound image and also MBF (BayesShrink) gives 1.17 dB and proposed scheme gives 1.13 dB better results than single resolution Bilateral filter. On analysing the Table 2, the proposed method gives better result for ultrasound image corrupted by poisson noise with 0.02 dB increase in PSNR value but gives unsatisfactory results with the other noisy images corrupted by Gaussian, speckle and impulse noise than that of MBF (BayesShrink). However, the results were not so good in case of impulse noise for impulse noise corrupted ultrasound images. The Fig. 3 displays the application of different types of methods on the ultrasound images corrupted by gaussian, speckle and poisson and impulse noise. Considering the individual application of BayesShrink and NormalShrink thresholding, it reveals that both methods results in lower PSNR values out of all other methods discussed and also the multiresolution

Table 1: PSNR comparison of different types of ultrasound noisy image at 1 and 2 level of decomposition using MBF with BayesShrink and normal shrink thresholding with noise variance of 0.02 and 0.04

	0.02 variance		0.02 variance		0.04 variance		0.04 variance	
	1-level		2-level		1- level		2-level	
Noise	Bayes	Normal	Bayes	Normal	Bayes	Normal	Bayes	Normal
Gaussian	24.90	23.40	24.46	24.69	21.40	19.40	21.77	21.02
Speckle	27.35	27.31	25.18	27.33	23.71	23.63	22.51	24.52
Poisson	33.37	33.3 9	28.18	31.66	33.37	33.37	25.45	31.66
Impulse	22.38	22.38	18.17	19.75	18.88	18.88	16.53	18.56

Table 2: PSNR comparison of different algorithms for different types of ultrasound noisy image with noise of variance 0.02

Noise	Bilateral filter	Bayes shrink	Normal-Shrink	MBF-(Bayes)	Proposed method
Gaussian	21.54	21.93	20.22	24.90	23.40
Speckle	26.18	24.65	24.58	27.35	27.31
Poisson	34.53	30.76	30.59	33.37	33.39
Impulse	21.46	21.54	21.54	22.38	22.38



(a) (b) (c) (d)

Fig. 2: Results displayed from top to bottom for ultrasound images corrupted by (a) Gaussian noise, denoised image using multiresolution bilateral filter with BayesShrink and bottom one is the denoised image using multiresolution bilateral filter with NormalShrink, (b) speckle noise, (c) poisson noise and (d) impulse noise, at noise of variance 0.02, for 2- level of decomposition

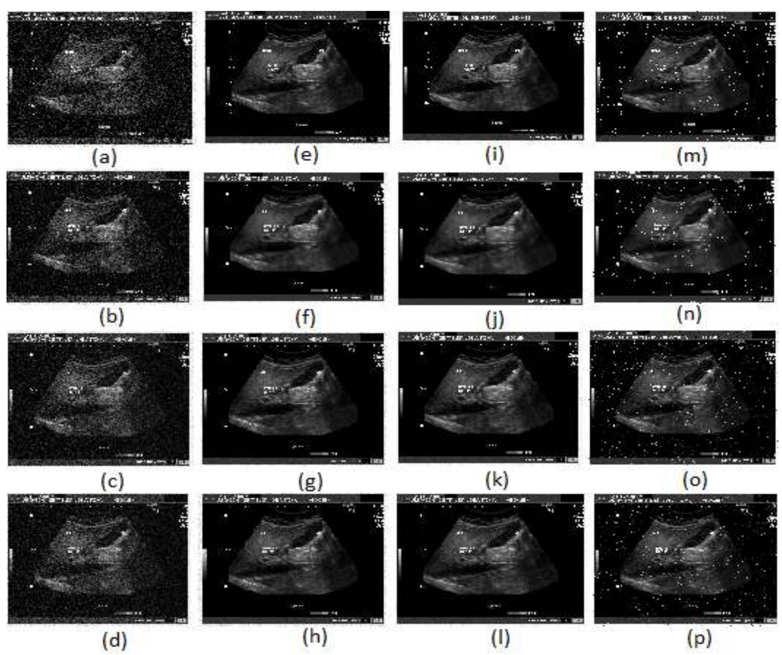


Fig. 3: Results obtained on applying different methods on ultrasound images corrupted by different types of noise at a variance of 0.02, from (a) to (d), shows (a) Gaussian noise, (b) Bilateral filter, (c) BayesShrink, (d) NormalShrink. Images from (e) to (h) for Speckle noise, from (i) to (l) for Poisson noise and from (m) to (p) for Impulse noise

bilateral filter gives better results than the single resolution bilateral filter.

CONCLUSION

In this study, we proposed an image denoising framework which combines multiresolution bilateral filtering and wavelet thresholding. In this framework, we decompose an image into low and high frequency parts and bilateral filtering is applied on the approximation subband and wavelet thresholding on the detail subbands. The algorithm is tested against ultrasound images of gall bladder corrupted by different types of noise namely gaussian, speckle, poisson and impulse. The result shows that bilateral filter performs better in multiresolution nature than that of the single resolution one and also from the other methods when compared. The proposed algorithm performs better with speckle and poisson noise at 2- level of decomposition. However, the proposed algorithm does not give satisfactory results with other noise when compared with the MBF in combination with BayesShrink. On comparing the results for 1 and 2- decomposition level, the algorithm presented gives better result at 2-decomposition level i.e., with increase in decomposition levels this algorithm is effective in eliminating noise but results in overly smoothed images.

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