SPECKLE NOISE REDUCTION USING HYBRID TMAV BASED FUZZY FILTER

Nagashettappa Biradar[1], M.L.Dewal[2], ManojKumar Rohit[3]

[1]*Research Scholar, Electrical Engineering Department, Indian Institute of technology Roorkee, Roorkee, India*
[2]*Professor, Electrical Engineering Department, Indian Institute of technology Roorkee, Roorkee, India*
[3]*Professor, Cardiology Department, PGIMER, Chandigarh, Punjab, India*

Abstract

The multiplicative nature of speckle noise present in imaging modalities like echocardiography complicates the despeckling procedure as it would be necessary to remove noise with the edges well preserved. A novel speckle reduction technique based on integration of moving average filter using fuzzy triangulation membership function (TMAV) with moving average center with wiener filter is proposed and analyzed in this paper. Fuzzy TMAV filter is experimented for reduction of speckle noise in homomorphic domain. Denoising features of this filter are fine tuned by sequentially embedding it with wiener filter. This hybrid TMAV filters result in the enhancement of edges with higher amount of noise reduction. The performance of proposed filter is compared with ten state-of-art denoising techniques. Figure of merit (FOM), structural similarity (SSIM) index along with traditional parameters are superior for hybrid fuzzy filters in comparison to methods like probability patch based (PPB), Non-local means (NLM), and posterior sampling based Bayesian estimation (PSBE) based filters.

Keywords: *Speckle reduction, TMAV based fuzzy filter, Wiener filter, Hybrid Fuzzy filter, Edges preservation*

---***---

1. INTRODUCTION

Multiplicative noise in the coherent imaging modalities like synthetic aperture RADAR (SAR), laser, remote sensing, optical coherence tomography (OCT), and ultrasound (US) proposes lot of difficulties like masking of finer details and abrogating human interpretation due to low contrast and low visibility. It is therefore necessary to incorporate post processing steps to remove noise with edge preservation and enhance the contrast of the images [1-5].

The omnipresence of noise has lead to development of various types of filters based on the principles like anisotropic diffusion (AD) [2, 6], wavelets [1, 3, 5, 7], adaptive filters like enhanced Lee, enhanced Frost, wiener [1, 2, 4, 5, 7], homomorphic[1, 7], Bayesian estimation [3], and non-local (NL) means [8]. Each of the filters behaves differently with different types of images offering their own advantages and drawbacks; compelling researchers to fine tune each for its variants.

Basic noise reduction techniques like median filter, adaptive weighted median filter (AWMF), and moving average (MAV) filter are very popular for additive noise removal but their application on ultrasound images are less researched [1]. Poor noise removing capacity, loss of finer image details, selection of appropriate window size and shape are the basic issues which need to be sorted out in basic techniques [1, 3, 5, 9]. The denoising characteristics of spatially adaptive wiener filter for additive Gaussian denoising are highly acceptable. It is put to use for speckle noise reduction in homomorphic scheme. Homomorphic wiener filter is used by many researchers for comparison of despeckling results obtained by their respective methods [5, 7, 10, 11].

Noise reduction capability of diffusion based despeckling is under question when noise contamination is higher as in the cases of OCT [3]. An extension of NLM filter was proposed by Deledalle et al. [12] by incorporating noise distribution model instead of computing Euclidean distance for pixel similarity calculations. Fuzzy filters incorporating the concepts moving average and median were tested and proven to be effective in reducing various types of additive noise [13, 14] but are not extensively experimented for multiplicative noise reduction. The performance of fuzzy filters are being reported only in-terms of MSE and number of looks (ENL)[13, 14] , but in medical image applications it is necessary to preserve edges like medical images [1].

To address the issue of speckle noise reduction in general and fine tune the denoising characteristics of fuzzy filter in particular, an integrated despeckling technique based on the sequential combination of TMAV based fuzzy filter with adaptive wiener filter in homomorphic domain is being proposed, and analyzed in this paper. Also, in this paper the performance of proposed method is expressed in terms of seven performance parameters along with visual quality assessment. Importance is being to edge preservation, overall quality of denoised image and the structural integrity is maintained.

2. MODELING EMPLOYED FOR DENOISING

The multiplicative speckle noise is modeled as

$$f(i,j) = g(i,j)n(i,j) \tag{1}$$

Where $g(i,j)$ is noise free image, $f(i,j)$ is the acquired image and $n(i,j)$ is the multiplicative noise, i and j are the variables indicating the spatial locations [1, 15].

The process of converting multiplicative noise to approximated additive noise is performed by projecting the image into logarithmic space [1]

$$\begin{aligned}\log[f(i,j)] &= \log[g(i,j)n(i,j)] \\ &= \log\{g(i,j)\} + \log\{n(i,j)\}\end{aligned} \tag{2}$$

The above eq.(2) is rewritten with $f_{ij} = \log[f(i,j)]$,

$g_{ij} = \log\{g(i,j)\}$ and $n_{ij} = \log\{n(i,j)\}$ as

$$f_{ij} = g_{ij} + n_{ij} \tag{3}$$

This provision using eq.(3) makes way for application of methods developed for additive white Gaussian noise, to be tested and analyzed on images under the curse of multiplicative noise. In these methods the input is a logarithmic transformed, $f(i,j) = \log(f(i,j))$ and output is being obtained by taking the exponential of denoised image,

$$\hat{g}(i,j) = \exp(MX(\log(f(i,j))) \tag{4}$$

Where MX represents filter being used

2.1 Fuzzy Filters

Median filter effectively suppresses the speckle noise but the edges are not well preserved [13, 14]. Fuzzy filters with moving average center preserve image sharpness but the edges are not preserved. To address this issue it is proposed to integrate the noise reduction capabilities of wiener filter with fuzzy filter.

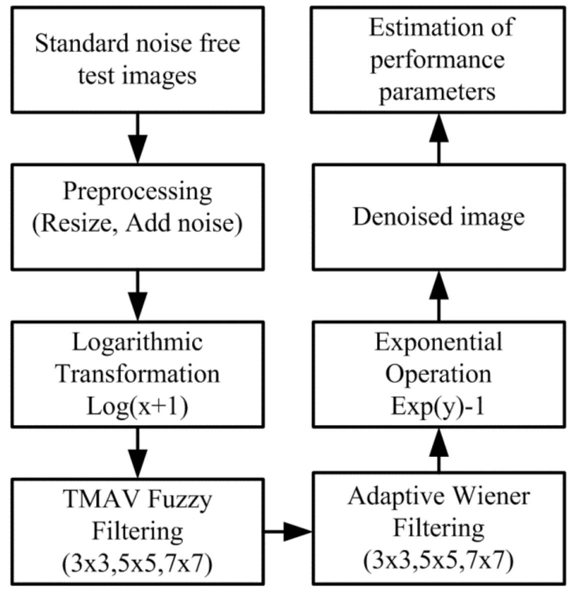

Fig-1: Proposed hybrid TMAV based fuzzy filter

2.2 Proposed Hybrid TMAV Based Fuzzy Filtering Algorithm

The block diagram of proposed hybrid TMAV based fuzzy filter is shown in Fig.1 and each of the step incorporated in the implementation are stepwise described below:

Step 1: Consider standard noise free image, resize the image size to 512x512, convert it to gray scale and embed each of the image with synthetic speckle noise.

Step 2: Project the noisy image into the logarithmic space according to eq.(2). The output is of the form f=log(double(f)+1); where f is noisy image .

Step 3: Median value are calculated using fuzzy triangulation membership function with moving average center (TMAV) defined by eq.(5) and eq.(6) with different window and padding size.

$$F\left[f(i+r,j+s)\right] = \left\{\begin{array}{l} 1 - \dfrac{\left|f(i+r,j+s) - f_{mav}(i,j)\right|}{f_{mv}(i,j)}, \\ for \left|f(i+r,j+s) - f_{mav}(i,j)\right| \le f_{mv}(i,j) \\ 1,\ for\ f_{mv} = o \end{array}\right\} \tag{5}$$

$$f_{mv}(i,j) = \max[f_{\max}(i,j) - f_{mav}(i,j), \\ f_{mav}(i,j) - f_{\min}(i,j)] \quad (6)$$

The maximum, minimum and moving average values are respectively represented by $f_{\max}(i,j)$, $f_{\min}(i,j)$, and $f_{mav}(i,j)$ with $s,r \in A$, the window at indices (i,j).

Step 4: The output of the fuzzy TMAV filter are estimated using eq.(7) given below:

$$y(i,j) = \frac{\sum_{(r,s)\in A} F[f(i+r, j+s)].f(i+r, j+s)}{\sum_{(r,s)\in A} F[f(i+r, j+s)]} \quad (7)$$

Where $F[f(i,j)]$ and A are the window function and area respectively.

Step 5: Output of fuzzy filter is passed through adaptive wiener filter with different window size.

Step 6: The output of fuzzy filter is projected back to the non-logarithmic space using exponential operation which is represented by Ydenoised=exp(y)-1.

Step 7: Performance parameter computation and result analysis using eq.(8) to eq.(14) along with visual quality assessment.

The above steps are being repeated for different levels of noise artificially added on to the noise free images and for different window size of fuzzy and wiener filters varying in the range 3x3, 5x5, 7x7 and 9x9.

All experimentations are performed using seven standard test images of Lena, Mandril, Cameraman, Barbara, Monarch, Woman dark hair and House of size 512x512 [12]. Synthetic noise is being embedded to each of these images using matlab inbuilt function imnoise with variance varying from 0.01 to 0.5. The matlab inbuilt function wiener2 is employed for wiener filtering and experimentations are performed with different combination of window size of both fuzzy and wiener filters. All the experimentations are being performed using MATLAB R2010a.

3. RESULTS AND DISCUSSIONS

The denoising capabilities of fuzzy filter, wiener filter and proposed filtering technique are evaluated using peak signal to noise ratio (PSNR), mean square error (MSE), correlation coefficient (ρ) and signal to noise ratio (SNR) using original image f_{ij} and denoised image g_{ij} [1, 2]. The edge preservation and distortion of images is measured using figure of merit (FOM), beta metric (β) and structural similarity (SSIM) index[2, 16]. The parameters are defined as follows:

$$\text{PSNR} = 20 \text{ x} \log\left(255 \Big/ \sqrt{\text{MSE}(f_{ij}, g_{ij})} \right) \quad (8)$$

$$\text{MSE} = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} \left(f(i,j) - g(i,j) \right)^2 \quad (9)$$

$$\text{SNR} = 10 \text{ x} \log\left(\text{var}(f_{ij}) \Big/ \text{MSE}(f_{ij}, g_{ij}) \right) \quad (10)$$

$$\text{FOM} = \frac{1}{\max(n_d, n_r)} \sum_{j=1}^{n_d} \frac{1}{1+\gamma d_j^2} \quad (11)$$

$$\rho = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} g_{ij}.f_{ij}}{\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N} g_{ij}^2}\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N} f_{ij}^2}} \quad (12)$$

$$\beta = \frac{D(\Delta g - \overline{\Delta} g, \Delta f - \overline{\Delta} f)}{\sqrt{D(\Delta g - \overline{\Delta} g, \Delta g - \overline{\Delta} g).D(\Delta f - \overline{\Delta} f, \Delta f - \overline{\Delta} f)}} \quad (13)$$

$$\text{SSIM} = \frac{(2\sigma_{f,g} + c_2)(2\overline{l} \text{ x } \overline{l} + c_1)}{(\sigma_f^2 + \sigma_g^2 + c_2)(\overline{l}^{\,2} + \overline{l}r^2 + c_1)} \quad (14)$$

Where γ is the scalar multiplier being utilized as penalization factor with typical value 1/9, nd and nr are the number of pixels in original and processed images respectively, d_j is the Euclidean distance, Δg and Δf represent the filtered version of original and processed images, pixel mean intensities in the region Δg, Δf are represented by $\overline{\Delta} g$ and $\overline{\Delta} f$ respectively, and $c_1 = (K_1 \text{x} L)^2$, $c_2 = (K_2 \text{x} L)^2$.

Table -1: Comparison of performance parameters obtained proposed hybrid TMAV based fuzzy filter

Metric	Image	Without filter	Wiener Filter	Fuzzy TMAV Filter	Proposed Filter
SSIM	Lena	0.5733	0.7394	0.8356	0.8576
	Monar	0.6742	0.8192	0.8855	0.8862

	House	0.4569	0.6512	0.8238	0.8445
	DHair	0.6173	0.7978	0.9126	0.9206
FOM	Lena	0.3833	0.4913	0.8219	0.8338
	Monar	0.4440	0.5517	0.8536	0.8547
	House	0.3393	0.3896	0.5101	0.5727
	DHair	0.3792	0.4285	0.6259	0.7481
ρ	Lena	0.9767	0.9963	0.9963	0.9965
	Monar	0.9768	0.9965	0.9955	0.9953
	House	0.9765	0.9968	0.9986	0.9988
	DHair	0.9784	0.9967	0.9983	0.9984
SNR	Lena	26.370	41.987	39.202	39.334
	Monar	26.456	42.405	37.247	36.688
	House	26.293	43.261	44.829	44.963
	DHair	27.247	42.342	41.634	41.638
MSE	Lena	849.082	140.62	193.78	190.86
	Monar	738.898	117.79	213.31	227.513
	House	1024.85	145.30	121.29	119.437
	DHair	669.937	117.83	127.84	127.793
IQI	Lena	0.2781	0.4286	0.4610	0.4839
	Monar	0.3232	0.5438	0.6151	0.6309
	House	0.1491	0.3365	0.3892	0.4002
	DHair	0.1667	0.4000	0.5320	0.5589
PSNR	Lena	18.841	26.650	25.258	25.324
	Monar	19.445	27.419	24.841	24.561
	House	19.149	24.033	21.920	22.082
	DHair	19.870	27.418	27.064	27.066

Table- 2: Comparison of IQI, PSNR, FOM, SSIM

Ref.	Filter Name	Performance parameter			
		IQI	PSNR	FOM	SSIM
[17]	Geometric	0.2630	17.94	0.3507	0.5202
[11]	Wiener	0.3702	23.45	0.3888	0.6263
[18]	OWT	0.3042	19.78	0.3604	0.6096
[19]	BayesShrink	0.4470	26.97	0.5193	0.7454
[20]	Curvelet	0.3025	19.73	0.3651	0.6070
[3]	PSBE	0.3032	19.76	0.3813	0.6101
[8]	NLM	0.4230	23.34	0.5931	0.7884
[12]	PPB	0.3880	24.94	0.6517	0.7949
[21]	PMAD	0.3111	19.95	0.3848	0.6138
[22]	CED	0.4231	23.46	0.4166	0.6843
Proposed		0.4290	22.16	0.6911	0.8032

The performance parameters of proposed hybrid TMAV based fuzzy filter are compared with fuzzy filter and wiener filter (WF) in Table 1. Analysis of results tabulated in Table 1 and Table 2 reveals that adaptive wiener filter in homomorphic domain is superior compared to fuzzy TMAV filter terms of traditional parameters like SNR and PSNR.

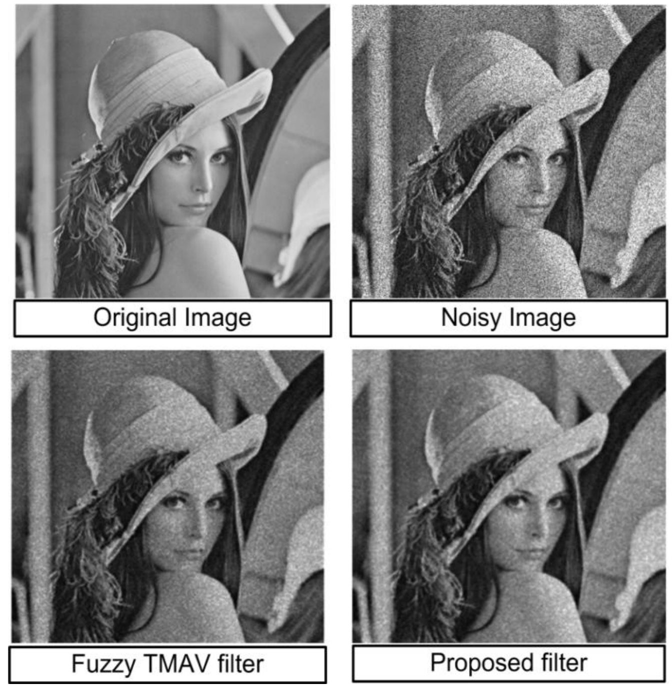

Fig-3: Comparison of visual quality of Lena image at σ=0.1 for Fuzzy TMAV filter, WF and proposed filter

But the performance of fuzzy filter is superior in-terms of IQI, SSIM and FOM. It is also observed that performance of the proposed hybrid algorithm is superior compared to both fuzzy and wiener filters in terms of both edge preservation and noise reduction for all noise levels and images. The values of SSIM, FOM, IQI and ρ are enhanced with the integration of fuzzy filter with wiener filter. Denoising results obtained for noise variance equal to 0.1 are compared in Table 1. The results obtained for various values of noise variance ranging from 0.01 to 0.5. Improvements are noise at higher values of noise variance using proposed denoising technique. It is also observed that with lower noise levels embedding of wiener filter results in over-smoothing but the edges and structure of the images are well preserved. FOM and IQI obtained using proposed method is almost double that of noisy filter. The value of correlation coefficient $\rho \geq 0.99$ for all images shows that the input and output values are highly correlated.

Based on the analysis of results in Table 1, it can be concluded that embedding of wiener filter in fuzzy TMAV filter edge preservation and structural similarity are enhanced. The visual quality of denoised Lena image using fuzzy filter and proposed filters are compared in Fig.1 for noise variance equal to 0.1 and it is observed that large amount of noise is retained in fuzzy filters.Noise reduction is more pronounced using proposed filters as clearly observed from Fig.1. The performance of proposed hybrid TMAV based fuzzy filter is compared with 10 state-of-art denoising techniques in Table 2.

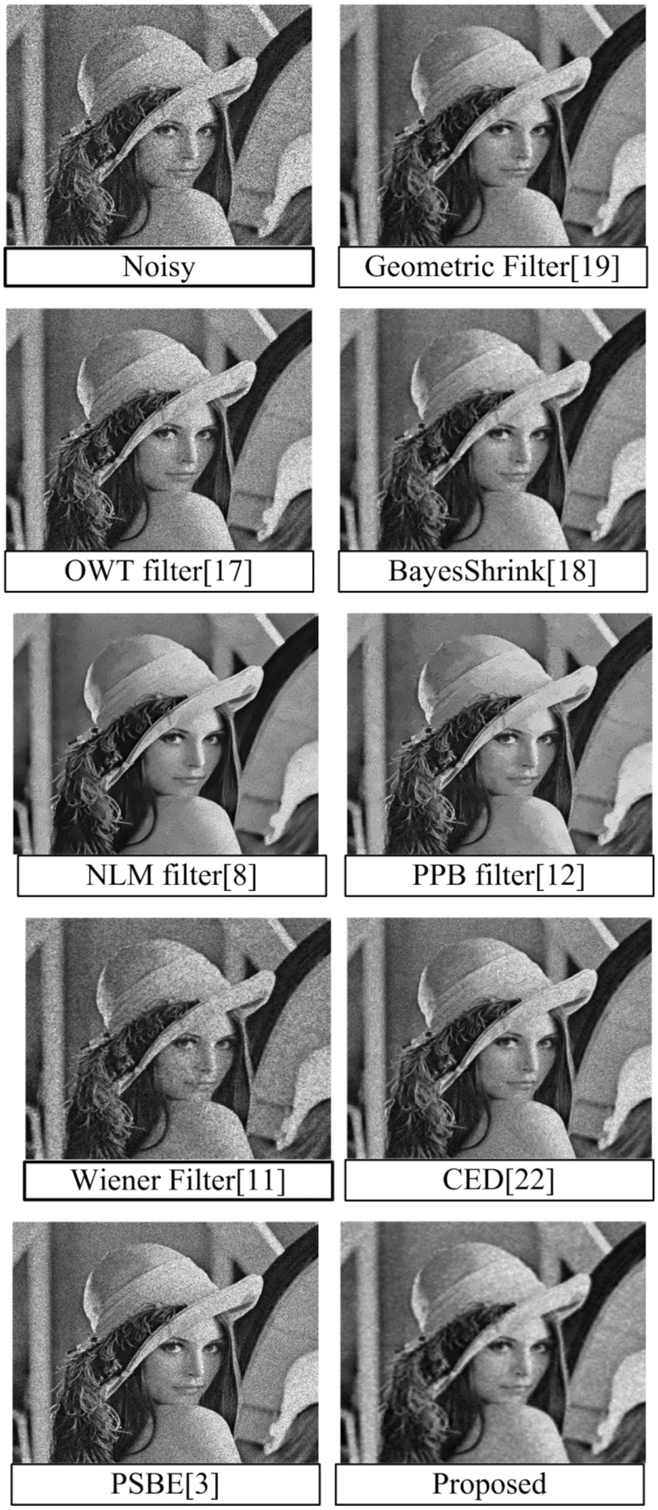

Fig-4: Visual quality comparison between proposed and other denoising techniques

The Matlab functions provided by the authors of NLM [8], PPB [12], orthogonal wavelet thresholding (OWT) [18], and Bayes shrinkage (BayesShrink) [19], are being used for the purpose of comparing the results. The visual quality of the denoised images using proposed method and state-of-art denoising techniques are compared in Fig.3. PSNR of proposed method is higher compared to geometric filter operated with four iterations, OWT, curvelet, logarithmic PSBE and inferior compared to BayesShrink, NLM, PPB, and CED based denoising techniques. IQI of proposed method is superior compared to all methods except for BayesShrink based denoising. SSIM and FOM obtained for hybrid TMAV based filter are superior in comparison to all other methods tabulated in Table 2.

4. CONCLUSIONS

The edge preservation capabilities of TMAV based fuzzy filter are enhanced with integration of wiener filters. Not only the edges, structures are well preserved but also higher amount of speckle noise is removed using the proposed integration techniques. The proposed denoising scheme would be useful for edge preserved denoising of images acquired from the coherent imaging modalities but with fractionally higher computation time. Comparison of performance parameters and visual quality assessment reveals that proposed scheme is the refined versions of fuzzy filter in terms of noise reduction and edge preservation. Improvement in the performance is proved with enhanced IQI, FOM and SSIM parameters along with visual quality.

CONFLICT OF INTEREST

NagashettappaBiradar, M.L.Dewal, and ManojKumarRohit declare that they have no conflict of interest.

ACKNOWLEDGEMENTS

The authors are thankful to BKIT,Bhlaki for sponsoring the first author to pursue PhD with financial assistance.

REFERENCES

[1] Mateo, J.L., and Fernández-Caballero, A.: ‘Finding out general tendencies in speckle noise reduction in ultrasound images’, Expert Systems with Applications, 2009, 36, (4), pp. 7786-7797

[2] Finn, S., Glavin, M., and Jones, E.: ‘Echocardiographic speckle reduction comparison’, Ultrasonics, Ferroelectrics and Frequency Control, IEEE Transactions on, 2011, 58, (1), pp. 82-101

[3] Wong, A., Mishra, A., Bizheva, K., and Clausi, D.A.: ‘General Bayesian estimation for speckle noise reduction in optical coherence tomography retinal imagery’, Opt. Express, 2010, 18, (8), pp. 8338-8352

[4] Qiu, F., Berglund, J., Jensen, J.R., Thakkar, P., and Ren, D.: ‘Speckle noise reduction in SAR imagery using a local adaptive median filter’, GIScience& Remote Sensing, 2004, 41, (3), pp. 244-266

[5] Ozcan, A., Bilenca, A., Desjardins, A.E., Bouma, B.E., and Tearney, G.J.: ‘Speckle reduction in optical coherence tomography images using digital filtering’, JOSA A, 2007, 24, (7), pp. 1901-1910
[6] Yu, Y., and Acton, S.T.: ‘Speckle reducing anisotropic diffusion’, Image Processing, IEEE Transactions on, 2002, 11, (11), pp. 1260-1270
[7] Nicolae, M.C., Moraru, L., and Onose, L.: ‘Comparative approach for speckle reduction in medical ultrasound images’, Romanian j. biophys, 2010, 20, (1), pp. 13-21
[8] Coupé, P., Hellier, P., Kervrann, C., and Barillot, C.: ‘Nonlocal means-based speckle filtering for ultrasound images’, Image Processing, IEEE Transactions on, 2009, 18, (10), pp. 2221-2229
[9] Czerwinski, R.N., Jones, D.L., and O'Brien Jr, W.D.: ‘Ultrasound speckle reduction by directional median filtering’, ConfProc IEEE Image Processing. 1995; 358-61.
[10] Gupta, S., Chauhan, R., and Sexana, S.: ‘Wavelet-based statistical approach for speckle reduction in medical ultrasound images’, Medical and Biological Engineering and computing, 2004, 42, (2), pp. 189-192
[11] Pizurica, A., Philips, W., Lemahieu, I., and Acheroy, M.: ‘A versatile wavelet domain noise filtration technique for medical imaging’, Medical Imaging, IEEE Transactions on, 2003, 22, (3), pp. 323-331
[12] Deledalle, C.-A., Denis, L., and Tupin, F.: ‘Iterative weighted maximum likelihood denoising with probabilistic patch-based weights’, Image Processing, IEEE Transactions on, 2009, 18, (12), pp. 2661-2672
[13] Kwan, H., and Cai, Y.: ‘Fuzzy filters for image filtering’, ConfProc IEEE Circuits and Systems. 2002. 3: III-672-5.
[14] Kwan, H.K.: ‘Fuzzy filters for noise reduction in images’: Fuzzy Filters for Image Processing. Springer Berlin Heidelberg.2003; 25-53.
[15] Zong, X., Geiser, E.A., Laine, A.F., and Wilson, D.C.: ‘Homomorphic wavelet shrinkage and feature emphasis for speckle reduction and enhancement of echocardiographic images’, ConfProc SPIE1996; 658-67.
[16] Mittal, D., Kumar, V., Saxena, S.C., Khandelwal, N., and Kalra, N.: ‘Enhancement of the ultrasound images by modified anisotropic diffusion method’, Medical & biological engineering & computing, 2010, 48, (12), pp. 1281-1291
[17] Luisier, F., Blu, T., and Unser, M.: ‘A New SURE Approach to Image Denoising: Interscale Orthonormal Wavelet Thresholding’, Image Processing, IEEE Transactions on, 2007, 16, (3), pp. 593-606
[18] Chang, S.G., Yu, B., and Vetterli, M.: ‘Adaptive wavelet thresholding for image denoising and compression’, Image Processing, IEEE Transactions on, 2000, 9, (9), pp. 1532-1546
[19] Crimmins, T.R.: ‘Geometric filter for speckle reduction’, Applied optics, 1985, 24, (10), pp. 1438-1443
[20] Starck, J.-L., Candès, E.J., and Donoho, D.L.: ‘The curvelet transform for image denoising’, Image Processing, IEEE Transactions on, 2002, 11, (6), pp. 670-684
[21] Perona, P., and Malik, J.: ‘Scale-space and edge detection using anisotropic diffusion’, Pattern Analysis and Machine Intelligence, IEEE Transactions on, 1990, 12, (7), pp. 629-639
[22] Weickert, J.: ‘Coherence-enhancing diffusion filtering’, International Journal of Computer Vision, 1999, 31, (2-3), pp. 111-127