Block Based thresholding in Wavelet Domain for Denoising Ultrasound Medical Images

P.V.V.Kishore MIEEE, A.S.C.S.Sastry, A.Kartheek, Sk.Harshad Mahatha
Dept. of E.C.E, K.L. University, Green Fields, Vaddeswaram, Guntur DT, INDIA

***Abstract*—Medical ultrasound imaging has transformed the disease identification in the human body in the last few decades. The major setback for ultrasound medical images is speckle noise. Speckle noise is created in ultrasound images due to numerous reflections of ultrasound signals from hard tissues of human body. Speckle noise corrupts the medical ultrasound images dropping the detectable quality of the image. An endeavor is made to recover the image quality of ultrasound medical images by using block based hard and soft thresholding of wavelet coefficients. Medical ultrasound image is transformed to wavelet domain using debauchee's mother wavelet. Divide the approximate and detailed coefficients into uniform blocks of size 8×8, 16×16, 32×32 and 64×64. Hard and soft thresholding on these blocks of approximate and detailed coefficients are applied. Inverse transformation to original spatial domain produces a noise reduced ultrasound image. Experiments were conducted on medical ultrasound images obtained from diagnostic centers in Vijayawada, India. Quality of improved images in measured using peak signal to noise ratio (PSNR), image quality index (IQI), structural similarity index (SSIM).**

***Keywords*—Ultrasound medical imaging; speckle noise; wavelet transform; hard and soft thresholding; block processing;**

I. INTRODUCTION

Medical ultrasound imaging [1]-[3] has been employed extensively to diagnostics of internal human body parts invasively. Ultrasound imaging tool has been cost effective, portable and time saving. Computed Tomography (CT), Magnetic Resonance Imaging (MRI) produce quality images compared to ultrasound imaging. Drawbacks include high operating costs along with dangerously harmful electromagnetic radiations. With the advent of signal processing algorithms demand for ultrasound image enhancements are on the high among the research communities around the world[4].

Image quality is the primary concern in ultrasound imaging due to the presence of speckle signals that are picked up by the receiver from the hard tissues in the human body[5]-[6]. To understand and investigate ultrasound images in order to obtain quantitative information from them is a daunting task even for a trained eye. Safety and inexpensive nature of ultrasound technology is the reason behind their extensive use in many clinical applications. The challenge before researchers is to appendage medical ultrasound images for legitimate and accurate information for diagnosis [7].

Medical ultra sonographic images are meagerly visible as the scanning process results in speckle noise [8] which occurs especially in the images of fetus of pregnant woman, whose underlying structures are too small to be resolved by large wavelengths [9]. Thus speckle reduction (de-speckling)is an important characteristic for analysis of ultrasound images. Many algorithms have been developed on despeckling in spatial[10] and transformed[11] domains in last decade. The algorithms in literature offer good denoising leaving their effect on the edges of the objects in the image.

Some of these techniques use the concepts of partial differential equations and computational fluid dynamics such as level set methods[12], total variation methods [13], nonlinear isotropic and anisotropic diffusion[14].

The most widely used techniques for denoising in image processing are wavelet transform based hard and soft thresholding [15][16]. These two techniques operate globally on images damaging high frequency content of the objects in an ultrasound image. To make these two operations local we propose to use block based wavelet domain hard and soft thresholding on ultrasound medical images. This procedure will reduce noise locally thus preserving the high frequency edge information. The ultrasound medical image is enhanced for quality viewing which offers momentum to a rather slow diagnostics. Debauches mother wavelet at level-2 is used for the all the transformation from spatial domain to wavelet domain. Performance of the proposed techniques is evaluated visually and quantitatively by computing peak signal to noise ratio (psnr), image quality index(IQI) and structures similarity index(SSIM)[17].

The rest of the paper is organized as follows. Section 2 briefly introduces 2D discrete wavelet transform and block based soft and hard thresholding techniques used for noise reduction. Section 3 handles experimental results for real ultrasound medical images from radiology labs. Conclusions are put together in section 5 based on the discussions in section 4.

II. DE-NOISING WITH BLOCK THRESHOLDING ON WAVELETS

The DWT [18]-[20] approximate coefficients for a 2D signal I(x,y) is formulated as

$$A^L = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1} I(x,y)\psi^L{}_{ab}(x,y) \tag{1}$$

And the detailed coefficients are formulated as

$$D^L = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1} I(x,y)\psi^L{}_{a,b}(x,y) \tag{2}$$

Wavelet decomposition level L can be iteratively used to putrefy the image into various frequency planes.

Hard Thresholding is the simplest form of thresholding where the threshold value is chosen by the user. Hard thresholding is applied on the detailed coefficients using the formulation $D_m{}^L(i,j) = \begin{cases} D(i,j) & \text{if } |D(i,j)| > \mathrm{T} \\ 0 & \text{if } |D(i,j)| \leq \mathrm{T} \end{cases}$

(3)

Where $D_m(i,j)$ are the modified or thresholded coefficients at level L at location (i,j). T is the soft threshold value. In this research the soft threshold value is computed using the following equation.

$$\mathrm{T}^L = \frac{\max(\max(D^L)}{M} \quad (4)$$

Threshold value changes with wavelet level of decomposition. M is the maximum number of gray levels in the original image. T is the maximum value in the detailed coefficients.

Soft thresholding – 1, according to [25], the threshold value is computed as

$$\mathrm{T} = \chi\sqrt{2\log(M)} \quad (5)$$

Where M is the number of pixels in the image and χ is estimated as

$$\chi = \frac{|median(I(x,y))|}{0.6745} \quad (6)$$

From eq.9 numerator gives the absolute of median values of original Ultrasound medical image under consideration.

Soft thresholding – 2 is similar to that of 1, with a change in χ value which is estimated as

$$\chi = \frac{|median(D^L)|}{0.6745} \quad (7)$$

In soft thresholding – 2, χ is estimated as absolute median values of detailed coefficients.

Soft thresholding – 3 is computed on detailed coefficients of wavelet transformed ultrasound medical image using the following expression

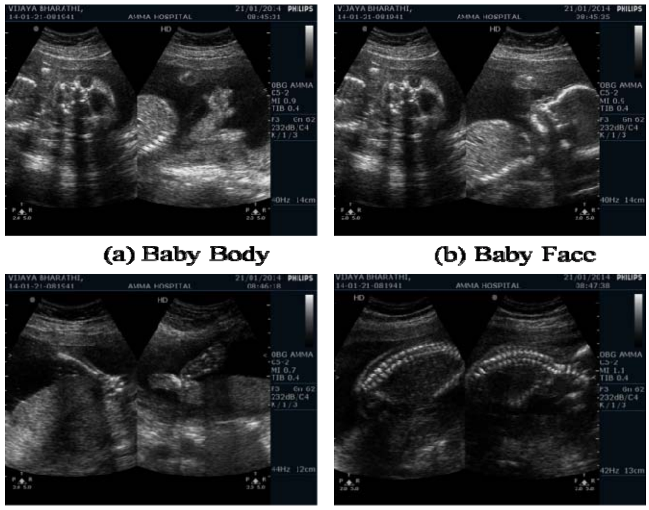
$$D_m{}^L(i,j) = \begin{cases} \mathrm{sgn}\left(D^L(i,j) \times (\left|D^L(i,j)\right| - \mathrm{T}\right) & \text{if } |D(i,j)| > \mathrm{T} \\ 0 & \text{if } |D(i,j)| \leq \mathrm{T} \end{cases} \quad (8)$$

Where sgn() is a signum function. Where $D_m(i,j)$ are the modified or thresholded coefficients at level L at location (i,j). T is the hard threshold value.

III. De-noising Results and Discussions

The choice of mother wavelet in this research is cut across orthogonal and bi-orthogonal functions. 'Haar', 'db2', 'sym3' and 'bior1.1' are 4 mother wavelets that are used for experimentation in this work. For this part the decomposition level is kept at one.

The set of ultrasound images on which the following experimentation is carried out are shown in figure 1. The images are obtained in .png format from AMMA Hospital, Ultrasound Lab, Vijayawada, Andhra Pradesh, INDIA. Figure 1(a) is ultrasound image of baby body of a healthy pregnant female. Similarly figures 1(b), 1(c) and 1(d) are ultrasound scans of baby face, legs and spinal cord. The considered pregnant female is around six months pregnant[21]-[22].



(a) Baby Body (b) Baby Facc

(c) Baby Legs (d) Baby Spinal Cord

Fig. 1: Ultrasound Test Images used in this experimentation

Wavelet transforming ultrasound images with mother wavelets 'Haar', 'db2', 'sym3' and 'bior1.1' respectively. Out of the 4 mother wavelets proposed 'db2' has produced good quality images visually. Hence we present results pertaining to mother wavelet 'db2'.

The following figures from 2-3 show the response of the proposed thresholding pardigrams on various ultrasound medical images. The first row is original ultrasound image. The second row consisting of thresholding techniques applied on original ultrasound image. The third row is fused ultrasound images. The figures show a improved quality in visual content compared to original ultrasound image.

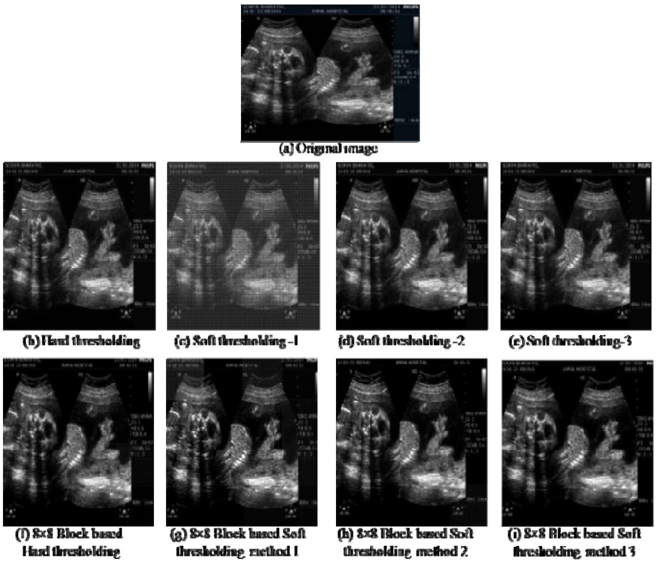


Fig.2: Body (a) Original Ultrasound Image (b) Hard Threshold (c) Soft Thresholding -1 (d) soft Thresholding -2 (e) Soft Thresholding -3. (f) Block Based Hard Threshold (g) Block Based Soft Thresholding -1 (h) Block Based soft Thresholding -2 (i) Block Based Soft Thresholding -3.

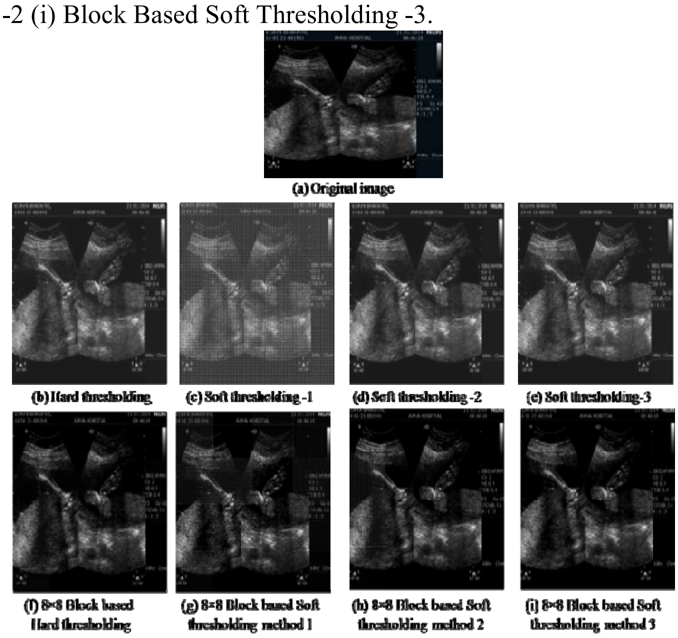


Fig.3: Legs (a) Original Ultrasound Image (b) Hard Threshold (c) Soft Thresholding -1 (d) soft Thresholding -2 (e) Soft Thresholding -3. (f) Block Based Hard Threshold (g) Block Based Soft Thresholding -1 (h) Block Based soft Thresholding -2 (i) Block Based Soft Thresholding -3.

There is no big difference in image quality at level-2 wavelet decomposition. However as the level of decomposition increases the reconstructed image lost edges and therefore reduction in image quality was observed. The radiologist at AMMA hospital was indeed impressed with the results and the processed images helped doctors access the condition of the patient faster than the usual. Choosing the correct block size impacts the outcome of the result.

But the blocking artifacts due block processing do not cause much of problem visually to a human visual system. The proposed block based thresholding in wavelet domain for denoising ultrasound images is tested against traditional denoising algorithms such as linear filter with gaussian kernel (lf), adaptive wiener filter(wf) and median filter(mf) in wavelet domain as shown in figure 4.

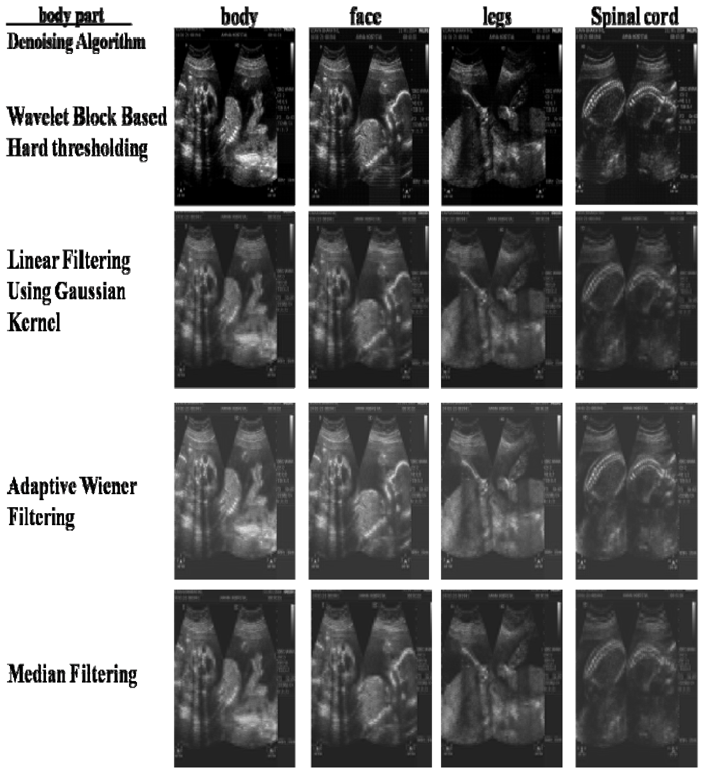


Fig.4: Comparison of Proposed Block based hard thresholding in wavelet domain with other popular denoising methods, linear filtering with gaussian kernel(lf), adaptive wiener filtering(wf) and Median filtering (mf) in wavelet domain.

Figure 4 demonstrates the effectiveness of our proposed algorithm against popular denoising algorithms.

Visually good results for the proposed techniques prompted us to test the quantitatively using math models such as peak signal to noise ratio(PSNR), image quality index(IQI) and structured similarity index(SSIM) for 4 different test images shown in figure1. Table 1 provides the values computed between the proposed de-noising techniques for ‘db2’ wavelet at level -1 for a 8×8 block. From table-1 it can be observed that the values computed for block based thresholding are within acceptable range compared to most of the traditional medical image de-noising techniques

Denoising Algorithm	PSNR	IQI	SSIM	PSNR	IQI	SSIM	PSNR	IQI	SSIM	PSNR	IQI	SSIM
	Body			Face			Legs			Spinal Chord		
Hard Thresholding	35.441	0.831	0.853	35.484	0.799	0.810	36.006	0.764	0.796	35.121	0.877	0.857
Block Based Hard Thresholding	30.212	0.909	0.931	30.255	0.877	0.888	30.777	0.842	0.874	29.892	0.955	0.935
Soft Thresholding 1	33.983	0.832	0.854	34.026	0.800	0.811	34.548	0.765	0.797	33.663	0.878	0.858
Block Based Soft Thresholding 1	28.445	0.931	0.953	28.488	0.899	0.910	29.01	0.864	0.896	28.125	0.977	0.957
Soft Thresholding 2	32.776	0.811	0.833	32.819	0.779	0.790	33.341	0.744	0.776	32.456	0.857	0.837
Block Based Soft Thresholding 2	26.654	0.932	0.954	26.697	0.900	0.911	27.219	0.865	0.897	26.334	0.978	0.958
Soft Thresholding 3	33.434	0.809	0.831	33.477	0.777	0.788	33.999	0.742	0.774	33.114	0.855	0.835
Block Based Soft Thresholding 3	25.854	0.916	0.938	25.897	0.884	0.895	26.419	0.849	0.881	25.534	0.962	0.942
Linear Filtering With Gaussian Kernel	43.580	0.719	0.741	43.623	0.687	0.698	44.145	0.652	0.684	43.26	0.765	0.745
Adaptive Wiener Filtering	39.680	0.754	0.776	39.723	0.722	0.733	40.245	0.687	0.719	39.36	0.800	0.780
Median Filtering	42.900	0.733	0.755	42.943	0.701	0.712	43.465	0.666	0.698	42.58	0.779	0.759

Table-I Performance Evaluation of Proposed De-Noising Methods

IV. CONCLUSION

The focal point of this paper is denoising algorithms for medical ultrasound images using block based hard and soft thresholding in wavelet domain. On field based ultrasound images are obtained and are transformed into wavelet domain using two dimensional filter bank model of wavelet transform. A block based hard thresholding algorithm and three types of soft thresholding algorithms are applied on detailed components of decomposed ultrasound images at level-1. Four types of mother wavelets are used in this process and found that 'db2' preserves the visual quality of the image compared to 'sym', 'haar' and 'biro' wavelets. The visual quality of medical ultrasound images is greatly improved by blocks of various dimensions. 4 different dimensions are proposed in this work such as 8×8, 16×16, 32×32 and 64×64. Block based approach preserves most of the quality information in the image when compared to normal thresholding algorithms. The block based hard thresholding is also compared with traditional image denoising algorithms such as linear filter, adaptive wiener filter and median filter. Comparisons mark the superiority of block based thresholding of detailed wavelet coefficients over other techniques. The qualitative performance of various de-noising techniques is compared with the proposed algorithms by using PSNR, IQI and SSIM values. It was found that 'db2' wavelet with block based soft thresholding -3 outperforms the remaining block based thresholding modalities for de-noising ultrasound medical images with a block size of 8×8.

REFERENCES

[1] Hennersperger, C.; Baust, M.; Waelkens, P.; Karamalis, A; Ahmadi, S.; Navab, N., "Multiscale Tubular Structure Detection in Ultrasound Imaging", *IEEE Transactions on Medical Imaging,* vol.PP, no.99,pp.1-11, 2014.

[2] Rabinovich, A; Friedman, Z.; Feuer, A, "Multi-line acquisition with minimum variance beamforming in medical ultrasound imaging", *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control,*vol.60, no.12, pp.2521-2531, 2013.

[3] Anquez, J.; Angelini, E.D.; Grange, G.; Bloch, I, "Automatic Segmentation of Antenatal 3-D Ultrasound Images", *Biomedical Engineering, IEEE Transactions on* , vol.60, no.5, pp.1388-1400, 2013.

[4] Meriem Hacini; Fella Hachouf; Khalifa Djemal, "A new speckle filtering method for ultrasound images based on a weighted multiplicative total variation", *Signal Processing: Image Restoration and Enhancement: Recent Advances and Applications*, Vol 103,pp. 214-229,2014.

[5] Tianzhu Liang; Lingsing Yung; Weichuan Yu, "On Feature Motion Decorrelation in Ultrasound Speckle Tracking," *Medical Imaging, IEEE Transactions on* , vol.32, no.2, pp.435,448, Feb. 2013

[6] Donati, S.; Martini, G.; Tambosso, T., "Speckle Pattern Errors in Self-Mixing Interferometry", *IEEE Journal of Quantum Electronics,* vol.49, no.9, pp.798-806, Sept. 2013.

[7] Mauldin, F.R.; Dan Lin; Hossack, J.A, "The Singular Value Filter: A General Filter Design Strategy for PCA-Based Signal Separation in Medical Ultrasound Imaging", *IEEE Transactions on Medical Imaging,* vol.30, no.11, pp.1951-1964, 2011.

[8] Tay, P.C.; Garson, C.D.; Acton, S.T.; Hossack, J.A, 'Ultrasound Despeckling for Contrast Enhancement", *IEEE Transactions on Image Processing*, vol.19, no.7, pp.1847-1860, 2010.

[9] Rueda, S, et.al., "Evaluation and Comparison of Current Fetal Ultrasound Image Segmentation Methods for Biometric Measurements: A Grand Challenge", *IEEE Transactions on Medical Imaging*, vol.33, no.4, pp.797-813, 2014.

[10] Abd-Elmoniem, K.Z.; Youssef, A-B.M.; Kadah, Y.M., "Real-time speckle reduction and coherence enhancement in ultrasound imaging via nonlinear anisotropic diffusion", *IEEE Transactions on Biomedical Engineering,* vol.49, no.9, pp.997-1014, 2002.

[11] Rabbani, H.; Vafadust, M.; Abolmaesumi, P.; Gazor, S., "Speckle Noise Reduction of Medical Ultrasound Images in Complex Wavelet Domain Using Mixture Priors", *IEEE Transactions on Biomedical Engineering*, vol.55, no.9, pp.2152-2160, 2008.

[12] Estellers, V.; Zosso, D.; Rongjie Lai; Osher, S.; Thiran, J.; Bresson, X., "Efficient Algorithm for Level Set Method Preserving Distance Function", *IEEE Transactions on Image Processing,* vol.21, no.12, pp.4722-4734, 2012.

[13] Drapaca, C.S., "A Nonlinear Total Variation-Based Denoising Method With Two Regularization Parameters", *IEEE Transactions on Biomedical Engineering*, vol.56, no.3, pp.582-586, 2009.

[14] Abd-Elmoniem, K.Z.; Youssef, A-B.M.; Kadah, Y.M., "Real-time speckle reduction and coherence enhancement in ultrasound imaging via nonlinear anisotropic diffusion", *IEEE Transactions on Biomedical Engineering,* vol.49, no.9, pp.997-1014, 2002.

[15] Jing Jin; Yipeng Liu; Qiang Wang; Shen Yi, "Ultrasonic speckle reduction based on soft thresholding in quaternion wavelet domain," *IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*, pp13-16, 2012.

[16] Cheng Chen; Ningning Zhou, "A new wavelet hard threshold to process image with strong Gaussian Noise", *IEEE Fifth International Conference on Advanced Computational Intelligence (ICACI)*, pp.558-561, 18-20, 2012.

[17] AlZahir, S.; Kashanchi, F., "A new image quality measure", *26th Annual IEEE Canadian Conference on Electrical and Computer Engineering (CCECE)*, pp.1-5, 5-8 May 2013.

[18] Kishore, P.V.V., Venkatram, N., Sarvya, Ch., Reddy, L.S.S., "Medical image watermarking using RSA encryption in wavelet domain," *Networks & Soft Computing (ICNSC), 2014 First International Conference on* , vol., no., pp.258,262, 19-20 Aug. 2014
doi: 10.1109/CNSC.2014.6906662.

[19] Kishore, P.V.V., Sastry, A.S.C.S., Kartheek, A., "Visual-verbal machine interpreter for sign language recognition under versatile video backgrounds," *Networks & Soft Computing (ICNSC), 2014 First International Conference on* , vol., no., pp.135,140, 19-20 Aug. 2014
doi: 10.1109/CNSC.2014.6906696.

[20] Kishore, P. V. V., & Rajesh Kumar, P. (2012). A Video Based Indian Sign Language Recognition System (INSLR) Using Wavelet Transform and Fuzzy Logic. International Journal of Engineering & Technology (0975-4024), 4(5).

[21] Kishore, P. V. V., and P. Rajesh Kumar. "Segment, Track, Extract, Recognize and Convert Sign Language Videos to Voice/Text." *International Journal of Advanced Computer Science & Applications* 3.6 (2012),pp 120-132.

[22] Kishore, P. V. V., L.S.S.Reddy, N.Venkatram Multiresolution Medical Image Watermarking for Telemedicine Applications, International Journal of Digital Image Processing, CiiT Journals, 6(1), pp6-15,2014..