

COMPARATIVE APPROACH FOR SPECKLE REDUCTION IN MEDICAL ULTRASOUND IMAGES[#]

MARIANA CARMEN NICOLAE^{*,**}, LUMINIȚA MORARU^{**}, LAURA ONOSE^{***,**}

*"Buna Vestire" Hospital, Galați, Romania

**Department of Physics, Faculty of Sciences, "Dunărea de Jos" University of Galați,
47, Domnească St, 800008 Galați, Romania

*** Metallurgical High School, Galați, Romania

Abstract. Medical images are often deteriorated by noise due to various sources of interferences and other phenomena that affect the measurement processes in an imaging and acquisition system. Speckle noise is a random mottling of the image with bright and dark spots, which obscures fine details and degrades the detectability of low-contrast lesions. Speckle noise occurrence is often undesirable, since it affects the tasks of human interpretation and diagnosis. On the other hand, its texture carries important information about the tissue being imaged. Speckle filtering is thus a critical pre-processing step in medical ultrasound imagery, provided that the features of interest for diagnosis are not lost. In ultrasound images, the speckle energy is comparable to the signal energy in a wide range of frequency bands. Several speckle reduction techniques are applied to ultrasound images in order to reduce the noise level and improve the visual quality for better diagnoses. The optimum choice of wavelet bases for ultrasound images is investigated in this study. In order to realize a fair comparison, the same analysis for three frequency values is used. The comparison proves that the wavelet transform gives a much better result than both median filtering and homomorphic Wiener filtering methods for speckle reduction of ultrasound images.

Key words: medical ultrasound, discrete wavelet transform, speckle suppression.

INTRODUCTION

Speckle is a characteristic phenomenon in laser, synthetic aperture radar images, or ultrasound images. Its effect is a granular aspect in the image. Speckle is caused by interference between coherent waves that, backscattered by natural surfaces, arrive out of phase at the sensor [4, 6]. Speckle can be described as random multiplicative noise. It hampers the perception and extraction of fine details in the image. Speckle reduction techniques can be applied to ultrasound

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images in order to reduce the noise level and improve the visual quality for better diagnoses. Several methods have been proposed for speckle reduction. We chose to enhance the ultrasound image using statistical models for both noise and signal. Some other methods use an adaptive technique [8] and others use a statistical approach based on wavelet transform. In [16] a review of wavelet applications in biomedical signals is presented. Some other methods using contrast enhancement [1, 3, 15] were applied to treat multiplicative noise. Wavelet speckle reduction in ultrasound was recently tackled [13, 17], but the approaches used in these methods are based on statistical models, which is costly from a computational and modeling estimation viewpoint.

The paper presents a novel despeckling method, based on wavelet transform, for medical ultrasound images. The proposed method has been compared with the median filter and the Wiener filter. By means of experimental results it has been shown that the present method yields far better results than the two others. For the image quality performance measure we used mean absolute error (MAE) and signal-to-noise ratio (SNR), as they are better measurements for speckle noise.

MATERIALS AND METHODS

Because of the limited capability of a display system, the optical imaging noises, and many other factors, the acquired medical images usually have poor quality. Image enhancement is the procedure used to alter the appearance of an image or the subset of the image for better contrast or visualization of certain features and to facilitate the subsequent image-based medical diagnosis.

There are a variety of image enhancement algorithms available. They are usually categorized into two types: spatial domain- and transform-domain-based methods. The spatial domain methods include image operations on a whole image or a local region based on the image statistics. Histogram equalization, image averaging, sharpening of images using edge detection and morphology operators, and nonlinear median filtering all belong to this category. The other class is a transform-domain-based method because the image operations are performed in the transform domain, such as in the Fourier and wavelet domain. The frequency transform methods facilitate the extraction of certain image features that cannot be derived from the spatial domain. One can manipulate the transformation coefficients in the frequency domain and then recover the image in the spatial domain to highlight interested image contents. As one of powerful image transforms, wavelet approaches have been used for medical image analysis in recent years. We will use the wavelet approaches for image contrast enhancement. Finally, we will discuss how to evaluate the performance of enhancement algorithms and use three different liver ultrasound image enhancements as an example to compare among different image enhancement approaches.

Image enhancement techniques are mathematical techniques that are aimed at realizing improvement in the quality of a given image. The result is another image that demonstrates certain features in a manner that is better in some sense as compared to their appearance in the original image.

A method for speckle reduction of ultrasonic images was described and implemented in the Matlab [2, 10, 16] simulation environment, by using the median filtering, Wiener filtering, and Wavelet transform.

Median filter is a well-used nonlinear filter that replaces the original gray level of a pixel by the median of the gray values of pixels in a specific neighborhood. The median filter is also called the order specific filter because it is based on statistics derived from ordering the elements of a set rather than taking the means. This filter is popular for reducing noise without blurring edges of the image [9]. The noise-reducing effect of the median filter depends on two factors: the spatial extent of the neighborhood and the number of pixels involved in the median calculation.

In many cases, filtering in frequency domain is more straightforward than in spatial domain when reducing noises because noises can be easily identified in frequency domain. When an image is transformed into the Fourier domain, the low frequency components usually correspond to smooth regions or blurred structures of the image, whereas high-frequency components represent image details, edges, and noises. Thus, one can design filters according to image frequency components to smooth images or remove noise [4, 5]. Low-pass filtering will usually smooth images by attenuating high-frequency components, and high-pass filtering will emphasize the image edges or sharp details by attenuating low-frequency components. The Wiener filter is an optimal filter derived under a minimum of mean-squared error criteria [1, 4]. However, the conventional Wiener filter has limitations.

Wavelets are developed in applied mathematics for the analysis of multiscale image structures [14]. Wavelet functions are distinguished from other transformations such as Fourier transform because they not only dissect signals into their component frequencies but also vary the scale at which the component frequencies are analyzed. As a result, wavelets are exceptionally suited for applications such as data compression, noise reduction, and singularity detection in signals.

The application of wavelets to medical image enhancement has been extensively studied. We used the wavelet coefficient transforms and the enhancement algorithms based on these transforms.

From the structural computation point of view, wavelet denoising involves three stages: (1) Compute the DWT (discrete wavelet transform) of the image; (2) Threshold details wavelet coefficients; (3) Compute the IDWT (inverse discrete wavelet transform) to obtain the denoised estimate. The key idea of wavelet shrinkage is that the wavelet representation can separate the signal from the noise.

The choice of wavelet filter bases depends on the signal. Signals coming from different sources have different characteristics. For image signals the best choices of wavelet bases are known. The best choice for ultrasound images is not clear. The problem is to represent typical signals with a small number of convenient computable functions. An investigation to choose the best wavelet bases for ultrasound images was performed here. Some of the wavelets bases existing in Matlab-7 software [2, 10, 16] were tested. The criterion used to determine the best wavelet basis was the one which optimizes the signal-to-noise ratio in a broad spectrum of spatial frequencies.

Generally, speckle noise is modeled as a multiplicative noise. The speckle reduction is done by multiplying wavelet coefficients by a speckle reduction ratio. It should be mentioned that the speckle reduction aims to improve the subjective image quality and the resulting images should look natural [11, 12].

RESULTS

Here we present performance of the proposed method and compare our results with other conventional despeckling methods like the median, and the Wiener. The methods described here were applied on an ultrasound image.

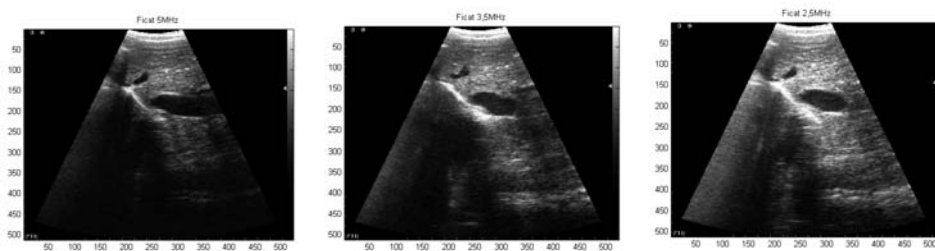


Fig. 1. Original liver ultrasound image.

Figure 1 shows experimental results for 5 MHz, 3.5 MHz and 2.5 MHz frequencies liver image captured from a convex probe. We used several methods for removing speckle. First of them is the classical Wiener filter that is not adequate, since it is designed mainly for additive noise suppression. To address this issue, Jain [7] developed a homomorphic approach which, by taking the logarithm of the image, converts the multiplicative into additive noise, and consequently applies the Wiener filter. Also, the adaptive weighted median filter can effectively suppress speckle but it fails to preserve many useful details, being merely a low-pass filter. We show simulation results obtained by processing ultrasound images.

In order to obtain speckle images, we degraded the original test images by multiplying them with unit-mean random fields. We controlled the correlation length of the speckle by appropriately setting the size of the kernel used to

introduce correlation to the underlying Gaussian noise. In practice uncorrelatedness of the noise could be achieved by decimating the image to the theoretical resolution limit of the imaging device. Thus, a short-term correlation obtained with a kernel of size three was sufficient to model reality. We considered three different levels of simulated speckle noise (Fig. 2). We compared the results of our approach with the classical median filter, and wavelet shrinkage denoising using soft thresholding.

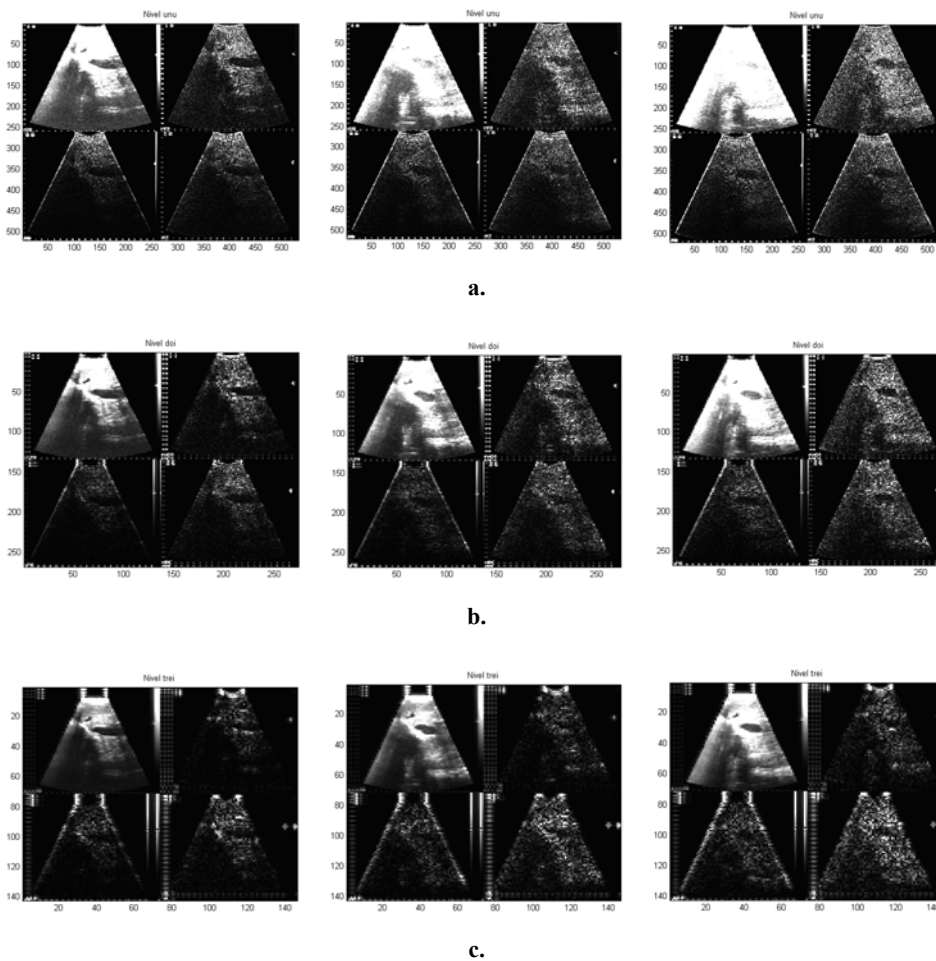


Fig. 2. Three different levels of simulated speckle noise: image degraded (upper left corner) with simulated speckle noise and details.

In the result from homomorphic Wiener filtering in Figure 3, the speckle is reduced well and structures are enhanced. But some details are lost and some are over-enhanced. Meanwhile, in the result given by Median filtering in Figure 4, the

speckle is reduced relatively well, but structures are blurred and some visible artifacts are introduced. Although it achieves a good speckle suppression performance, the median filter loses many of the signal details and the resulting image is blurred (Fig. 4). Also, images in Figures 3 and 4 look artificial.

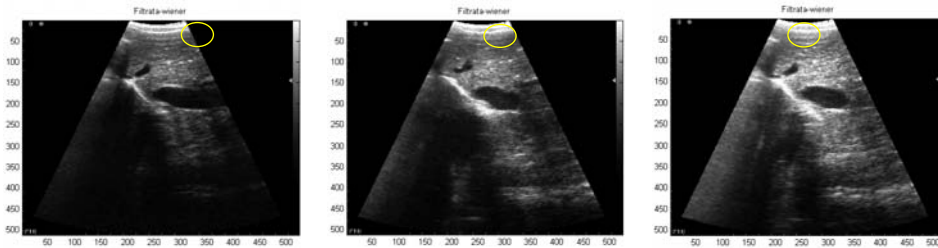


Fig. 3. Homomorphic Wiener filtering (area with an over-enhanced structure).



Fig. 4. Median filtering (blurred structure area).

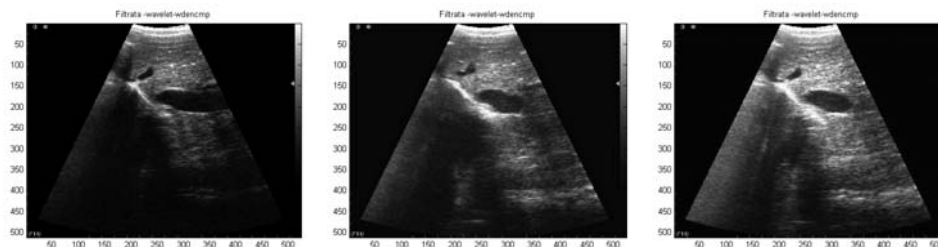


Fig. 5. Wavelet filtering – the proposed method.

Meanwhile, the result of the proposed algorithm given in Figure 5 shows that speckle is efficiently reduced and structures are enhanced with almost no loss or noticeable artifact. It seems that the wavelet transform performs like a feature detector, retaining the features that are clearly distinguishable in the speckled data but cutting out anything which is assumed to be constituted by noise (Fig. 5).

The results of these experiments are shown in Tables 1–5.

Table 1

Quantitative 5 MHz image enhancement measures obtained using three denoising methods

	Signal-to-noise ratio SNR	Peak signal-to-noise ratio PSNR (dB)	Mean absolute error MAE
Wiener Filtering	25.4835	41.1110	1.1445
Median Filtering	17.3490	32.9765	1.4620
Wavelet filtering	235.5557	251.1832	0.0000

Table 2

Quantitative 3.5 MHz image enhancement measures obtained using three denoising methods

	Signal-to-noise ratio SNR	Peak signal-to-noise ratio PSNR (dB)	Mean absolute error MAE
Wiener Filtering	24.9846	38.6181	1.6257
Median Filtering	18.9643	32.5977	1.8263
Wavelet filtering	29.0928	42.7262	1.1458

Table 3

Quantitative 2.5 MHz image enhancement measures obtained using three denoising methods

	Signal-to-noise ratio SNR	Peak signal-to-noise ratio PSNR (dB)	Mean absolute error MAE
Wiener Filtering	25.1816	36.6584	2.0850
Median Filtering	19.8537	31.3305	2.3761
Wavelet filtering	30.6520	42.1289	1.2392

Table 4

Quality index: ratio of 2.5 MHz image enhancement coefficients to 5 MHz image enhancement coefficients

	Signal-to-noise ratio SNR	Peak signal-to-noise ratio PSNR(dB)	Mean absolute error MAE
Wiener Filtering	1.5841	17.2116	20.3527
Median Filtering	1.5813	17.2088	20.3295
Wavelet filtering	1.4972	17.1247	20.4704

Table 5

Quality index: ratio of 3.5 MHz image enhancement coefficients to 5 MHz image enhancement coefficients

	Signal-to-noise ratio SNR	Peak signal-to-noise ratio PSNR (dB)	Mean absolute error MAE
Wiener Filtering	5.6429	21.2704	10.8604
Median Filtering	5.5899	21.2174	10.8460
Wavelet filtering	5.5229	21.1504	11.0366

Depending on the original image, the test value and the evaluation are not always correlated with the impression of quality of a subjective observation. The evaluation deals with the PSNR and MAE coefficients of image and the SNR. Higher values of SNR imply higher image enhancement.

CONCLUSIONS

We present an ultrasound image enhancement algorithm based on the wavelet transform. In ultrasound images, the speckle energy is comparable to the signal energy in a wide range of frequency bands. So it is not easy to discriminate speckle from the signal by only using magnitude statistics of wavelet coefficients in the decomposed image. In the proposed algorithm, to discriminate speckle from the signal, we obtain the structural information from the wavelet decomposed image at each resolution scale. Then, based on the structural information, we adaptively apply the directional filtering and speckle reduction procedures to the multi-resolution image. The experimental results show that the proposed algorithm considerably improves the subjective image quality without generating any noticeable artifact, and provides better performance compared with the existing enhancement schemes. Also, we perform speckle noise removal using nonlinear processing of wavelet coefficients. Our algorithm was tested and found to be effective for an exact matching of the signal and noise distributions at different scales and orientations. Finally, we note that our algorithm could be easily adapted for the purpose of denoising other types of biomedical images.

REFERENCES

1. AHN, C.B., Y.C. SONG, D.J. PARK, Adaptive template filtering for signal-to-noise ratio enhancement in magnetic resonance imaging, *IEEE Trans. Med. Imaging*, 1999, **18**(6), 549–556.
2. DAUBECHIES, I., Ten lectures on wavelets, In *CBMS-NSF Regional Conference Series in Applied Mathematics SIAM*, Publisher Soc. for Industrial & Applied Math., 1992, pp. 53–107.
3. DHAWAN, A.P., Medical image analysis, In *IEEE Press Series on Biomedical Engineering*, John Wiley & Sons, Inc, 2003, pp. 149–176.
4. GAGNON, L., A. JOUAN, Speckle filtering of SAR images: A comparative study between complex-wavelet based and standard filters, In *SPIE Proc.*, **3169**, 1997, pp. 80–91.
5. GUPTA, S., R.C. CHAUHAN, S.C. SAXENA, Robust non-homomorphic approach for speckle reduction in medical ultrasound images, *Medical and Biological Engineering and Computing*, 2005, **43**, 189–195
6. HALLIWELL, M., P.N.T. WELLS, Acoustical imaging chapter, In *Ultrasonic Tissue Characterization*, Johan M. Thijssen ed., Springer U, 2001, pp. 189–197.
7. JAIN, A.K., *Digital Image Processing*, Prentice-Hall, 1989, pp. 352–357.
8. LIEN, H. C., J.C. FU, S.T.C. WONG, Wavelet-based histogram equalization enhancement of gastric sonogram images, *Comput. Med. Imaging Graphics*, 2000, **24**, 59–68.
9. MALLAT, S., S. ZHONG, Characterization of signals from multiscale edges, *IEEE Trans. Pattern Anal. Machine Intell*, 1992, **14**(7), 710–732.
10. MEYER, Y., *Wavelets and operators*, Cambridge UK, Cambridge University Press, 1993, 81–98.
11. NICOLAE, M.C., MORARU L., Solution for tissue improving image quality, *The Annals of the “Dunărea de Jos” University of Galați, Mathematics, Physics, Chemistry, Informatics*, fascicle II, Supplement, year II (**XXXII**), 2009, pp. 27–33.
12. NICOLAE, M.C., MORARU L., GOGU A., Speckle noise reduction of ultrasound images, *Medical Ultrasonography an International Journal of Clinical Imaging*, Supplement, **11**, 2009, 50–51

13. PAPANIMITRIOU, S., A. BEZERIANOS, Multiresolution analysis and denoising of computer performance evaluation data with the wavelet transform, *J. Syst. Architect.*, 1996, **42**, 55–65.
14. SAAD, A.S., Simultaneous speckle reduction and contrast enhancement for ultrasound images: Wavelet versus Laplacian pyramid, *Pattern Recognition and Image Analysis*, 2008, **18**, 63–70.
15. SONG, K.S. et al., Adaptive mammographic image enhancement using first derivative and local statistics, *IEEE Trans. Med. Imaging*, 1997, **16**(5), 495–502.
16. STRANG, G., T. NGUYEN, *Wavelets and Filter Banks*, Wellesley–Cambridge Press, 1997, pp. 221–259.
17. XU, Y, J.B. WEAVER, D.M. HEALY, J. LU, Wavelet domain filters: A spatial selective noise filtration technique, *IEEE Trans. Image Process.*, 1994, **3**(11), 747–757.