A Suitable Threshold for Speckle Reduction in Ultrasound Images

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***Abstract*—This paper presents a novel parametric thresholding procedure to reduce the effect of speckle noise in ultrasound (US) medical images. The method comprises the use of an adaptive data-driven exponential operator that operates on wavelet coefficients of the US image to suppress undesired effects of disturbances, preserving signal details. The obtained results demonstrate that the proposed denoising method increases the medical image quality and, therefore, it can be a useful tool in medical diagnosis.**

***Index Terms*—Scattering, speckle noise, thresholding, ultrasound medical imaging, wavelet transform.**

I. Introduction

MEDICAL IMAGES are very useful tools to investigate the anatomy of the human body, to diagnose diseases, and to examine various illnesses. This discipline incorporates radiology, nuclear medicine, computed tomography (CT), magnetic resonance imaging (MRI), and ultrasonography. Each of these methods ensures important performances but has different limitations. CT provides high resolution images, especially for bone structures, but exposes patients to radiation dose [1]; instead, MRI provides high quality images, especially for soft tissues, but requires long examination time [2].

Ultrasound (US) imaging has been considered, for many years, the best technique for organ and soft tissue imaging and today, it is often preferred because it is economic, portable, adaptable, non-surgical, and without ionizing radiation. US images are obtained in real time by processing the echo signals reflected by body tissues, which have different acoustic impedances. Unfortunately, ultrasonography gives low quality images, which makes their interpretation difficult as they strongly depend on the operator's skill.

This limitation is mainly due to the presence of speckle noise [3]. Speckle is an undesirable interference effect occurring when two or more US waves interfere with each other, constructively or destructively, producing bright and dark spots. It reduces both spatial and contrast resolutions in US images, and contributes to a lower signal-to-noise ratio (SNR), reducing the ability to resolve details and to detect objects of size comparable to its own size. Therefore, filtering techniques for speckle noise are of particular interest for medical US imaging.

Many denoising techniques have been developed to improve US image quality, each of them with its advantages and limitations and all practically ascribable to single and multiscale methods. The single scale methods are based on the application of denoising filters directly in the original image. Median and Wiener filters [4]–[8] are the most popular approaches. Even though these filters offer simplicity of implementation, they fail to preserve many useful details and to distinguish boundaries between areas with small differences in gray level.

Other filtering typologies are based on the mathematical morphology [9]. They use suitable structuring elements to model the characteristics of the speckle, such as shape and size. This issue is very difficult because of the irregular shape of the speckle noise.

On the other hand, multiscale methods apply the single scale method to sub-images obtained by using wavelet decomposition or Laplacian pyramid. Recently, wavelet transform (WT) has been widely used to recover signals from noisy medical image [10]–[15]. In this way the wavelet decomposition simplifies the statistic of the signal and tries to remove the noise while preserves the signal characteristics.

Another reason for choosing the multiscale decomposition is that it provides information on how the amplitude content of the signal along horizontal, vertical, and diagonal orientations varies with the frequency.

Generally, in the denoising methods, the wavelet coefficients are passed through a threshold testing that requires replacing noisy coefficients below a fixed value with zeros, and keeping the others because they have the most of information. Then, the resulting coefficients are used to reconstruct the signal.

This nonlinear process known as wavelet shrinkage depends hardly on the choice of threshold value because it determines the efficacy of the whole denoising operation. Thresholding methods are particularly effective for sparse representations where most of image information is concentrated in few large coefficients [16], [17]. The sparsity is a typical characteristic of wavelet domain where noise is uniformly spread throughout all coefficients, while the signal is represented by a small subset of high coefficients.

In this paper, we propose an adaptive wavelet thresholding operator that depends on both noise level and signal

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characteristics and differs with resolution scales. So, a new expression of thresholding operator is suggested here. The proposed method is based on the assumption that speckle noise commonly manifests itself as a fine-grained structure and generates low wavelet coefficients that can be removed by a suitable thresholding algorithm. This formulation is grounded on the empirical observation that the wavelet details in the sub-bands of a high quality US image exhibit a heavy-tailed distribution (as shown successively), whereas a noisy image provides wavelet coefficients generally characterized by a smoothed distribution. The application of a traditional soft thresholding on noisy image provides a highly impulsive distribution of the relevant wavelet coefficients because it removes significant pixels too. Therefore, it is suitable to modify the thresholding algorithm to provide a more effective image filtering.

II. Wavelet Thresholding

The main filtering techniques based on the wavelet transform use a thresholding operator for signal denoising. These methods involve three steps: 1) the computation of the forward wavelet transform of the noisy image; 2) the filtering of the wavelet coefficients by means of a thresholding processor; and 3) the image reconstruction obtained by the inverse wavelet transformation with the filtered coefficients.

A. Wavelet Thresholding in US Images

The choice of a threshold value is a crucial phase in the wavelet denoising filtering because the threshold separates the undesired coefficients corresponding to the noise and the significant coefficients useful to reconstruct the image signal. Generally, a low threshold value preserves the details but does not reduce sufficiently the noise; in this case, both the filtered and the unfiltered images are very close. On the other hand, a large threshold value reduces the noise but destroys many details. To overcome these limitations, different thresholding rules were proposed in the literature; the most known of them are summarized below.

1) *VisuShrink:* This technique was pioneered by Donoho and Johnstone [16], [18] and applies the universal threshold; it consists of the use of a fixed (or universal) threshold defined by the following equation:

$$T_u = \sigma_n^2 \sqrt{2 \log N}. \tag{1}$$

VisuShrink is a general purpose threshold selector that takes into account only the image size (N) and the noise standard deviation σ_n; though it minimizes the maximum error overall number of pixels in the image it produces an overly smoothed estimation that is ill suited to discontinuities in the signal, introducing artifacts in the images [12]. An estimate of the noise level σ_n in (1) is based on the median absolute deviation given by [19]

$$\sigma_n^2 = \left[\frac{median(HH1(n,m))}{0.6745}\right]^2 \tag{2}$$

where n and m are pixel indexes of *HH1* that represents the diagonal sub-band of first level wavelet decomposition of the image.

The universal threshold is not signal adaptive because it does not take into account signal properties. Moreover, for a typical dimension image of 512×512 (or greater size), universal threshold can be overly large due to the direct link with N in (1); this produces an excessively smoothed image that removes too many coefficients.

2) *SureShrink:* This method is a combination of the universal threshold and the Stein's unbiased risk estimator (SURE) technique [19]. It computes a separate threshold for each sub-band and it is suited for images with sharp discontinuities; it yields good denoising performance and assures little values of the mean square error. In this case, the soft threshold is defined as

$$T_S = \min(T, \sigma_n^2 \sqrt{2 \log N}) \tag{3}$$

where T denotes the value that minimizes the SURE.

3) *BayesShrink:* It is a method based on the assumption that the wavelet coefficients are modeled as random variables with general Gaussian distribution (GGD) within each sub-band. Under this condition, a threshold is estimated to find the value that minimizes the Bayesian risk [20]

$$T_B(\sigma_x) = \frac{\sigma_n^2}{\sigma_x} \tag{4}$$

where σ_x is the image standard deviation evaluated in each wavelet sub-band.

Practically, *BayesShrink* works in the same way as *SureShrink*, and gives good results when a GGD is assumed [19]. This threshold adapts both signal properties and noise characteristics. Unfortunately, in medical US images the noise is multiplicative [21] so the direct applications of the above-mentioned techniques cannot be adequate to remove speckle.

Another important issue in coefficients processing is the thresholding operator, which defines the function used to discriminate the wavelet coefficients. There are two different methods normally used for the thresholding process [22], shortly described below.

1) *Hard thresholding*, where the wavelet coefficients are preserved if they are greater than the threshold, otherwise they are set to zero

$$ht(x) = \begin{cases} 0 & |x| < T \\ \mathrm{x} & |x| \geq T \end{cases} \tag{5}$$

where x is the generic image value;

2) *Soft thresholding* (also called shrinkage threshold) involves first setting to zero the elements whose absolute values are lower than the threshold and then scaling the nonzero coefficients toward zero

$$st(x) = \begin{cases} 0 & |\mathrm{x}| < \mathrm{T} \\ sign(x) \cdot (|x| - T) & |x| > T. \end{cases} \tag{6}$$

Soft thresholding avoids spurious oscillations since it eliminates the discontinuity that is inherent in hard thresholding. This is a very common method.

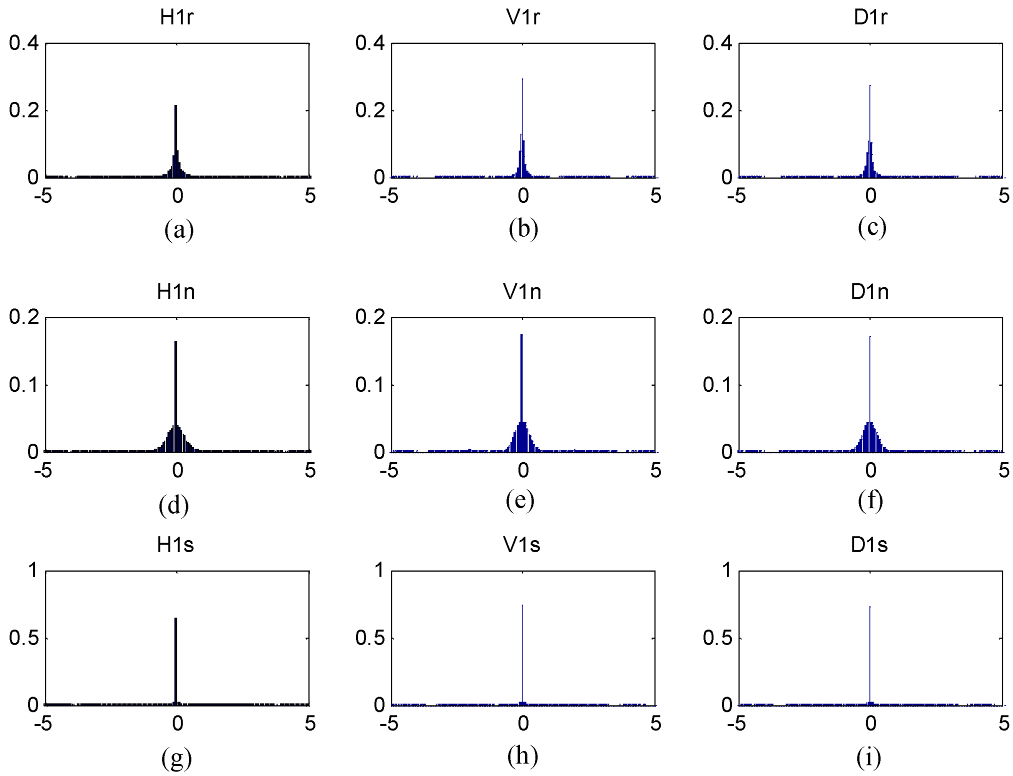


Fig. 1. Histogram of one-level wavelet details for (a)-(c) the logarithm of a reference ultrasound image, (d)-(f) the logarithm of a noisy image, and (g)-(i) the soft thresholding with the use of the universal threshold.

Most of the efforts in literature have been devoted to improve the performance of the conventional standard thresholding methods by developing new threshold values or different operators.

It has been proved that spatially and scale-wise adaptive threshold based on context modeling [11], [19], [23] are very effective.

Recently, some research has addressed the development of statistical models for wavelet coefficients of image decomposition. Hence, statistical approaches have emerged as a new tool for wavelet filtering based on Bayesian approach that models wavelet coefficients with prior probability distributions [24], [25].

B. Problem Formulation

As a general rule, the wavelet denoising based on thresholding processor runs well in presence of additive noise.

Many studies [3], [22], [23] have proved that the speckle noise that affects the US images can be modeled as a multiplicative noise

$$I(i, j) = I_r(i, j) \cdot n(i, j) \tag{7}$$

where I and I_r are the noisy and the noise-free image respectively, while n is the noise component having real and imaginary parts independent, zero mean, and identically distributed [3], [22].

Then, a very widely used approach in US denoising is to preprocess the speckled data by resorting to the logarithmic function to transform the multiplicative noise model into an additive one

$$\log I(i, j) = \log I_r(i, j) + \log n(i, j). \tag{8}$$

After the logarithmic transformation, it is possible to decompose the noisy US images by a suitable wavelet transform, where the noise is assumed approximately Gaussian and additive [10], [26], [28]. For each decomposition level (l), the WT produces four wavelet sub-images: A_l, H_l, V_l and D_l, where A_l is the low resolution residual at the scale l, and H_l, V_l and D_l, represent the horizontal, the vertical, and the diagonal details at the same scale, respectively.

Wavelet methods usually perform well in denoising medical images if the noise is assumed additive and homoscedastic [27]. Both the distortion of the image and loss of the information may occur when the noise is characterized by non-constant variance even if the enhancement of images can be obtained with the use of adaptive thresholding [28]–[30]. The wavelet thresholding procedure filters only the coefficients of the details sub-bands, keeping the low resolution coefficients unaltered.

III. Materials and Method

Wavelet denoising involves a linear forward wavelet transform, a nonlinear thresholding step and a linear inverse wavelet transform. So, finding a suitable threshold is the principal and not easy task.

In this paper, the authors propose a new wavelet thresholding procedure to reduce the noise effect on US images.

TABLE I

THRESHOLDING PARAMETERS FOR DIFFERENT US TRANSDUCER FREQUENCIES

	1–level decomposition		**2-level decomposition**		**3-level decomposition**	
US frequency	k_1	n_1	k_2	n_2	k_3	n_3
15 MHz	3.2	3	2.0	2	1.5	0.5
10 MHz	3.2	3	2.0	2	1.5	0.5
8 MHz	3.2	3	2.5	2	2.0	0.5
6 MHz	3.2	3	2.7	2	2.0	1.0
5 MHz	3.2	3	3.0	2	2.0	1.0
4 MHz	3.2	3	3.5	2	2.5	1.0

1) *Materials:* To evaluate the effects of thresholding operator on noisy images, it is necessary to have reference images (without noise or with low noise level), to compare them with the output of the filters. In this paper, the US images simulator Field II [31] is used to generate the reference images for thresholding evaluation. In this respect, we have set the simulation parameters according to the suggestions on the Field II website to obtain high quality US images. So the used parameters are: 1 000 000 scatterers number, 13 MHz as transducer frequency, and transducer with 128-elements linear array, each of them a height of 5 mm. These parameters have been chosen with the aim of generating high quality US images, used as reference data.

The reference images in this paper represent a kidney, a heart, and a liver, i.e., the most common tissues analyzed in US diagnosis. Two supplementary reference images have been generated by adding some cysts on the kidney and the liver images, respectively. Each of them has a resolution of 256 grey levels and a dimension of 408×480 pixels. Subsequently, the images have been corrupted with multiplicative speckle noise; then for each of the five reference images, 20 noisy images have been generated. The noise variance ranges from 0.001–0.2 to simulate the noise levels affecting the images produced by ordinary US systems. The used variance levels are referred to image intensity with normalized values ranging from 0 to 1.

To use the wavelet multiresolution analysis (decomposition), homomorphic processing (logarithmic transform) [10], [12], [21] is first applied to the noisy images to convert the multiplicative speckle noise model to an additive one; then a wavelet transform with mother Symlet 7 is performed on the log-transformed images followed by an exponential operation. Successively the images are reconstructed by using the wavelet coefficients passed through the proposed thresholding testing.

The quality of reconstructed images has been measured by a traditional quality index, such as peak signal-to-noise ratio (PSNR)

$$PSNR = 10 \cdot \log_{10} \frac{L^2}{\frac{1}{n \cdot m} \sum_{i=1}^{n} \sum_{j=1}^{m} \left[I_{ref}(i,j) - I_{nr}(i,j) \right]^2} \tag{9}$$

where I_{ref} is the reference US image, I_{nr} is the reconstructed image obtained by wavelet thresholding of noisy image; n and m are the row and column numbers of the images, and L is the number of the image grey levels, respectively.

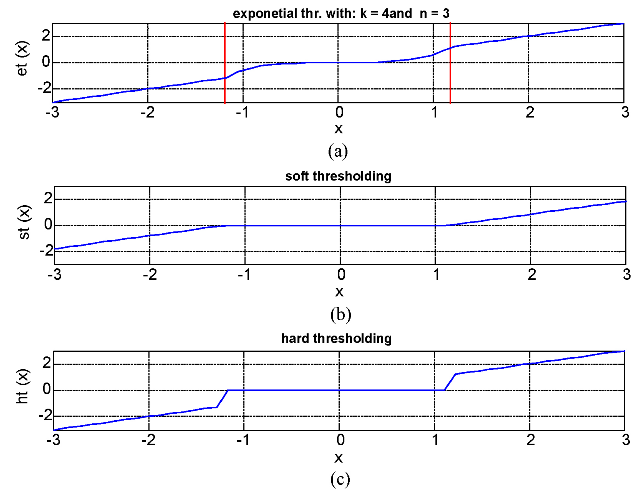


Fig. 2. (a) Exponential, (b) soft, and (c) hard thresholding realization.

In addition to *PSNR, beta* metric [32] is used to evaluate the edges preservation in the filtered image

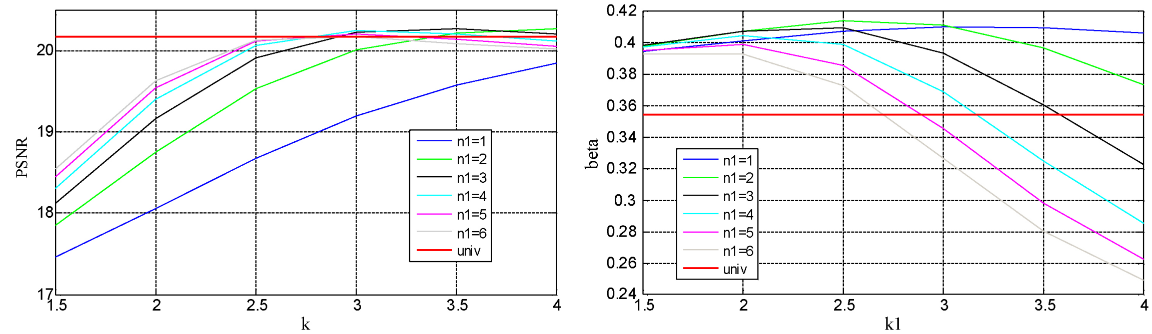
$$\beta = \frac{\Gamma\left(\Delta_I - \overline{\Delta_I}, \widehat{\Delta}_I - \overline{\widehat{\Delta}_I},\right)}{\sqrt{\Gamma\left(\Delta_I - \overline{\Delta_I}, \Delta_I - \overline{\Delta_I}\right) \cdot \Gamma\left(\widehat{\Delta}_I - \overline{\widehat{\Delta}_I}, \widehat{\Delta}_I - \overline{\widehat{\Delta}_I}\right)}};$$

$$\Gamma(\mathrm{I}_1, \mathrm{I}_2) = \sum_{(i,j) \in ROI} I_1(i,j) \cdot I_2(i,j) \tag{10}$$

where Δ_I is the highpass filtered version of image *I(i,j),* obtained with 3×3-pixel standard approximation of the Laplacian operator. Of course, an increase in this parameter indicates better performances.

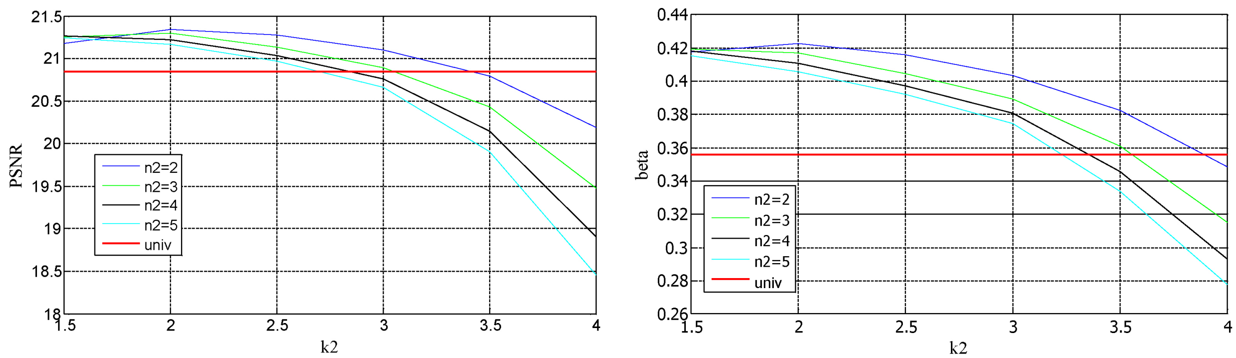
2) *Threshold Selection and Proposed Procedure:* As previously specified, many experimental and theoretical studies have proved that the wavelet coefficients have a heavy-tailed distribution [19], [33]. This is particularly emphasized in US noisy-free images. It was thus deemed necessary to investigate the influence of speckle noise on wavelet coefficients distribution.

Let L_{ref} be the logarithm of the reference image and L_n the logarithm of the reference image corrupted with speckle noise. Both images have been decomposed with one-level wavelet transform. It is possible to highlight that the wavelet details of L_{ref} exhibit a heavy-tailed distribution (as shown in Fig. 1 (a)–(c)), according to the previous observations. On the contrary, the distribution shape of the wavelet coefficients of



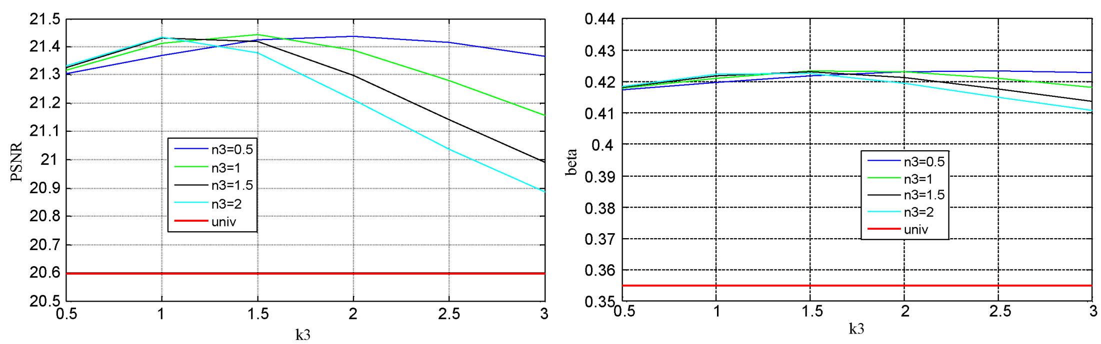
(a) (b)

Fig. 3. Behavior of (a) PSNR and (b) β versus k_1 variation for different n_1 values. The results refer to one-level wavelet decomposition of the logarithm of a liver noisy ultrasound image. The performance of the proposed operator has been compared to one-level universal threshold (bold red line).



(a) (b)

Fig. 4. Behavior of (a) PSNR and (b) β versus k_2 variation for different n_2 values. The results refer to two-level wavelet decomposition of the logarithm of a liver noisy ultrasound image. The performance of the proposed operator has been compared to two-level universal threshold (bold red line).



(a) (b)

Fig. 5. Behavior of (a) PSNR and (b) β versus k_3 variation for different n_3 values. The results refer to three-level wavelet decomposition of the logarithm of a liver noisy ultrasound image. The performance of the proposed operator has been compared to three-level universal threshold (bold red line).

L_n is lightly tailed (Fig. 1 (d)–(f)). Moreover, the application of *VisuShrink* soft thresholding to L_n coefficients provides a highly impulsive distribution (as shown in Fig. 1 (g)–(i)). This is due to the large value of the universal threshold that sets to zero too many coefficients.

To overcome this limit, a new parametric thresholding operator was proposed. Thresholding, essentially, creates a region around zero where the wavelet coefficients are considered negligible. The goal of the proposed method is to provide an alternative function, with respect to hard and soft thresholding, able to gradually reduce the coefficients in the zero zone. For this aim the following thresholding operator based on exponential function was defined as

$$et(x) = \begin{cases} x \cdot e^{n_l \cdot (|x| - T_{k_l})} & |x| < T_{k_l} \\ x & |x| \geq T_{k_l} \end{cases} \quad ; \quad T_{k_l} = k_l \cdot T_{u_l} \tag{11}$$

where n_l is a real parameter identifying the fall degree of exponential function for l decomposition level, while k_l factor provides a modified version of l-level universal threshold, which offers more flexibility in the threshold choice.

The thresholding function is applied to each sub-band on three wavelet detail coefficients after estimation of the sigma value from the data. This procedure makes the proposed

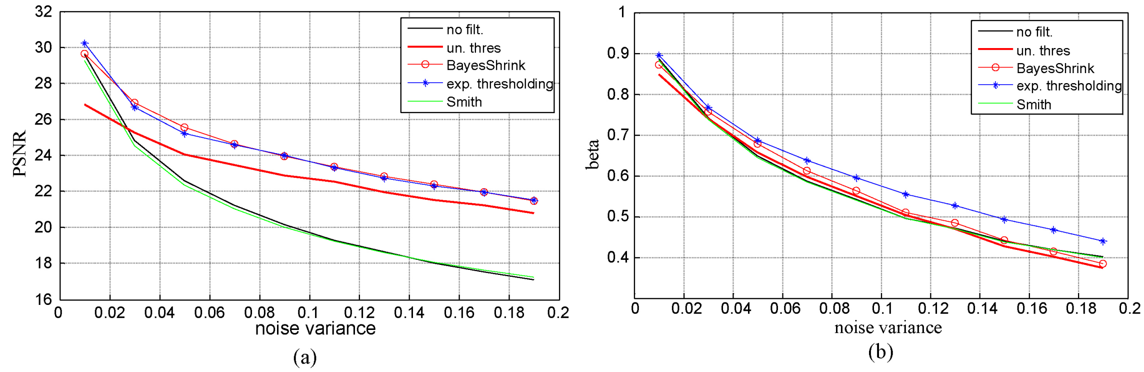


Fig. 6. Comparison of (a) PSNR and (b) β for different thresholding methods and for different noise variance applied to liver ultrasound images.

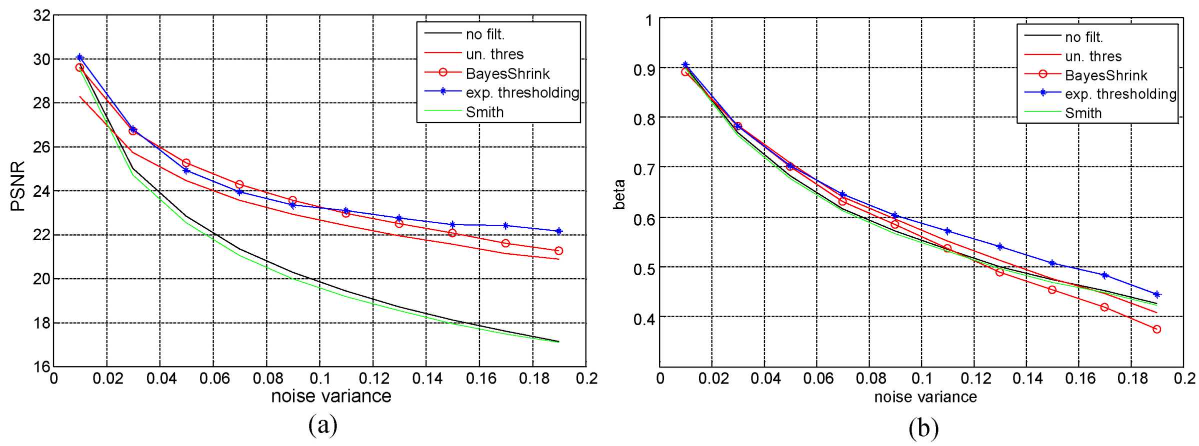


Fig. 7. Comparison of (a) PSNR and (b) β for different thresholding methods and for different noise variance applied to kidney ultrasound images.

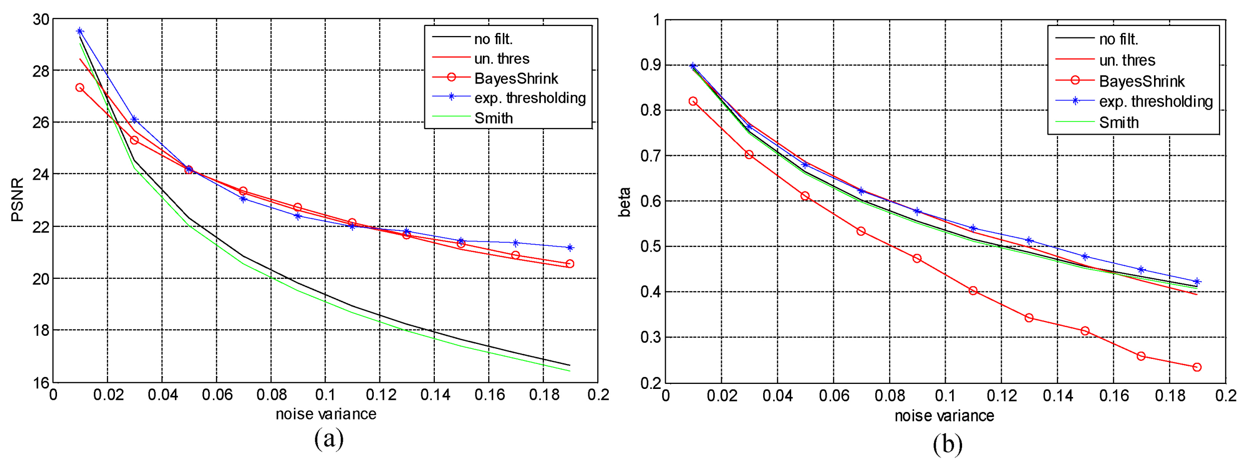


Fig. 8. Comparison of (a) PSNR and (b) β for different thresholding methods and for different noise variance applied to heart ultrasound images.

method very adaptive to data and can be optimized for each image and for different noise conditions.

The presence of x factor in (11) produces the zero setting of the thresholding function in $x = 0$ and avoids discontinuity in $x = T_k$. Fig. 2 shows an example of the new thresholding realization and compares it with the traditional soft thresholding operator.

In order to estimate the best values for n_l and k_l parameters, many simulation tests have been carried out with the aim to maximize both *PSNR* and β metric of the proposed procedure comprising the following steps.

1) Perform the logarithm of speckled images L_n.
2) Perform the wavelet transform of the logarithmic speckled images with l level decomposition.
3) Obtain noise variance for l level decomposition using (2).
4) Compute the universal threshold for each level decomposition by (1).
5) Process all l level sub-band coefficients by using the thresholding function (11).
6) Perform the inverse wavelet transform to reconstruct the denoised image.

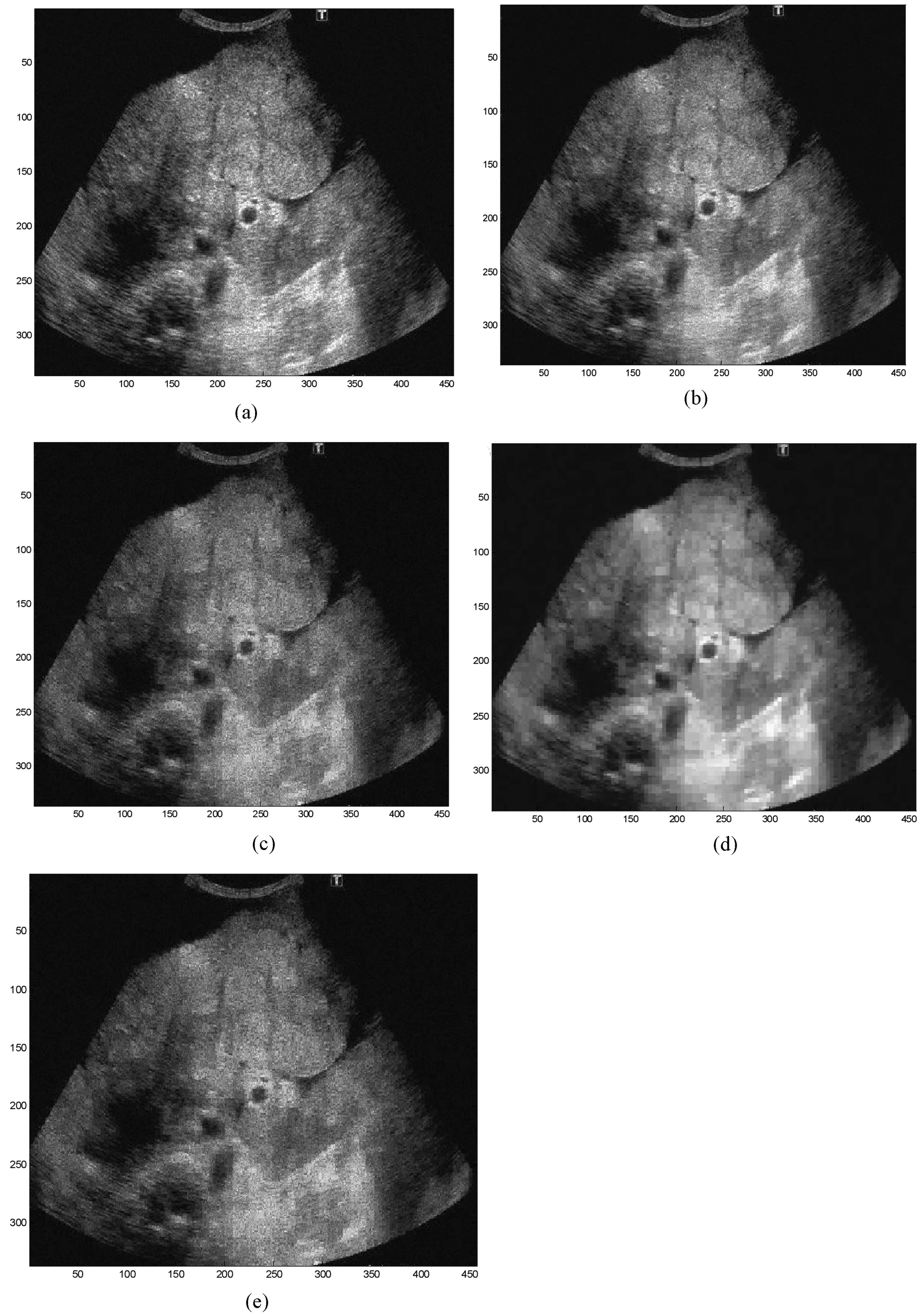


Fig. 9. (a) Real ultrasound image of a liver metastasis, (b) its filtered version with the proposed method, (c) the Bayesian Shrink thresholding, (d) the universal thresholding, and (e) the Smith thresholding.

7) Take the exponent.

Finally, the obtained results have been compared with other threshold techniques for different noise levels.

IV. Experimental Results

In a first step, a liver reference US image has been considered. In order to verify the performance of the proposed method in the most critical conditions, the maximum noise variance value (previously defined in Section II-A) has been initially used to corrupt reference US image.

Then, experimental tests have been carried out for evaluating the performance of the new thresholding operator applied to one-level wavelet decomposition of logarithmic noisy images. Different values for n_1 and k_1 parameters have been tested; the relevant experimental results are shown in Fig. 3. In the proposed tests, k_1 is always greater than 1. In fact, the proposed operator sets the wavelet coefficients to zero gradually and so it is suited to enlarge the thresholding zone with respect to T_u to make the thresholding procedure more effective. The obtained results have been compared with one-level universal threshold.

Fig. 3 show that PSNR increases when both n_1 and k_1 increase, while β is characterized by an opposite behavior. Then, it is necessary to choose suitable parameter values to ensure a good compromise between the two quality indexes. Consequently, $k_1 = 3.2$ and n_1=3 have been selected as optimal values that provide good performance for both *PSNR* and β and improve the image quality with respect to the use of universal threshold. Similar tests have been carried out for two-level wavelet decomposition. The obtained results are shown in Fig. 4.

In this case $k_2 = 2$ and $n_2 = 2$ have been chosen as optimum values. The values of parameters decrease when the decomposition level increases. This result, partially confirmed in a previous work [34], agrees with the observation that the image details are emphasized when the level decomposition increases. Then, to preserve image edges, the increase of l requires a decrement in smoothing signal, obtained by reducing both the threshold and the exponential degree values. Fig. 4 highlights that the two-level wavelet decomposition of the proposed thresholding is more effective than the two-level wavelet decomposition of the universal threshold. In fact, the switch from one-level to two-level decomposition improves *PSNR* and β of about 5.3% and 9.9%, respectively, in the new exponential thresholding; while it provides an increase of about 3.7% and 1.3%, respectively, in the universal thresholding. Then the proposed method is more *scale* adaptive, because it allows changing both threshold and shape of the thresholding function for each decomposition level. Further tests have been repeated for three-level wavelet decomposition; the obtained results are shown in Fig. 5. Then, $k_3 = 1.5$ and $n_3 = 0.5$ have been chosen as optimum values confirming that the thresholding parameters decrease when the decomposition level increases. In this case, the universal threshold operator provides worse performance with respect to the two-level decomposition, while the proposed method offers a further improvement in *PSNR* and β of about 0.07% and 1.3%, respectively.

Additional experimental tests have proved that a further increase in decomposition level does not significantly improve the quality image for the exponential thresholding.

The produced results have been obtained starting on a reference US images generated by Filed II with a high frequency of US transducer (13 MHz) to have a high resolution image. In this way, the high resolution characteristic has been empathized with respect to the loss of penetration due to the use of high frequency.

However, further experimental tests have been carried out by using reference US images produced with different transducer frequencies. The obtained results show that the noisy images exhibit a *PSNR* and a *beta* metric, which reduce when the frequency decreases. The obtained results are summarized in the Table I.

It is possible to note that the parameters k_1 and n_1 are insensitive to frequency changes. Moreover, in the frequency range 10–15 MHz the thresholding parameters remain constant at each level of decomposition.

On the contrary, when the frequency ranges in 4–8 MHz, the optimal values of both the fall degree of the exponential function (n_l) and of the modified threshold (k_l) change with the decomposition level (l). Particularly, for two-level decomposition, the n_2 parameter does not vary with the frequency; instead k_2 parameter increases when the frequency decreases. These results can be justified because the images with low resolution need an enlarged threshold to provide more effective smoothing. For three-level decomposition both parameters increase, albeit slightly, when the frequency decreases.

Finally, in order to validate the performance of the proposed method, a comparison with the results obtained by using *BayesShrink* and the polynomial thresholding proposed by Smith [35] has been performed for different noise levels. Fig. 6 shows that the exponential thresholding is more effective in terms of β metric. With regards to *PSNR* index, both the proposed method and the *BayesShrink* provide very similar performances. Analogous results have been obtained on heart and kidney images (as shown in Figs. 7 and 8, respectively).

Finally, the filtering tests have been carried out with some real US images. Fig. 9 show a qualitative comparison of a real US image of liver metastasis filtered with different tresholding methods.

Although a visual image inspection is not always effective because it is not much sensitive to the loss of small size details, it is possible noting that 1) the universal thresholding offers worse performance in terms of preserving details, 2) the Bayesian Shrink and Smith tresholding provide a higher smhooting, and 3) the proposed method offers a good trade-off between noise reduction and edge preservation.

V. Conclusion

In this paper, the wavelet based denoising of US images was addressed by focusing the attention on the influence of thresholding operator. In particular, a new multiscale suitable data-driven thresholding operator grounded on parametric exponential function was presented to reduce speckle noise. The parametric approach was more flexible and effective because it adapted the thresholding parameters to the wavelet level decomposition and to the image characteristics. Several experiments were carried out on simulated US images with different US transducer frequencies to provide a wide case of study. The obtained results showed that the proposed method provides good performance, especially in terms of β metric. This one increased by about 10% with respect to the other thresholding methods.

Finally, experimental tests carried out on real US images seemed to confirm and validate the proposed technique. The suggested threshold operator assures good feature preservation performance and it is proposed as a useful method in medical image processing.

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