

Comparing Nonsampled Wavelet, Contourlet and Shearlet Transforms for Ultrasound Image Despeckling

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Abstract—Ultrasound images suffer of multiplicative noise named speckle. Bayesian shrinkage in transform domain is a well-known method based on finding threshold value to suppress the speckle noise. The main problem of applying Bayesian shrinkage is finding the optimum threshold value in appropriate transform domain. In this paper, we compare the performance of adaptive Bayesian thresholding when nonsampled Wavelet, Contourlet and Shearlet transforms are used. We processed two synthetic test images and three original ultrasound images as well to demonstrate the efficiency of the designed filters. In order to compare the performance of Bayesian shrinkage when employing the three mentioned transform domain, we used peak signal to noise ratio (PSNR), mean square error (MSE), and structural similarity (SSIM) as the full-reference (FR) objective criteria parameters and noise variance (NV), mean square difference (MSD), and equivalent number of looks (ENL) as the no-reference (NR) objective criteria parameters.

Index Terms—Nonsampled Wavelet, nonsampled Contourlet, nonsampled Shearlet, ultrasound image despeckling, Bayesian thresholding.

I. INTRODUCTION

For any coherent imaging like ultrasound, suppressing the multiplicative speckle noise is necessary before processing like image segmentation, edge detection, and in general any medical diagnosis. The goal of image denoising is to remove noise while retaining the important signal features. There are two basic approaches for image denoising; spatial domain methods and transform domain methods [1]. Although the spatial domain methods need less computation cost, the transform domain methods have less blurring effect.

Wavelet transform (WT) is the most well-known two dimensions and multi-resolution transform that decompose an image in horizontal, vertical and diagonal directions. Researchers attempt to find new two dimensions and multi-resolution transforms as the traditional WT with more directionality in contrast with WT. Due to, Contourlet transform (CT) [2]-[3] and

Shearlet transform (ST) [4]-[5] were proposed. Although CT was originally introduced in discrete domain, ST similar to continuous WT represents an affine system obtained by scaling and translation and in addition unlike WT it has an extra parameter called shear. The original WT, CT, and ST because of using up- and down-sampling are shift variant. That means, the coefficients are changing whenever the original signal is translating. The pseudo-Gibbs phenomena are seen around singularities for any shift variant transform [6]. So, nonsampled Wavelet (NSWT) [7], nonsampled Contourlet (NSCT) [8], and nonsampled Shearlet (NSST) [9] by omitting the up- and down-sampling blocks were introduced. As the coefficients do not decimate between the decomposition levels, all sub-bands sizes are the same as the original input image. However, in some papers, the original shift variant transforms were used [10]-[12] and in some papers, the nonsampled shift invariant transforms were used [9], [13].

The most well-known method in transform domain for speckle denoising is thresholding which is based on the idea that the energy of the signal concentrates on some of the transformed coefficients, while the energy of noise spreads throughout all transformed coefficients. So as much as being the transformed coefficients spares, the thresholding image denoising works appropriately. Anyway, the main problem in thresholding method is finding the optimum threshold value [14]. This threshold can be adaptive or non-adaptive per sub-band. Bayesian shrinkage [15] is the adaptive threshold method.

In this paper, we used Bayesian shrinkage in order to find the optimum threshold value for each decomposition level and each sub-band under employing three nonsampled transforms named NSWT, NSCT, and NSST. According to our results, for test images, the NSST domain outperforms both NSCT and NSWT whereas for true ultrasound images, the best performance is not always achieved by NSST.

The outline of this paper follows. In Section 2, the speckle noise model and image assessment parameters are explained. In Section 3, denoising in transform domain by thresholding is explained and in addition we have a short review on Bayesian shrinkage. Our experimental results for Bayesian shrinkage based on

three mentioned transforms are given in Section 4. Finally, we have conclusion in Section 5.

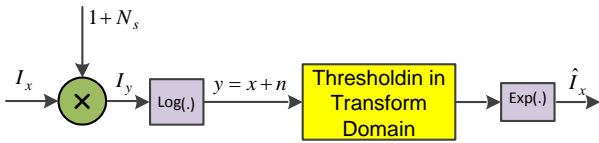


Fig. 1. The block diagram of speckle denoising method that works in transform domain.

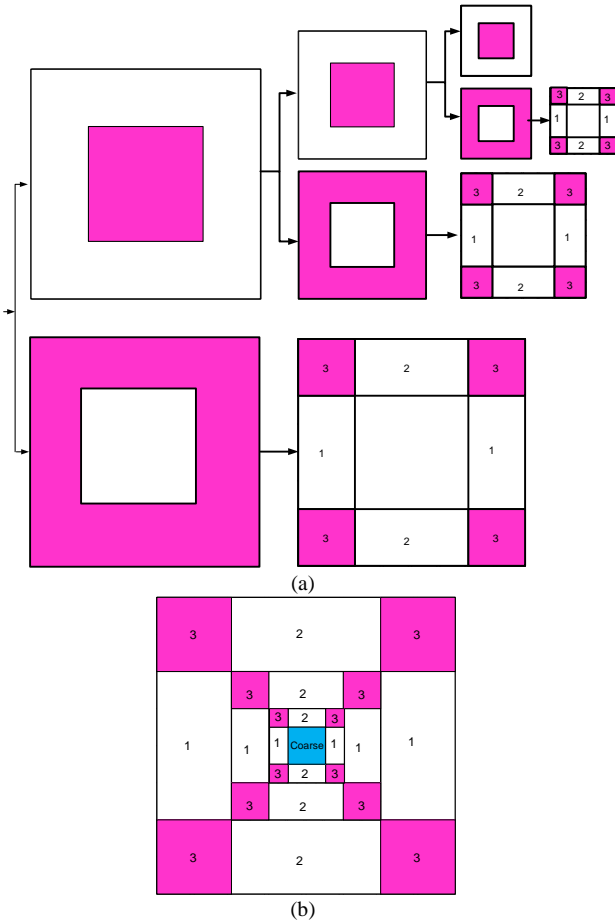


Fig. 2. Shown the NSWT of three levels decompositions (a) and the tilling frequency (b).

II. SPECKLE NOISE MODEL AND IMAGE ASSESSMENT PARAMETERS

In general, there are two different noise models, additive and multiplicative, such as Gaussian noise and speckle noise. The speckle noise is modeled as,

$$I_y = I_x + I_x N_s, \tag{1}$$

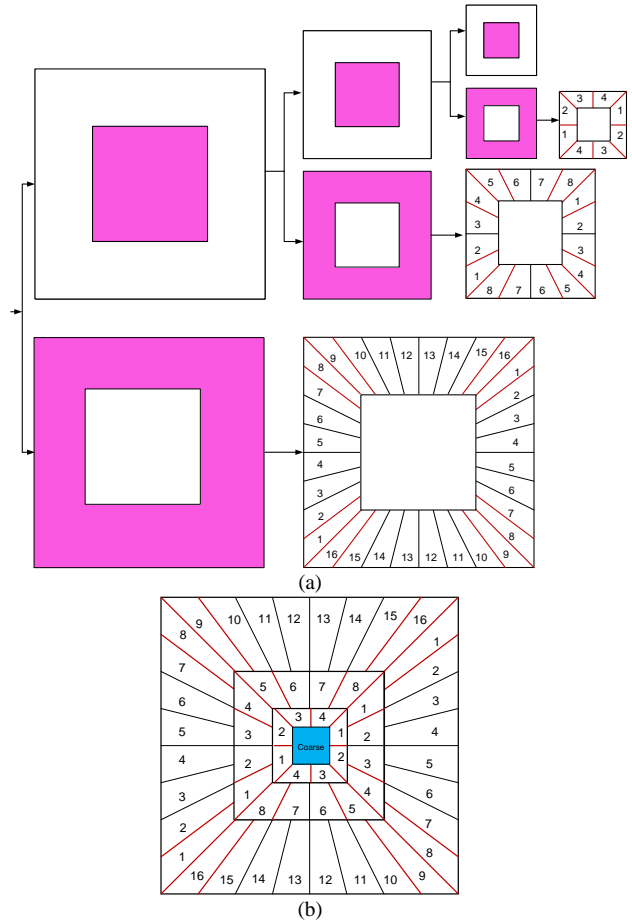


Fig. 3. Shown the NSCT and NSST of three levels decompositions (a) and the tilling frequency (b).

where I_x and I_y denotes the noise free signal and the observed signal, and N_s is the speckle noise in spatial domain. Equation (1) can be rewritten as, $I_y = I_x(1 + N_s)$. The multiplicative noise is converted to additive noise by using the logarithm transform,

$$y = \text{Log}(I_y) = x + n, \tag{2}$$

where $x = \text{Log}(I_x)$ and $n = \text{Log}(1 + N_s)$. So, additive noise reduction methods are applied to remove n component. The block diagram of suppression the speckle noise in transform domain using homomorphic frame work is shown in Fig. 1.

The performance evaluation of filters is a basic issue. In this work, we used peak signal to noise ratio (PSNR), mean square error (MSE), and structural similarity (SSIM) as the full-reference (FR) objective criteria parameters and noise variance (NV), mean square difference (MSD), and equivalent number of looks (ENL) as the no-reference (NR) objective criteria parameters. For any despeckled image, \hat{I}_x , as shown in Fig. 1, in spatial domain, the NV is

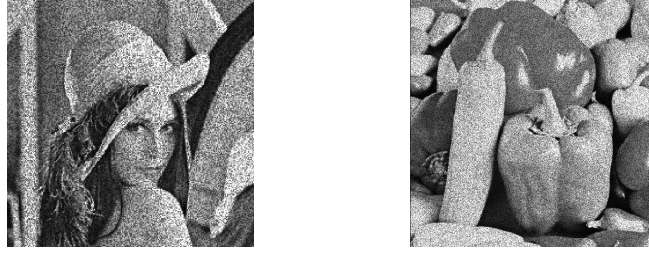


Fig. 4. Shown the speckled noisy images of Lena and Pepper where the noise power is 0.1.

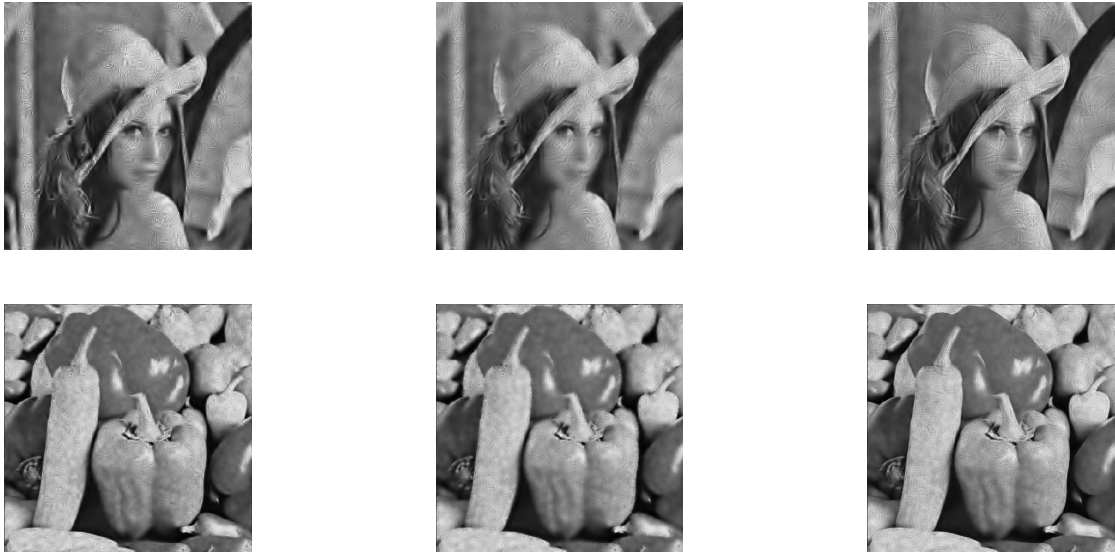


Fig. 5. Bayesian shrinkage based on using the NSWT (the left column), NSCT (the middle column), and NSST (the right column).

$$NV = \frac{\sum_{i=1}^M \sum_{j=1}^N [\hat{I}_x(i, j) - \bar{\hat{I}}_x]^2}{MN} \quad (3)$$

$$ENL = \frac{\bar{\hat{I}}_x}{NV} \quad (5)$$

where $\bar{\hat{I}}_x$ is the average intensity value of despeckled image and obtained as $\bar{\hat{I}}_x = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N \hat{I}_x(i, j)$, and MN refers to the image size. In general NV determines the contents of speckle in an image. It means, a lower variance gives a “smoother and cleaner” image as more speckle is removed though it does not necessarily depend on the intensity. Another NR objective parameter, MSD, is

$$MSD = \frac{\sum_{i=1}^M \sum_{j=1}^N [\hat{I}_x(i, j) - I_y(i, j)]^2}{MN} \quad (4)$$

where I_y as shown in Fig. 1 is the original noisy image. Although, high MSD shows the significant filter performance, we should be careful about blurring edges. The last used NR objective assessment parameter is ENL,

ENL is known as the best NR objective assessment parameter that estimates the speckle noise level in an image over uniform regions. On the other words, getting great ENL value shows appropriate performance of an algorithm. As ENL value depends on the tested region size, in Section 4 for experimental results, we split an image into blocks with 25×25 pixels and obtain ENL for each block separately, then we compute the average ENL and write the results in Tables.

III. DENOISING IN TRANSFORM DOMAIN

As mentioned before, thresholding is basically an approach for despeckling in transform domain. The main problem in thresholding method is finding the optimum threshold value [14]. This threshold can be adaptive or non-adaptive per sub-band. In transform domain, we represent Y_i , X_i and N_i as noisy signal coefficient, noise free signal coefficient and noise component coefficient for any coefficient indexed by i . Then, for any linear transform, we have

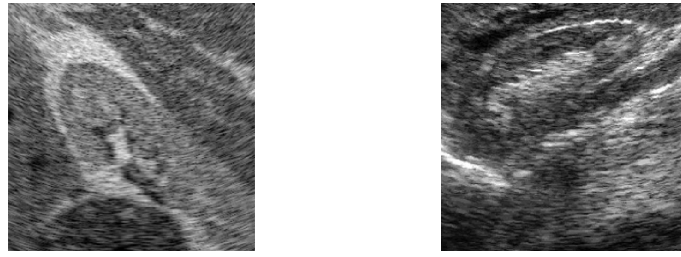


Fig. 6. Shown the original ultrasound images which in heritage including the speckle noise.

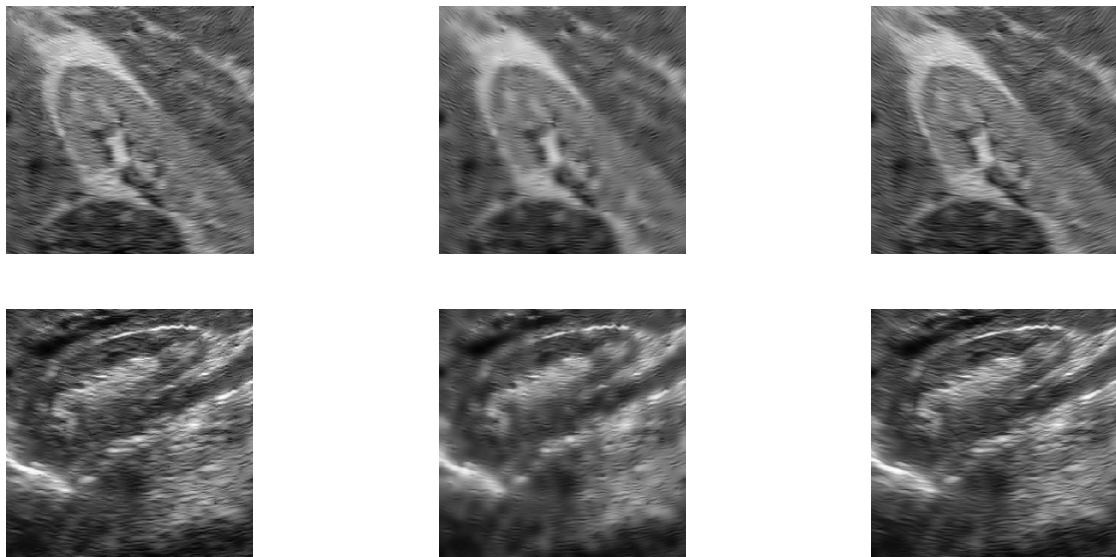


Fig. 7. Bayesian shrinkage based on using the NSWT (the left column), NSCT (the middle column), and NSST (the right column) for true ultrasound images.

$$Y_i = X_i + N_i \tag{6}$$

For soft thresholding we have

and the manipulated or estimated coefficient \hat{Y}_i based on the observed coefficients Y_i and the weighting factor R_i is obtained as

$$R_i = \begin{cases} 0 & |Y_i| < \lambda \\ 1 - \frac{\lambda}{|Y_i|} & |Y_i| \geq \lambda \end{cases} \tag{9}$$

$$\hat{Y}_i = R_i Y_i \tag{7}$$

In general, there are three ways to implement the threshold on transformed domain coefficients named hard, soft and semi-soft thresholding [16].

For hard thresholding we have

$$R_i = \begin{cases} 0 & |Y_i| < \lambda \\ 1 & |Y_i| \geq \lambda \end{cases} \tag{8}$$

In hard thresholding, as written in (7) and (8), all coefficients whose magnitude is smaller than the selected threshold value λ are set to zero and the others whose magnitude is greater than λ remains as they were.

In soft thresholding, as written in (9), the weighting factor R_i for all coefficients with greater magnitude than the threshold value λ shrink towards one and for other coefficients set to zero.

The aim of semi-soft thresholding is to offer a compromise between hard and soft thresholding by changing the gradient of the slope. This scheme requires two thresholds, a lower threshold value λ_1 and an upper threshold value λ_2

$$R_i = \begin{cases} 0 & |Y_i| \leq \lambda_1 \\ \frac{\lambda_2}{\lambda_2 - \lambda_1} \left(1 - \frac{\lambda_1}{|Y_i|}\right) & \lambda_1 < |Y_i| \leq \lambda_2 \\ 1 & |Y_i| > \lambda_2 \end{cases} \tag{10}$$

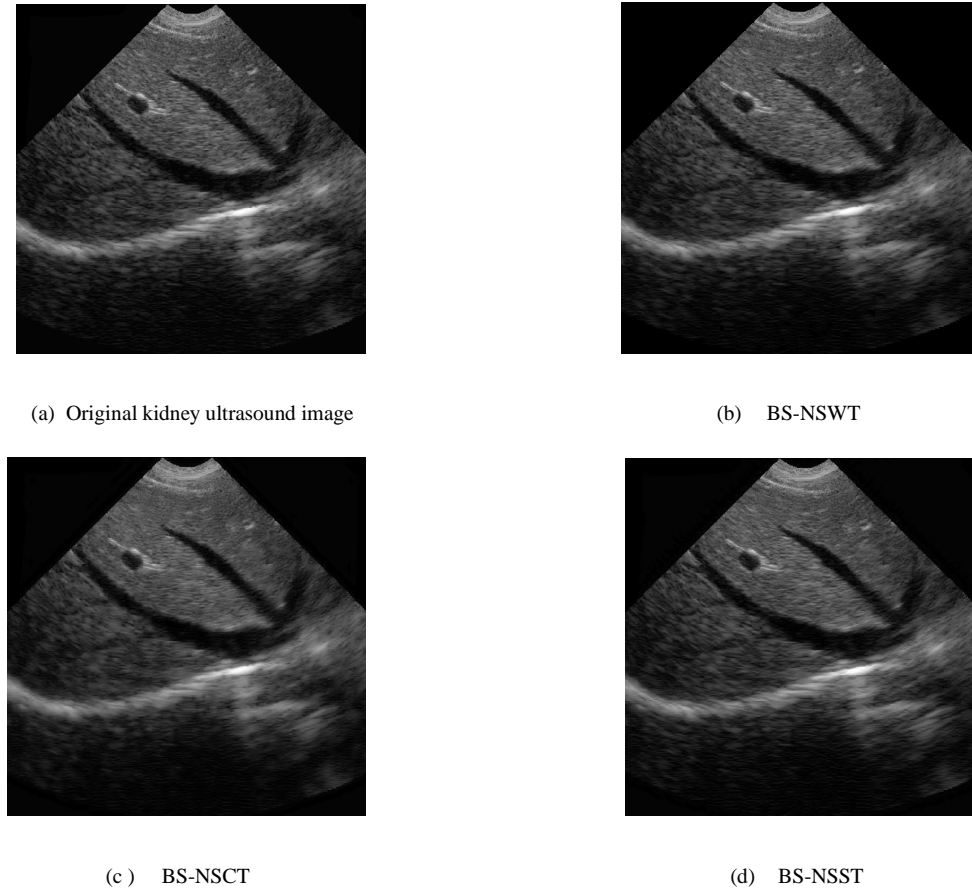


Fig. 8. Bayesian shrinkage based on three mentioned transform domains for visual evaluation.

VisuShrink is the simplest way to find the threshold value based on the standard deviation of noise for all coefficients [17]. The inheritance of finding the threshold value by this method is discarding many coefficients and therefore result a blurred image. In order to overcome this problem, the threshold value was obtained based on Stein's Unbiased Risk (SURE) which named as SureShrink [18]. In this method, the threshold value for every decomposition level including different sub-bands is obtained. The Bayesian shrinkage or BayesShrink [15] computes the optimum threshold values at each decomposition level and for every sub-bands separately, according to

$$\lambda_{l,k} = \frac{(\sigma_N^2)_{l,k}}{(\sigma_X)_{l,k}} \quad (11)$$

where $\lambda_{l,k}$ is BayesShrink [15] threshold, $(\sigma_N^2)_{l,k}$ is noise variance and $(\sigma_X)_{l,k}$ is the standard deviation of the noise free signal for any level 'l' and sub-band 'k'. For implementing the BayesShrink in transform domain based on (11), the noise variance and the free noise signal variance are to be estimated for each decomposition level and sub-band. To simplify the notation, in following, the subscripts l and k that indicate level and sub-band are

dropped. In this work, in order to estimate the standard deviation of noise, σ_N , we used the robust median estimator,

$$\sigma_N = \frac{\text{median}(Y_1)}{0.6745} \quad (12)$$

where Y_1 denotes the transformed coefficient of finest scale sub-bands. Furthermore, assuming a linear transformation, it can be written $Y = X + N$ for each level and any sub-band. Assuming that the signal coefficients and the noise coefficients are also independent at each level and any sub-band [19], i.e. we have $\sigma_Y^2 = \sigma_X^2 + \sigma_N^2$ where σ_X^2 is the signal variance without noise and σ_Y^2 is the variance of noisy signal obtained as,

$$\sigma_Y^2 = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N Y_{i,j}^2 \quad (13)$$

It was shown [19] that the variance of free noise signal can be estimated as,

$$\sigma_X^2 = \max(\sigma_Y^2 - \sigma_N^2, 0) \quad (14)$$

Table 1. Obtained the FR objective assessment parameters under different noise power in order to compare the performance of Bayesian shrinkage when NSWT, NSCT, and NSST are used as transform domains. Lena and Pepper are used as the test images.

		$\sigma^2 = 0.1$			$\sigma^2 = 0.3$			$\sigma^2 = 0.5$		
		SSIM	PSNR (dB)	MSE	SSIM	PSNR (dB)	MSE	SSIM	PSNR (dB)	MSE
Noisy Image	Lena	0.32	37.44	0.237	0.18	27.54	0.0637	0.143	23.72	0.0932
	Peppers	0.469	35.84	0.0278	0.310	26.25	0.0724	0.251	22.44	0.1060
BS-NSWT	Lena	0.66	56.09	0.0037	0.52	46.91	0.0092	0.485	42.61	0.0141
	Peppers	0.789	57.48	0.0032	0.681	45.39	0.0107	0.621	39.97	0.0184
BS-NSCT	Lena	0.65	54.55	0.0043	0.50	46.38	0.0097	0.452	42.30	0.0145
	Peppers	0.794	56.56	0.0035	0.664	44.98	0.0111	0.594	39.66	0.0189
BS-NSST	Lena	0.71	56.87	0.0034	0.57	47.34	0.0088	0.506	42.77	0.0139
	Peppers	0.797	58.38	0.0029	0.672	45.60	0.0105	0.602	39.96	0.0184

Table 2. Obtained the NR objective assessment parameters under different noise power in order to compare the performance of Bayesian shrinkage when NSWT, NSCT, and NSST are used as transform domains. Lena and Pepper are used as the test images.

		$\sigma^2 = 0.1$			$\sigma^2 = 0.3$			$\sigma^2 = 0.5$		
		NV	MSD	ENL	NV	MSD	ENL	NV	MSD	ENL
Noisy Image	Lena	0.065	0	5.30	0.097	0	2.52	0.120	0	1.80
	Peppers	0.076	0	7.30	0.106	0	3.09	0.130	0	2.11
BS_NSWT	Lena	0.037	0.019	35.72	0.028	0.054	28.43	0.023	0.081	28.57
	Peppers	0.046	0.023	95.71	0.033	0.061	69.31	0.026	0.092	64.39
BS_NSCT	Lena	0.035	0.022	50.45	0.027	0.056	33.77	0.022	0.081	30.13
	Peppers	0.045	0.023	110.81	0.033	0.060	66.07	0.027	0.087	52.70
BS-NSST	Lena	0.036	0.022	52.82	0.027	0.059	39.53	0.022	0.085	36.08
	Peppers	0.045	0.024	110.24	0.033	0.062	73.60	0.026	0.091	61.73

IV. BAYESIAN SHRINKAGE AND OUR EXPERIMENTAL RESULTS

Thresholding on coefficients in transform domain is a simple non-linear technique. It assumes that the small coefficients are dominated by noise, and coefficients with a large absolute value carry more signal information than noise. So, noisy coefficients, with small values, set to zero and an inverse transform on the manipulated coefficients may result an image with less noise. Obviously, an appropriate method removes more speckle noise and has less blurring effects. Among many transform domains, we have chosen NSWT, NSCT, and NSST. As we used the BayesShrink for three mentioned transform domain, they named as BS-NSWT, BS-NSCT, and BS-NSST. BayesShrink is a popular thresholding method that was applied in Shearlet [11], Contourlet [19] and Wavelet transform domain [20]. Finding the optimum threshold value to get an output image with the least blurring effect and the most noise reduction is the main goal of any algorithm.

The general block diagram of our proposed method is shown in Fig. 1, where the center block is thresholding operator in transform domain. In following, the procedures of our image denoising algorithm are written:

- Decompose an input image into three levels by NSWT, NSCT, and NSST. The decomposition levels, tiling frequency and the numbered sub-bands are shown in Figs. 2, 3.
- Determine the noise variance for each decomposition level based on (12). For NSWT, we

have used the diagonal sub-bands numbered 3 for the first, second and third decomposition levels. For NSCT, we have used sub-bands numbered 1,8,9,16 and 1,4,5,8 and 1,2,3,4 in order for the first, second and third decomposition levels. For NSST, we have used sub-bands numbered 8,16 and 4,8 and 2,3 in order for the first, second and third decomposition levels.

- Compute the variance of noisy signal for all sub-bands based on (13) and estimate the variance of noise free signal according to (14).
- Obtain the threshold value for each sub-band according to (11), and use the Bayesian soft thresholding for all sub-bands except the coarse one.
- Reconstruct the denoised image by using the inverse transform.

In this section, we have compared the performance of BS-NSWT, BS-NSCT, and BS-NSST in terms of subjective and objective image assessment. We were interested in performing experiments on images of different types and with various contents in order to be able to obtain results, which we could claim to be general enough. So, we used two synthetic noisy image and three true ultrasound images as well. In addition, the image assessment parameters averaged from 10 independent trials.

We used Lena with size 256×256 and Pepper with size 512×512 pixels and 256 gray levels as the synthetic images and two real ultrasound images with the same size 256×256 pixels and the last ultrasound image with size 512×512 as well. All input images are normalized

before using the logarithm transform. Sample noisy images where the speckle noise variance is 0.1 and the results of despeckled Lena, and Pepper are shown in Figs. 4, 5. In Tables 1, 2, we compute FR and NR parameters, for evaluating the despeckling methods where there is different variance of noise. Obviously, for all methods, the quality is decreasing while the noise variance is increasing. For easy comparison, we bold the best achieved values for PSNR and ENL. According to the results, BS-NSST almost all times got the best performance.

Ultrasound images are extremely affected by speckle noise which may cause error decision about a patient disease. In real application, including ultrasound images, there is not a clean signal or noise free signal. Two ultrasound original images and the processed images are shown in Figs. 6, 7. In addition the NR parameters for the true ultrasound images shown in Fig. 6 are written in Table 3 where for easy comparison, we bold the best achieved values for ENL. The parameters are obtained by averaging the results for 10 independent trials. According to the results, unexpectedly, BS-NSCT got the best value for ENL. Accordingly, although BS-NSST image denoising method enjoy superior performance in terms of both subjective and objective evaluation over other NSWT and NSCT for synthetic test images, for real ultrasound images, the BS-NSCT outperform the others according to NR image assessment parameters. It means when dealing with real ultrasound images, BS-NSCT despeckling method preserve most important point targets and texture structures. At the end, the original ultrasound image belongs to kidney with size 512×512 pixels and the despeckling results by BS-NSWT, BS-NSCT, and BS-NSST for visual evaluation are shown in Fig. 8.

V. CONCLUSION

In this paper, the threshold values are obtained by BayesShrink where we consider NSWT, NSCT, and NSST as the transform domain. In general, there is a trade-off between getting an accurate estimate of the signal and the ability to reduce noise. Different deblurring methods tries to remove the noise from the image approximation without lost the information. Our experimental results based on objective and subjective criteria verify that BS-NSST is the best method due to remove the most speckle noise and preserve the image edges and textures for synthesized noisy images, but the experimental results carried out on true ultrasound images and obtained NR parameters evaluate BS-NSCT as the best method. To overcome the BS-NSST draw back, in future, we focus on speckle noise analysis in different transform domains.

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Table 3. Obtained the NR objective assessment parameters for two ultrasound images shown in Fig. 6 to compare the performance of Bayesian shrinkage when NSWT, NSCT, and NSST are used as transform domains.

	Image#1			Image#2		
	NV	MSD	ENL	NV	MSD	ENL
Noisy Image	0.0243	0	15.47	0.0322	0	8.562
BS-NSWT	0.0211	0.0010	22.65	0.0289	0.0008	11.07
BS-NSCT	0.0184	0.0028	38.01	0.0242	0.0033	18.68
BS-NSST	0.0201	0.0015	25.92	0.0275	0.0014	12.57

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