Speckle Noise Reduction Method Combining Total Variation and Wavelet Shrinkage for Clinical Ultrasound Imaging

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Abstract— **Ultrasound imaging is a widely used and safe medical diagnostic technique; however, the usefulness of ultrasound imaging is degraded by the presence of signal dependant noise known as speckle. In this paper, we propose a new speckle reduction method and coherence enhancement of ultrasound images based on method that combines total variation (TV) method and wavelet shrinkage. In our method, a noisy image is decomposed into subbands of LL, LH, HL, and HH in wavelet domain. LL subband contains the low frequency coefficients along with less noise, which can be easily eliminated using TV-based method. More edges and other detailed information like textures are contained in the other three subbands, and we propose a shrinkage method based on the local variance to extract them from high frequency noise. The proposed method has been compared with Median, Anisotropic diffusion filtering, Geometric, Mean and variance local statistics, Wavelet and Total variation filter using quantitative parameters . It has been found that quality evaluation metrics the proposed method performs better than all other methods while still retaining the structural details and experimental results show that this method retains the edges and textures very well while removing noise .**

Keywords- ultrasound imaging ; speckle noise ; wavelet; total variation; local variance.

I. INTRODUCTION

Ultrasound image is often preferred over other medical imaging modalities and is a widely used and safe medical diagnostic technique, due to its noninvasive nature, low cost, capability of forming real time imaging, and the continuing improvements in image quality [1]. However, the main weakness of medical ultrasound image is the poor quality of images, which is interfere with multiplicative speckle noise that degrades the visual evaluation in ultrasound imaging [2].

Speckle in ultrasound B-scans is seen as a granular structure which is caused by the constructive and destructive coherent interferences of back scattered echoes from the scatterers that are typically much smaller than the spatial resolution of medical ultrasound system. This phenomenon is common to laser, sonar and synthetic aperture radar imagery (SAR). Speckle pattern is a form of multiplicative noise and it depends on the structure of imaged tissue and various imaging parameters. Speckle degrades the target delectability in B-scan images and reduces the contrast, resolutions which affect the human ability to identify normal and pathological tissue. It also degrades the speed and accuracy of ultrasound image processing tasks such as segmentation and registration. There are two main purposes for speckle reduction in medical ultrasound imaging (1) to improve the human interpretation of ultrasound images, (2) despeckling is the preprocessing step for many ultrasound image processing tasks such as segmentation and registration [3].

The image denoising problem has been widely studied and two main approaches have been developed: the variational methods [4-8] and wavelet techniques [9-15]. Among variational approaches, a classical variational denoising algorithm is the total variation minimization problem of Rudin-Osher-Fatemi (ROF) [5]: $\inf_{u}\{J(u) + (2\lambda)^{-1}\|f - u\|_{L^2}^2\}$, where *f* is the noisy image, *u* is the image we want to restore from *f*. The constant $\lambda > 0$ is a turning parameter. $J(u) = \int|\nabla_u|$ is often referred to as total variation (TV).Because of its virtue of preserving sharp edges, it is widely used in many applications of image processing. In [5], the authors solved this minimization problem through PDE-based schemes, which is numerical intensive. Besides, Chambolle's projection algorithm [6] is a recent and fast method to solve the ROF model, which solved by:

$$u = f - P_{G_\lambda}(f)\,, \tag{1}$$

where $G_{\lambda=}$ $\{v \in G/\|v\|_G\}$, $P_{G_\lambda}(f)$ is the orthogonal projection of *f* on G_λ and the space *G* is proposed by Meyer for modeling oscillating patterns[9]. However, these TV-based methods have some disadvantages.

On one hand, the TV-based methods have to undergo several iterations for denoising. Thus, estimating the number of iterations is the main disadvantage in TV-based denoising. On the other hand, the TV-based methods do not preserve fine structures, details and textures.

Wavelet shrinkage is another popular denoising method in image processing. Wavelet soft-thresholding method

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introduced by Donoho *et al* was studied and extended in several papers [10-12].

They have introduced a universal threshold T (σ^2 is the variance and N is the total number of pixels) [10-12]:

$$\mathrm{T} = \sqrt{2\sigma^2 \ \mathrm{l_g} N} \ . \qquad (2)$$

The threshold selection plays an important role in wavelet shrinkage method. If the threshold is too small, much noise is still in the denoised image. On the contrary, if the threshold is too large, some important small details such as textures will be removed. The use of universal threshold to denoise images in wavelet domain is known as Visushrink [11].

There has also been a rapidly increasing interest in designing hybrid methods using both wavelet shrinkage and TV denoising methods [16-20]. Durand *et al* [17] proposed a hybrid method to remove the pseudo-Gibbs phenomenon by replacing the thresholded coefficients by values minimizing the total variation. Based on a similar idea, Chan *et al* [18] postprocessed images obtained from wavelet shrinkage by a TV regularization technique. Coifman *et al* [19] postprocessed the signals that have been degraded by wavelet thresholding by solving functional minimization problems with wavelet constraints.

The aim of the hybrid method proposed in this paper is to resolve the contradiction between speckle noise suppression and texture preserving, which cannot be resolved by the TV-based method or wavelet method independently.

This method combining the wavelet approach and TV-based method. Using this method, we can not only remove the noise, but also preserve the details and textures. The noisy image is decomposed to one level which results in LL, HL, LH and HH subbands, where LL stands for the low frequency subband, HL, LH, HH stand for the high frequency subbands of horizontal, vertical and diagonal directions, respectively. We apply the TV method to LL subband which contains less textures and noise, so the noise can be easily removed. In order to extract textures from high frequency noise in the other three subbands, we will propose a shrinkage method based on the local variance.

The paper is organized as follows. Section 2, explains Material and Method Description which consists of TV and wavelet decomposition; Section 3 depicts the quantitative comparison among different filters which considers the experimental results and Discussions. Finally, the conclusion is presented in Section 4.

II. MATERIALS AND METHOD DESCRIPTION

A. Hybrid Denoising Method

The texture characterization is only based on local variance information. In. [15], the authors propose that image patches that correspond to noise will have similar variance with a low skewness value because noise has a symmetric behavior, while textures and edges will have larger local variance. In this paper we make an assumption that the local variance of the texture region is much larger than the variance of the noise region, and the noise is speckle noise. Let f be an image corrupted by the speckle noise. The wavelet representation of f can be described as:

$$f = \sum_{k\in Z^2} \langle f, \varphi_{0,k}\rangle \varphi_{0,k} + \sum_{k\in Z^2}\sum_{j=0}^{\infty}\sum_{i=1}^{3} \langle f, \Psi^i_{j,k} > \ \Psi^i_{j,k} \ \rangle , \qquad (3)$$

where φ is the scale function, and Ψ are two-dimensional wavelets constructed by tensor products of a one-dimensional orthogonal wavelet system. In order to decrease the computational complexity, we decompose the image to one level, which results in LL, HL, LH and HH subbands, i.e.,

$$f = \sum_{k\in Z^2} \langle f, \emptyset_{0,K}\rangle \emptyset_{0,K} + \sum_{k\in Z^2}\sum_{l=1}^{3} \langle f, \Psi^i_{j,k}\rangle \ \Psi^i_{0,K} \ . \qquad (4)$$

We denote the wavelet coefficients corresponding to the four subbands by:

$$C_{\mathrm{LL}} = \langle f, \varphi_{0,k}\rangle ; \ C_{LH} = \langle f, \Psi^1_{0,K}\rangle$$

$$C_{\mathrm{HL}} = \langle f, \Psi^2_{0,k}\rangle ; \ C_{HH} = \langle f, \Psi^3_{0,K}\rangle ,$$

where C_{LL} is called low frequency subband, C_{LH} ,C_{HL},C_{HH} are called high frequency subbands. Since the wavelet coefficients of the noise and textures mainly concentrate on the high frequency subbands, the LL subband contains less textures and noise, so we can apply Chambolle's method to denoise the LL subband without having to worry about the removal of textures. Then we apply Chambolle's projection algorithm to LL subband and get the modified coefficient.

$$\widetilde{\mathrm{C}}_{\mathrm{LL}} = C_{LL} - P_{G_\lambda}(C_{LL}) \ . \qquad (5)$$

In the other three subbands, we will use the local variance information to separate textures from noise based on the wavelet shrinkage method. Recently, hard and soft thresholding have been the most commonly used thresholding strategy:

- Hard– thresholding

$$\widehat{W}_{j,k} = \widehat{W}_{j,k} , |W_{j,k}| \geq T$$

$$\widehat{W}_{j,k} = 0, |W_{j,k}| < T ,$$

- Soft–thresholding

$$\widehat{W}_{j,k} = sgn\,(\widehat{W}_{j,k})(|W_{j,k}|T\,), |W_{j,k}| \geq \ T$$

$$\widehat{W}_{j,k} = 0, \ |W_{j,k}| < T ,$$

where $W_{j,k}$ is the wavelet coefficient, T is the threshold, $\widehat{W}_{j,k}$ is modified coefficient. We take LH subband for example .C_{LH} is essentially a matrix of wavelet coefficients. We assume the size of m times n and denote the element of C_{LH} by $C_{LH}(i,j)$ In practice, we compute the local variance $V(i,j)$ on C_{LH} on a small window centered on (i, j), where i, j are positive integers. Then $V(i,j)$ can be expressed by:

$$V(i\,,j) = \frac{1}{L^2}\sum_{(p\,,q)\in Z_{ij}} \mathrm{C}_{\mathrm{LH}}^2(\mathrm{p}\,,\mathrm{q}) - \frac{1}{\mathrm{L}^4}\left(\sum_{(p\,,q)\in Z_{ij}} \mathrm{C}_{\mathrm{LH}}\,(\mathrm{p}\,,\mathrm{q})\right)^2 \quad , \qquad (6)$$

where

$$Z_{\mathrm{i,j}} = \left[i-\frac{L-1}{2}, i+\frac{L-1}{2}\right]\times\left[j-\frac{L-1}{2}, j+\frac{L-1}{2}\right],$$

and L is odd size of a small window .

It is necessary to extend the boundary of the image when computing the local variance of the boundary pixel. There are many types of boundary extension.

In this paper, we use the mirror- symmetric boundary extension. Each element V (i, j) reflects the oscillatory behavior of the image on a local region. We can choose a Threshold $\mathrm{M}_{\mathrm{LH}} > 0$ so that the collection {(i,j): $V(i,j) > \mathrm{M}_{\mathrm{LH}}$ } can be considered as texture region, while {(i,j): $V(i,j) \leq \mathrm{M}_{\mathrm{LH}}$} corresponds to the noise region. So we propose the following shrinkage method:

$$\widetilde{\mathrm{C}}_{\mathrm{LH}} = 0\,, if\ V \leq M_{\mathrm{LH}}\ \ and\ C_{LH}\,(\mathrm{i}\,,\mathrm{j}) - Sign\big(C_{LH}\,(\mathrm{i}\,,\mathrm{j})\big)\mathrm{T}\,,\mathrm{if}\,V(i,j) > M_{\mathrm{LH}} \quad . \qquad (7)$$

Applying the similar procedure to HL, HH subbands, we can get the other modified wavelet $\widetilde{\mathrm{C}}_{\mathrm{HL}}$, $\widetilde{\mathrm{C}}_{\mathrm{HH}}$ Using the inverse wavelet transform on modified coefficients, we get back the restored image f:

$$\tilde{f} = \sum_{k\in Z^2}\widetilde{\mathrm{C}}_{\mathrm{LL}}\,\varphi_{0,\mathrm{k}} + \sum_{k\in Z^2}\widetilde{\mathrm{C}}_{\mathrm{LH}}\,\Psi^1_{0,K} + \sum_{k\in Z^2}\widetilde{\mathrm{C}}_{\mathrm{HL}}\,\Psi^2_{0,k} + \sum_{k\in Z^2}\widetilde{\mathrm{C}}_{\mathrm{HH}}\,\Psi^3_{0,K} \quad . \qquad (8)$$

B. Algorithm

According to the analysis of the combined method given above, the proposed algorithm is summarized as:

Step 1**:** Decompose f into four subbands of LL, LH, HL, HH get the corresponding wavelet coefficientsC_{LL}, , C_{LH} ,C_{HL},C_{HH}.

Step 2 **:** Apply TV method to the LL subband, i.e.,

$$\widetilde{\mathrm{C}}_{\mathrm{LL}} = C_{LL} - P_{G_\lambda}(C_{LL})$$

Step 3**:** Compute the local variance matrixes V_{LH} , V_{HL} , V_{HH} and choose the thresholds M_{LH} ,M_{HL} ,M_{HH} , respectively.

Step 4**:** Apply the shrinkage method based on local variance to C_{LH} ,C_{HL},C_{HH} . And get the modified wavelet $\widetilde{\mathrm{C}}_{\mathrm{LH}}$, $\widetilde{\mathrm{C}}_{\mathrm{HL}}$, $\widetilde{\mathrm{C}}_{\mathrm{HH}}$

Step 5: Apply inverse wavelet transform on $\widetilde{\mathrm{C}}_{\mathrm{LL}}$, $\widetilde{\mathrm{C}}_{\mathrm{LH}}$, $\widetilde{\mathrm{C}}_{\mathrm{HL}}$, $\widetilde{\mathrm{C}}_{\mathrm{HH}}$ and get the reconstructed image.

III. RESULTS AND DISCUSSIONS

In this section, we present numerical experiments to validate the method proposed above applied on ultrasound liver image available on website[1]. Figure1. shows an ultrasound image with speckle noise and results of various filter (Despeckled images) .The ultrasound image which has been selected from ultrasound website is corrupted by multiplicative noise (speckle) with variance σ_n =0.5 using the MATLAB command (>>imnoise(image,'speckle',0.5)) and various filters have been applied. The performance of noise removing algorithms is measured using quantitative performance measures such as MSE, RMSE ,SNR, PSNR ,Q as well as in term of visual quality of the images .

The Mean square error (MSE) : which measures the quality change between the original and processed image in an *MXN* window ,The root MSE (RMSE): which is the square root of the squared error averaged over an *MXN* window , The signal-to-noise ratio (SNR) : it better when higher , The peak SNR (PSNR) : is higher for a better-transformed image and lower for a poorly transformed image, It measures image fidelity, which is how closely the despeckled image resembles the original image . The mathematically defined universal quality index Q models any distortion as a combination of three different factors: loss of correlation, luminance distortion, and contrast distortion Q is computed for a sliding window of size 8×8 without overlapping , Its highest value is 1 ; its lowest value is -1 .

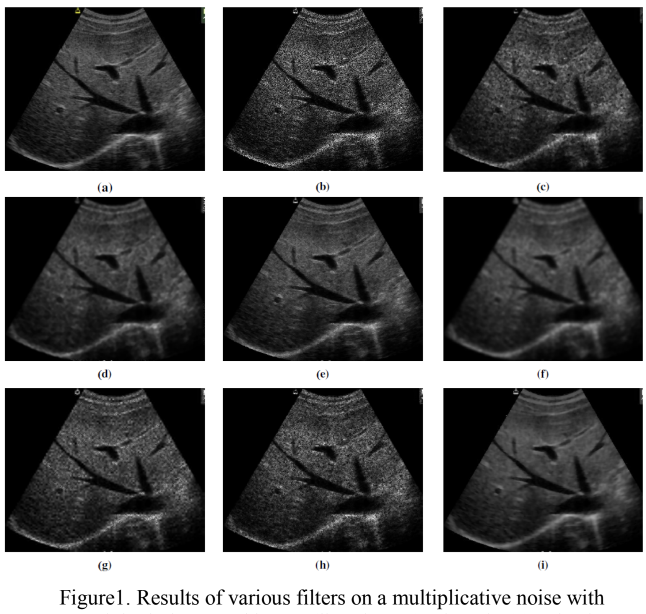

Figure1. Results of various filters on a multiplicative noise with σ_n=0.5Original ultrasound image (liver image) given in (a)Noisy image given in (b) , Median filter (median) in (c), Speckle reducing anisotropic diffusion filtering in(d) , Geometric despeckle filter (gf4d) in(e) , Mean and variance local statistics despeckle filter (lsmv) in (f) , Wavelet Shrinkage in (g), Total Variation despeckle filter(h) , and Proposed method in (i).

[1]http://www.medison.ru/uzi/eho240.htm

TABLE 1 . Image Quality Evaluation Metrics Computed For The Liver

Filter Type	Feature set				
	MSE	**RMSE**	**SNR**	**PSNR**	**Q**
median	112.1565	10.5904	23.6660	30.6429	0.7270
srad	29.4551	9.2014	**23.6755**	31.8640	0.7249
gf4d	30.5884	5.5307	23.6667	36.2855	**0.8681**
lsmv	67.4939	8.2155	23.6668	32.8485	0.7138
waveltc	94.5670	9.7246	22.6721	31.3837	0.7590
TV	124.2650	14.9755	23.6531	27.6335	0.7021
Proposed method	**25.2279**	**5.0227**	**23.6675**	**37.1223**	**0.8435**

Bold numbers indicate the best values.
MSE, mean square error ; RMSE, randomized mean square error; SNR, signal-to-noise ratio; PSNR, peak signal to-noise; Q, universal quality index.

Fig 1. shows an ultrasound image with noisy together and the despeckled images. This filters above compared with proposed method introduce in [21]. The best visual results obtained by the proposed method showed good visual results not only remove speckle but also preserve the details of the image, and preserves the edge properties, also from Figure 1. (g), one can see that although the result obtained by wavelet Shrinkage method contains abundant textures, much noise is retained in the image. Figure 1. (h) shows the result obtained by TV method. We see that most of the noise have been removed, but many textures are also removed. Figure 1. (i) shows the result by our method, from which we can see that the textures are better preserved while removing the noise. The proposed method successfully balances the relationship between noise suppression and texture preserving.

Table 1 tabulates the image quality evaluation metrics, ultrasound image between the original and the despeckled image,respectively Performance of all algorithms is tested with medical images. Best values were obtained for the proposed method with lower MSE, RMSE and higher SNR and PSNR and Best values for the universal quality index , Filters *median*, *lsmv*, *waveltc*, *TV* ,showed poorer visual results and a blurring effect ; but the filters *srad , gf4d*, shows better visual results compare to this filters . It has been found that the proposed method is better than all other in quantitative terms as well as visual quality of the image.

IV. CONCLUSIONS

In this paper, we propose a speckle reduction method combining the TV method and Wavelet. The proposed hybrid method takes full advantage of TV-based method to denoise the low frequency subband without losing textures, and uses the wavelet shrinkage method based on local variance information to extract textures from noise in the high frequency subbands.

Our method can preserve fine details like textures while removing the noise. Experimental results are shown to validate the proposed method in comparison with Wavelet and TV method. Experimental results showed that the proposed filter works better than another filters , not only remove speckle but also preserve the details of the image and is better than all other in quantitative terms as well as visual quality of the image. Initial findings show promising results; however, further work is required to evaluate the performance of the proposed despeckle method at a larger scale as well as their impact in clinical practice.

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