Wavelet Decomposition Based Speckle Reduction Method for Ultrasound Images by Using Speckle Reducing Anisotropic Diffusion

Byeongcheol Yoo, Hyunkyung Park, Jegoon Ryu, Kunsu Hwang and Toshihiro Nishimura

***Abstract*—In this paper, we introduce the modified speckle reducing anisotropic diffusion(SRAD) that uses wavelet decomposition for speckle reduction in medical ultrasound(US) images. As a first step of our approach, the coarse-to-fine classification is performed into each 2D wavelet sub-band to determine homogenous speckle-related region. Next, SRAD is played on each wavelet sub-band that uses investigated speckle regions as scale speckle function. With speckle determination, homogenous region can be details calculated without manual selection or preliminary exponential decay function. Moreover, variety pattern of speckle is reduced by the proposed modified SRAD on multiscale wavelet. Relying on this progress, the proposed method can improve the image quality for both subjective visualization and auto-segmentation. Finally, we validate our method to compare with current speckle reduction filters using simulated speckle images and clinical image. The experimental results show that the proposed method is effective in speckle reduction as well as edge preservation.**

Index Terms— speckle noise, speckle reducing anisotropic diffusion, wavelet decomposition, coarse-to-fine classification

I. Introduction

Ultrasound image is often preferred over other medical imaging modalities because it is noninvasive, non-ionizing, portable and low-cost [1]. However, the main weakness of medical ultrasound image is the poor quality of images, which is interfere with multiplicative speckle noise [2]. Speckle is a characteristic phenomenon in ultrasound images, which can be described as random multiplicative noise that occurrence is often undesirable, since it affects the tasks of human interpretation and diagnosis.

A number of techniques have been applied to address the problem of speckle noise based on temporal averaging, median filtering, Wiener filtering and wavelet based method [3]. However, these temporal averaging and multi-frame methods causes the loss of details such as texture patterns because of blurring.

Recently, a more reliable technique based on anisotropic diffusion was proposed such as nonlinear anisotropic diffusion, e.g., Perona & Malik filter [4], Weickert filter [5] and SRAD [6]. SRAD has introduced as a useful processing utility to ultrasound images attempting to reduce speckle that has been derived by casting typical adaptive filters into the nonlinear diffusion technique. Nowadays, several extend works using SRAD method have been applied to improve performance of both speckle reduction and edge preservation [7], [8]. Although these SRAD methods could improve the speckle reduction and edge preservation, the low-contrast edges were still blurred with speckle that remain in the high-intensity region and manual selection of homogeneous for speckle scale function. There is a consideration in using the wavelet [8], [9] as a powerful utility for noise reducing utility to significantly simplify the statistics of natural signals.

In this paper, we present the wavelet decomposition based adaptive SRAD method for the enhancement of Ultrasound images and reduction of processing progress. The coarse-to-fine classification is used as a speckle scale function based on the wavelet decomposition.

The paper is organized as follows. Section II, explains the background and methodology which consists of SRAD and wavelet decomposition; Section III delineates the proposed method that includes the coarse-to-fine classification; Section IV depicts the quantitative comparison among different filters which considers the experimental results and measures to assess the filtering algorithm. Finally, the conclusion is presented in Section V.

II. Background

A. Speckle Noise

Speckle noise is a common phenomenon in all coherent imaging systems such as US and SAR imaging [8]-[10]. The distribution of speckle in the US images changes with the type of scatters in biological tissues. Thus, speckle filtering turns out to be a critical pre-processing step for de-speckling and edge enhancement. Under the assumption that the real and imaginary parts of the speckle have zero-mean Gaussian density and noise intensity. A usual way to estimate the

Manuscript received July 21, 2008.

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speckle noise level in a SAR image is to calculate Eq. (1), often termed the Equivalent Number of Looks (ENL), using pixel intensity values over a uniform image area.

$$\left(\frac{mean}{standarddeviation}\right)^2 = L = constant \qquad (1)$$

The magnitude of the signal usually follows a heavy-tailed distribution, namely Rayleigh. The speckles are spatially correlated. The correlation length is usually a few pixels specifically 3 to 5 pixels.

B. SRAD Formulation

Yu and Acton [6] compared the Lee [10], Kuan [12] and Frost [9] works with the anisotropic diffusion filter proposed by Perona and Malik [14], leading to a modified anisotropic diffusion that they named it as speckle reducing anisotropic diffusion. Anisotropic diffusion is a method for smoothing speckled images. Given an intensity image $I_0(x,y)$ having finite power and non zero-values over the image domain Ω, the output image $I_0(x,y;t)$ is evolved according to the following partial differential equation (PDE):

$$\begin{cases} \partial I(x,y;t) = div[c(q)\nabla(x,y,;t)] \\ I(x,y;0) = I_0(x,y), (\partial(x,y;t)/\partial\vec{n})|\partial\Omega = 0 \end{cases} \qquad (2)$$

Where $\partial\Omega$ denotes the border of Ω, $\vec{n}$ is the outer normal to the $\partial\Omega$, $c(q)$ is the diffusion coefficient, and q is the ICOV. $q_0(x,y;t)$ is given by

$$q(x,y;t) = \sqrt{\frac{\left|(1/2)(\nabla I/I)^2 - (1/4^2)(\nabla^2 I/I)^2\right|}{[1+(1/4)(\nabla 2I/I)]^2}} \qquad (3)$$

The instantaneous coefficient of varying $q(x,y;t)$ serves as the edge detector in speckled images. The alteration reflects the encouraging isotropic diffusion in homogeneous regions of the image where $q(x,y;t)$ fluctuates around $q_0(t)$.

$$q_0(t) = \sqrt{\frac{\mathrm{var}[z(t)]}{\overline{z(t)}}} \qquad (4)$$

Equation (4) is similar to the parameter k in the study of Perona & Malik, the speckle scale function $q_0(t)$ effectively controls the amount of smoothing applied to the image by SRAD. We called the Eq. (2) as the SRAD PDE.

C. Wavelet Decomposition

The multiscale wavelet analysis has a very useful property of space and scale localization. It has variety significant applications in signal processing problems such as image coding and image de-noising. The principle of the wavelet decomposition is to transform the original raw particle image into several components: one low-resolution and high-resolution, it called approximation low-pass filter and details high-pass filter [15]-[18]. The noise is mainly appeared in the details. In practice, multi-resolution investigation is carried out using 4 channel filter banks composed of a low-pass and a high-pass filter and each filter bank is then sampled at a half rate of the previous frequency.

By repeating this process, it is possible to obtain wavelet transform of any order. The down sampling procedure keeps the scaling parameter at constant throughout the successive wavelet transforms so that it benefits for simple computer implementation. In the case of an image, the filtering is implemented in a separable way by filtering the lines and columns. Make a note of that [15] the discrete wavelet transform (DWT) of an image consists of a four frequency sub-band for each level of decomposition. The CA part at each scale is decomposed recursively, as sketched in Fig. 1.

D. Coarse-to-fine classification

The coarse-to-fine approaches can be detected speckle regions or background area, easily. We use coarse-to-fine classification method form [16] as follow:

$$\hat{x}_{i,j} = \begin{cases} 0, |w_{i,j}||\hat{y}_{i,j+l}| < \sigma_j^2, \\ 1, |w_{i,j}||\hat{y}_{i,j+l}| \geq \sigma_j^2 \end{cases} \qquad (5)$$

Where σ_j is the standard deviation of noise at the resolution scale 2^j. This property can be exploited in different ways to achieve a better classification of wavelet coefficients than using their intensity alone. From coarse to fine, and finds the speckle region in the target wavelet sub-band.

III. Proposed Method

The proposed multiscale wavelet decomposition based SRAD described in this section. The proposed approach aims to improve the US images quality both subjective visualization and auto-segmentation applications. The Proposed approach contains three steps (Fig.3).

1) The three-level wavelet decomposition is performed. In this processing implementation, the speckle noise and important feature detail are present in sub-band. The CA part at each scale is decomposed recursively, as showed in Fig. 1.
2) To determine the homogeneous region that include speckle pattern, the coarse-to-fine classification is performed after the wavelet decomposition. Fig.2 shows the schematic diagram of the proposed speckle classification method. To achieve a satisfactory de-speckled and edge preservative US image result, SRAD is performed iteratively with auto-selected homogeneous region.
3) For the US image reconstruct, inverse 2D DWT is preformed. Finally, the de-speckled and log-compressed image is converted to original log-compressed image during the proposed approach is converted to original spatial domain by exponential transformation.

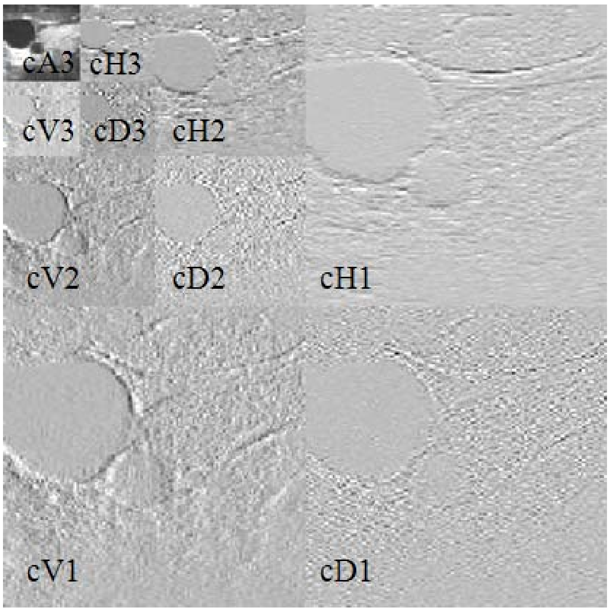

Fig.1.The results of multiscale wavelet decomposition for clinical ultrasound image.

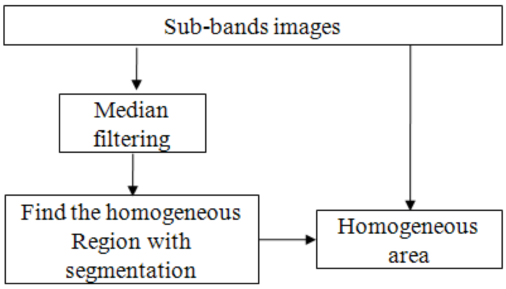

Fig.2. The schematic diagram of proposed homogeneous region selections.

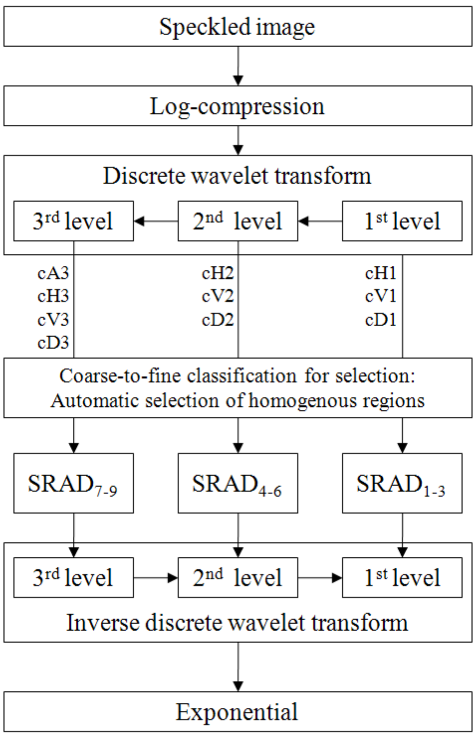

Fig.3. Block diagram of the proposed method using the coarse-to-fine threshold method

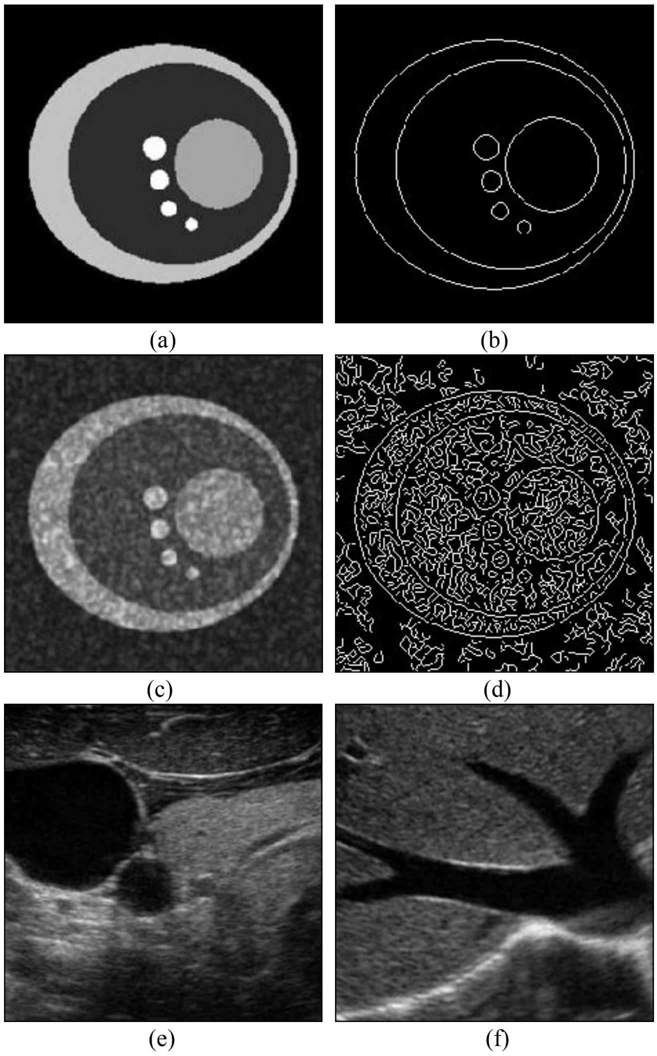

Fig.4. The simulated speckled US image and three clinical US images for the test. (a) Simulated speckle-free image (b) Edge map of (a). (c) Simulated speckle image (Yue *et al.*[12], Canny detector). (d) Edge map of (c). (e) Internal jugular vein. (f) Hepatic veins

IV. Experimental Results

A. *Quantitative Parameter*

For quantitative quality evaluation, we provide PSNR (Eq.6), S/MSE (Eq.7), MSSIM (Eq.8) and Partt's FOM (Eq.9). PSNR is defined as:

$$PSNR = 10 \times \log_{10}\left(\frac{g_{\max}^{2}}{\left\|x\text{-}y\right\|_{2}^{2}}\right) \tag{6}$$

Where g_{max} is the upper-bound gray level of the image x or y, and $\left\|\bullet\right\|_2$ is an l_2 -norm operator.

And S/MSE is expressed as:

$$S/MSE = 10\log_{10}\left(\sum_{i=1}^{K} S_i^2 \Big/ \sum_{i=1}^{K}\left(\hat{S}_i - S_i\right)^2\right) \tag{7}$$

And which corresponds to the standard SNR in case of additive noise.

MSSIM is expressed as:

$$MSSIM(X,Y) = \frac{1}{M}\sum^{M} SSIM(x_j, y_j) \tag{8}$$

Where X and Y are the reference and the distorted images, respectively; x_j and y_j are the image contents at j^{th} local window; and M is the number of local windows.

The Partt's figure of merit expressed as:

$$FOM = \frac{1}{\{\hat{N}, N_{ideal}\}} \sum_{i=1}^{\hat{N}} \frac{1}{1 + d_i^2 \alpha} \tag{9}$$

Where $\hat{N}$ and N_{ideal} are the number of detected and ideal edge pixels, respectively, d_i is the Euclidean-distance between the i^{th} detected edge pixel and the nearest ideal edge pixel, and α is a constant typically set to 1/9. FOM ranges between 0 and 1, with unity for ideal edge detection.

B. Simulated Speckle Image

To evaluate the performance of filters in quantitative manner, speckle is typically modelled as multiplicative noise using noise-free tissue mimicking image and speckle image.

The US images from clinical modalities have experimental properties, such as low-pass filtering, interpolation, log-compression and a few pixels specifically 3 to 5 pixels; that can be modelled as [17]:

$$\int(x) = \mu I(x) + \sqrt{\mu I(x) \cdot n(x)} \tag{10}$$

Where $\mu I(x)$ is the intrinsic signal, and $n(x)$ is a zero- mean Gaussian noise with mean one. Using Eq. (10), Yue *et al.* [12] generated simulated speckle image for the log-compressed image. The combined noise includes both the appearance of speckle and the norm distribution (Fig.4(a),(c)).

C. Test Results

The proposed method is compared with four exiting filtering methods which are adaptive Median filter, KUAN filter, Perona & Malik filter and original SRAD.

The proposed method of speckle reduction and edge preservation is tested by using one simulated US image (Fig.4(a),(b)) and three clinical US images (Fig.4(e)-(f)).

For simulated US images four quantitative parameters were used for assessing the performance which is peak signal-to-noise ratio (PSNR), signal mean square error ratio (S/MSE), mean structural similarity (MSSIM) index and Partt's figure of merit (FOM). In the clinical US image test, we examined the image quality improvement of the proposed algorithm for visualization using edge map test. Result are taken on all images of size 256 × 256.

The three clinical ultrasonic images (Fig. 6(a)-(h)) acquired by using ultrasound equipment for the experiment. The filtering variation of adaptive median uses a 5×5 window size and 10 iterations because this condition shows the best results for PSNR and S/MSE. Lee & Kuan filter uses a 7×7 window and one iterative processing, whereas the SRAD and proposed method using 100 iteration and λ =0.1 for experimental results.

Table. 1 summarizes the quantitative results obtained in the simulated and clinical images. The speckle reduction filter can eliminate speckle in most homogenous regions. However, the proposed method can significantly reduce speckle in both of the low and high intensity regions, as well as preserve edges (Fig.5 (i)) Especially, Fig. 6, Fig.7. Fig8 show the edge map results of clinical US images that enhanced the edge on the ROI. Comparing Fig. 5-8 with Table I, we realized that our proposed method successfully improved the speckle reduction and edge preservation.

TABLE I. PERFORMANCE COMPARIION FOR DIFFERENT SPECLE REDUCTION TECHNIQUES USING PSNR, S/MSE, MSSIM AND FOM

Filters	Performance Evaluation Parameter			
	PSNR	S/MSE	MSSIM	FOM
Noisy	15.6740	15.8502	0.9971	0.1475
Median	15.8606	16.2799	0.9970	0.4293
KAUN	15.8928	16.3540	0.9971	0.1992
Perona	16.0348	16.6809	0.9971	0.5774
SRAD	16.3992	17.5201	0.9973	0.6255
Proposed	**19.8526**	**25.4717**	**0.9991**	**0.6525**

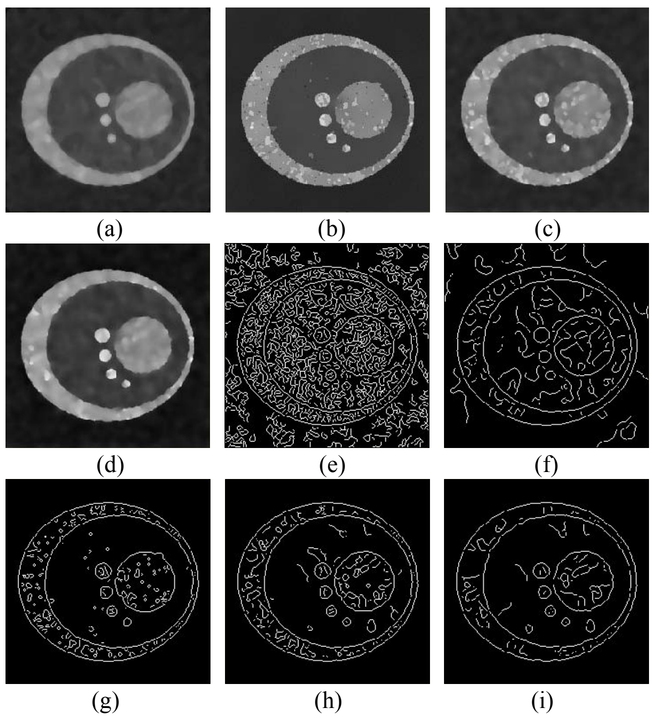

Fig.5. The speckle reduction and edge map results (Yue *et al.*[12],

Canny detector) for simulated speckled US image. Adaptive median filter (a), (f). Perona and Malik filter (b), (g). Original-SRAD filter (c), (g). Proposed method (d), (h). (c) Edge map of Fig.4.(e).

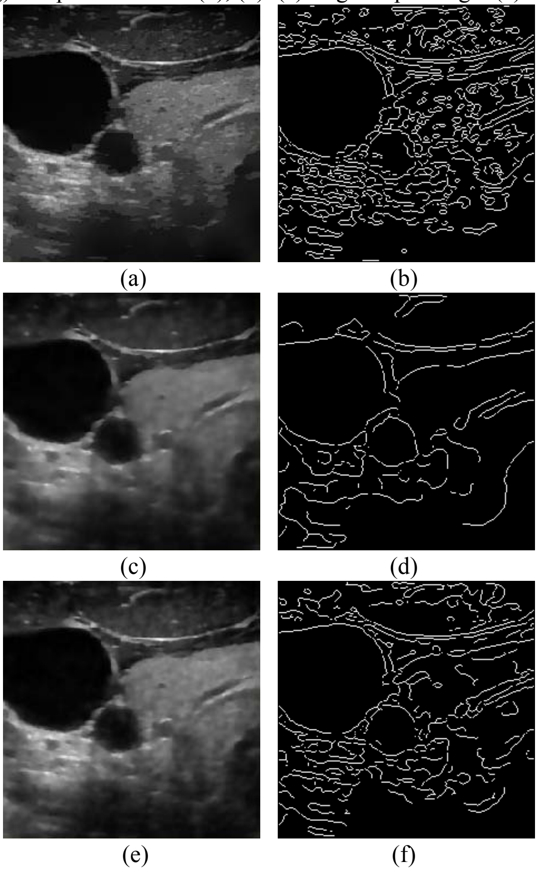

Fig.6. De-speckling results for internal jugular vein images; (a), (b) Perona and Malik filter. (c), (d). original SRAD filter.(e), (f) proposed method (c), (f), (i).

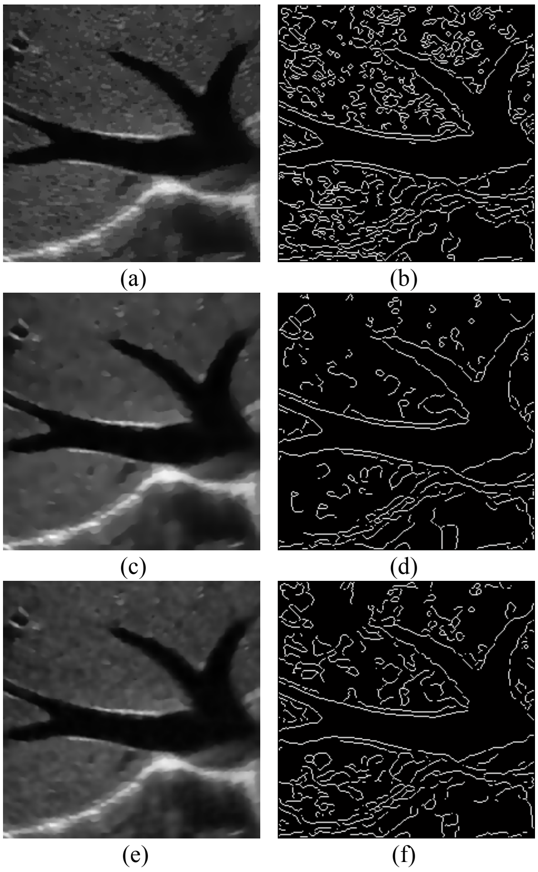

Fig.8. De-speckling results for hepatic veins images; (a), (b) Perona and Malik filter. (c), (d). original SRAD filter.(e), (f) proposed method (c), (f), (i).

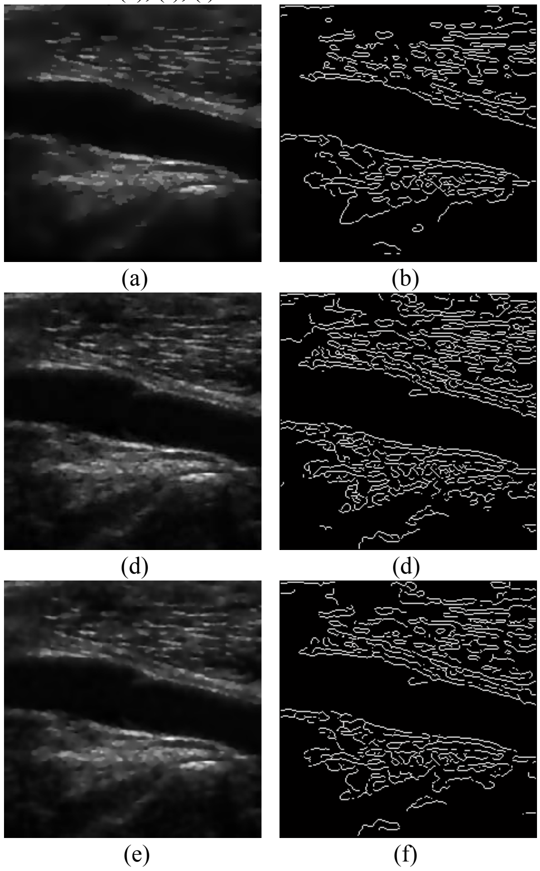

Fig.8. De-speckling results for venous valve images; (a), (b) Perona and Malik filter. (c), (d). original SRAD filter.(e), (f) proposed method (c), (f), (i).

V. Conclusion

In this paper, a novel we introduced the improved speckle reducing anisotropic diffusion that uses wavelet decomposition for medical ultrasonic images. First, the SRAD, wavelets decomposition and coarse-to-fine classification were described. Second, the progress of the proposed method using 2DWT log compression and automatic determination of homogenous speckle region to pick a speckle scale function were explained. Relying on this progress, the proposed method successfully improved the image quality for visualization. Third, we validate our method by comparing with present speckle reduction filters using both the simulated and clinical speckled ultrasonic images. We discovered that the proposed method is more effective, both in terms of speckle reduction and edge preservation. Our comparative experiments with 4 standard speckle filters have shown that our improved SRAD filter is among the best speckle filters. Experimental results show that the proposed method gives significant improvement in speckle reduction and edge preservation over previous techniques.

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