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A Modified hybrid Filter for Echocardiographic Image Noise Removal

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Abstract

Noise is the major difficulty that arises in echocardiographic image processing. The problem is especially important if the noise has a multiplicative nature (speckle noise).In this Paper we introduced a hybrid filter. This filter is combination of Speckle removal SRAD and Relaxed median filter. Experiments are carried out on Echocardiographic images. Results show Speckle reduced edge preserved images. This hybrid filter removes speckle noise as well as removes impulse noise. This model also enhances the edges in the image.

Keywords: *hybrid, echocardiographic, SRAD, realaxed median, speckle*

1. Introduction

Use of Ultrasound images is increasing day by day for the diagnosis different type of diseases related to different parts of the body. However compared to other medical images these images suffer from lower contrast, lower signal to noise ratios, variable intensity of structures, signal dropout, and shadowing of structures. Echocardiography is a widely used method for diagnosis of heart diseases but Echocardiographic images have poor contrast and suffer from high noise content. Therefore, the edge detection operation results in a very ambiguous edge map, containing missing edge points, spurious edge points, and genuine edge points which are not part of cardiac borders. Furthermore, there is variability and complexity in the shape of target borders. Due to speckle noise it is very difficult to extract these types of boundaries. So there is a requirement to develop a suitable filter which is able to remove noises from these images.

The speckle and scene models used as the basis for filter development decide the Speckle filter performance. The multiplicative and the product speckle models are the well known models, which have been used as the basis for the development of almost all the existing speckle filters,. The multiplicative speckle model serves for the development of the minimum mean-square error (MMSE) filters Lee [1], Kuan *et al.* [2], and Frost *et al.* [3], whereas the product model has been used as the basis for the development of the maximum *a posteriori* (MAP) Bayesian Gaussian [4], Gamma [5, 6], and model-based despeckling [7] filters. Various mathematical expressions have been developed and used for the named “multiplicative speckle model” [1, 2, 3, 8, 9]. All these speckle-scene models implicitly incorporate certain assumptions about speckle, observed signals and scene and this strongly influences speckle filtering, as well as scene reconstruction, during the inversion process based on these models [10, 11, 12].

Recently, the well known single-stage speckle filter, the refined Lee filter [13] and the Frost *et al.* [3] filter that have been used for many years, were prematurely rejected in [14]: “Single-stage filters are inadequate for effective speckle removal; MMSE reconstruction can be rejected because structure is not retained upon iteration" [14]. On the other hand, the Hagg edge-preserving optimized speckle filter [15], which is basically a multiresolution box (average) filter, has been recognized as the best speckle filter [16, 17]. All these literature leads to a lot of confusion, and it is difficult for the user to identify which filter to use in each neither application nor suitable window size to associate to each filter for unbiased reconstruction of the scene signal.

Major limitations are encountered in the filtering approach of existing despeckle filters termed as "edge preserving" and "feature preserving". The limitation is that the filter window of the filters is sensitive in size and shape. If a filter window is too large (compared to the scale of interest), over-smoothing will occur and edges will be blurred. But if a small window is used it will decrease the smoothing capability of the filter and will leave speckle. Second, these filters only inhibit smoothing near edges but the existing filters do not enhance on the edges. The coefficient of variation will be high and smoothing will be inhibited, if any portion of the filter window contains an edge. Therefore, noise/speckle in the neighborhood of an edge (or in the neighborhood of a point feature with high contrast) will remain after filtering. Third, the despeckle filters are not directional. In the vicinity of an edge, all smoothing is precluded, instead of inhibiting smoothing in directions perpendicular to the edge and encouraging smoothing in directions parallel to the edge. Last, the thresholds used in the enhanced filters, although motivated by statistical arguments, are *ad hoc* improvements that only demonstrate the insufficiency of the window-based approaches. The hard thresholds that enact neighborhood averaging and identity filtering in the extreme cases lead to blotching artifacts from averaging filtering and noisy boundaries from leaving the sharp features unfiltered.

In the present paper we use the SRAD [18] in combination with relaxed median filter [19]. SRAD not only preserves edges but also enhances edges by inhibiting diffusion across edges and allowing diffusion on either side of the edge. SRAD is adaptive and does not utilize hard thresholds to alter performance in homogeneous regions or in regions near edges and small features. The new diffusion technique is based on the same minimum mean square error (MMSE) approach to filtering as the Lee (Kuan) and Frost filters. In fact, it has been shown that the SRAD can be related directly to the Lee and Frost window-based filters. So, SRAD is the edge sensitive extension of conventional adaptive speckle filter, in the same manner that the original Perona and Malik anisotropic diffusion [20] is the edge sensitive extension of the average filter. In this sense, the application of anisotropic diffusion has been extended to applications such as radar and medical ultrasound in which signal-dependent, spatially correlated multiplicative noise is present.

SRAD filter despeckles the image with edge preservation but impulse noise is generated after application of SRAD filtering so we use relaxed median filter for its removal. This hybrid modal is able to give noise free image.

2. Speckle Reducing Anisotropic Diffusion

Given an intensity image $I_0(x, y)$ having finite power and no zero values over the image support Ω, the output image $I(x, y; t)$ is evolved according to the following PDE:

$$\begin{cases} \partial I(x,y;t)/\partial t = div[c(q)\nabla I(x,y;t)] \\ I(x,y;0) = I_0(x,y), (\partial I(x,y;t)/\partial \vec{n})|\partial\Omega = 0 \end{cases} \quad \ldots\ldots (1)$$

Where $\partial\Omega$ denotes the border of Ω, $\vec{n}$ is the outer normal to the $\partial\Omega$, and , the diffusion coefficient is:

$$c(q) = \frac{1}{1+[q^2(x,y;t)-q_0^2(t)]/[q_0^2(t)/[q_0^2(t)(1+q_0^2(t))]} \text{..................}(2)$$

or

$$c(q) = \exp\left\{-\left[q^2(x,y;t)-q_0^2(t)\right]/\left[q_0^2(t)(1+q_0^2(t)\right]\right\} \text{.........................}(3)$$

In (2) and (3), $q(x,y;t)$ is the instantaneous coefficient of variation determined by

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

And $q_0(t)$ is the speckle scale function. We call (1) the SRAD PDE.

In the SRAD, the instantaneous coefficient of variation $q(x,y;t)$ serves as edge detector in speckle imagery. The function exhibits high values at edges or on high-contrast features and produces low values in homogeneous regions. Speckle scale function effectively controls the amount of smoothing applied to the image by SRAD. It is estimated using

$$q_0(t) = \sqrt{\frac{\mathrm{var}[z(t)]}{\overline{z(t)}}} \text{.............}(5)$$

Where $\mathrm{var}[z(t)]$ and $\overline{z(t)}$ are the intensity variance and mean over a homogeneous area at t, respectively.

Because of the need of computing (5), the SRAD requires knowing a homogeneous area inside the image being processed. Although it is not difficult for a user to select a homogeneous area in the image, it is nontrivial for a computer. So, automatic determination of $q_0(t)$ is desired in real applications to eliminate heuristic parameter choice.

First of all, we state that $q_0(t)$ can be approximated by

$$q_0(t) \approx q_0 \exp[-\rho t] \text{.............}(6)$$

Where ρ is a constant, and q_0 is the speckle coefficient of variation in the observed image. For fully developed speckle, $q_0 = 1$, for ultrasound intensity data (without compounding) and $q_0 = 1/\sqrt{N}$ for N -look SAR intensity data. For partially correlated speckle, q_0 is less than unity.

Here is the derivation of (6). As we expected, in a uniform area the diffusion should be isotropic. Adopting the discrete isotropic diffusion update, we have

$$I_{i,j}^{t+\Delta t} = I_{i,j}^t + \frac{\Delta t}{4}(I_{i+1,j}^t + I_{i-1,j}^t + I_{i,j+1}^t + I_{i,j-1}^t - 4I_{i,j}^t) \text{ ..}(7)$$

Given $\sigma(t)$, the slandered deviation of $I_{i,j}^{t}$ in a homogeneous region, we can estimate the standard deviation of $I_{i,j}^{t+\Delta t}$ in the region. Assuming that pixels in the region are stationary in dependent and identically distributed. We have from (7 and statistical formula for the variance of a sum of random variables

$$\sigma(t+\Delta t)=\sqrt{(1-\Delta t)^{2}\sigma^{2}(t)+(\Delta t/4)^{2}4\sigma^{2}(t)} \quad \ldots\ldots(8)$$

On the other side, the local means remains the same before after one iteration. So, we have

$$q_{0}(t+\Delta t)=q_{0}(t)\sqrt{(1-\Delta t)^{2}+(\Delta t)^{2}/4} \quad \ldots\ldots\ldots\ldots\ldots..(9)$$

For $\Delta t << 1$, the $(\Delta t)^{2}$ terms in (9) can be neglected, and we have

$$\sqrt{1-2\Delta t}\approx 1-\Delta t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(10)$$

By Taylor series expansion and neglecting the second and higher order terms. So (9) becomes

$$\dot{q}_{0}(t)+q_{0}(t)\approx 0 \quad \ldots\ldots\ldots\ldots\ldots\ldots.(11)$$

Where $\dot{q}_{0}(t)$ is the first derivative of $q_{0}(t)$ with respect to t. solving (11), yields

$$q_{0}(t)\approx q_{0}\exp[-t] \quad \ldots\ldots\ldots\ldots\ldots\ldots(12)$$

3. Relaxed Median Filter

Relaxed median filter can be used in combination with SRAD to remove large spike noises.

Let $\{X_{i}\}$ be a $m-$ dimensional sequence, where the index $i\in Z^{m}$. A sliding window is defined as a subset $W\subset Z^{m}$ of odd size $2N+1$. Given Sliding window W , define $W_{i}=\{X_{i+r}: r\in W\}$ to be the window located at position i .

If we let X_{i} and Y_{i} be the input and the output at location i , respectively, of the filter, then we have for the standard median (SM) filter:

$$Y_{i}=med\{W_{i}\}=med\{X_{i+r}: r\in W\} \quad \ldots\ldots\ldots\ldots\ldots\ldots..(13)$$

Where $med\{.\}$ denotes the median operator.

Denote by $[W_{i}]_{(r)}$, $r=1,\ldots\ldots..2N+1$ the r^{th} order statistic of the samples inside the window W_{i} :

$$[W_{i}]_{(1)}\leq[W_{i}]_{(2)}\leq\ldots\ldots.[W_{i}]_{(2N+1)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(14)$$

The relaxed median filter works as follows: two bounds l and u --lower and upper, respectively—define a sub list inside the

$[W_i]_{(.)}$, which contains the gray levels that we assume to be good enough not to be filtered.

If the input belongs to the sublist, then it remains unfiltered, otherwise the standard median filter is output.

Let $m = N + 1$ and l, u such that $l \leq m \leq u \leq 2N + 1$. The relaxed median filter with bounds l and u is defined as:

$$Y_i = RM_{lu}\{W_i\} = \begin{cases} X_i & if X_i \in [[W_i]_{(l)}, [W_i]_{(u)} \\ [W_i]_{(m)} & otherwise \end{cases} .....(15)$$

Where $[W_i]_m$ is the median value of the samples inside the window W_i .

4. Proposed Method

The discrete isotropic diffusion update from eq. (7) is

$$I_{i,j}^{t+\Delta t} = I_{i,j}^{t} + \Delta t(\nabla^2 I_{i,j}^{t}).......(16)$$

Where $$\nabla^2 I_{i,j}^{t+\Delta t} = \frac{\Delta t}{4}(I_{i+1,j}^{t} + I_{i-1,j}^{t} + I_{i,j+1}^{t} + I_{i,j-1}^{t} - 4I_{i,j}^{t})$$

Where Δt is time space step size.

Relaxed median filter can be used in combination with SRAD to remove large spike noises. The proposed hybrid method is defined as follows:

$$I_{i,j}^{t+\Delta t} = RM_{l.u}[I_{i,j}^{t} + \Delta t(\nabla^2 I_{i,j}^{t})]........(17)$$

Where *RM* is the relaxed median filter with lower bound l and upper bound u .The lower bound and upper bounds for relaxed median used in the experiments are 3 and 5 respectively. Here we show example which results from proposed hybrid model.

Figure 1 shows the Echocardiographic images taken from different views of heart of different patients . Here we can see that there is lots of speckle noise present in these images which makes difficult to extract boundaries. Other important diagnosis also becomes difficult with this noise.

Figure 2 shows the SRAD filtered images we can see that these images are speckle free but impulse noise or salt and pepper noise is introduced. Which also creates problem in diagnosis. So there is requirement of a filter that removes these types of disturbing noises.

Proposed hybrid filter removes speckle noise as well as impulse noise. Fig. 3 shows images filtered with proposed hybrid filter. Relaxed median filter hybrid with speckle reducing filter removes impulse noise in parallel.

Table 1 shows the statistical analysis of these two filters. Here statistical parameters are PSNR (peak signal to noise ratio), MSE (mean square error) and RMSE(root mean square error). High PSNR and low value of MSE and RMSE shows the better filter. Analysis in table 1 shows that proposed filter have high PSNR and Low MSE and RMASE than SRAD in case of echocardiographic images.

Figures 4, 5 and 6 shows the statistical comparison between two filters in graphical form. It can be seen that the data line related to SRAD filter is above the data line related to proposed method in case of PSNR. But in case of MSE and RMSE data line related to SRAD is below the data line related to proposed method.

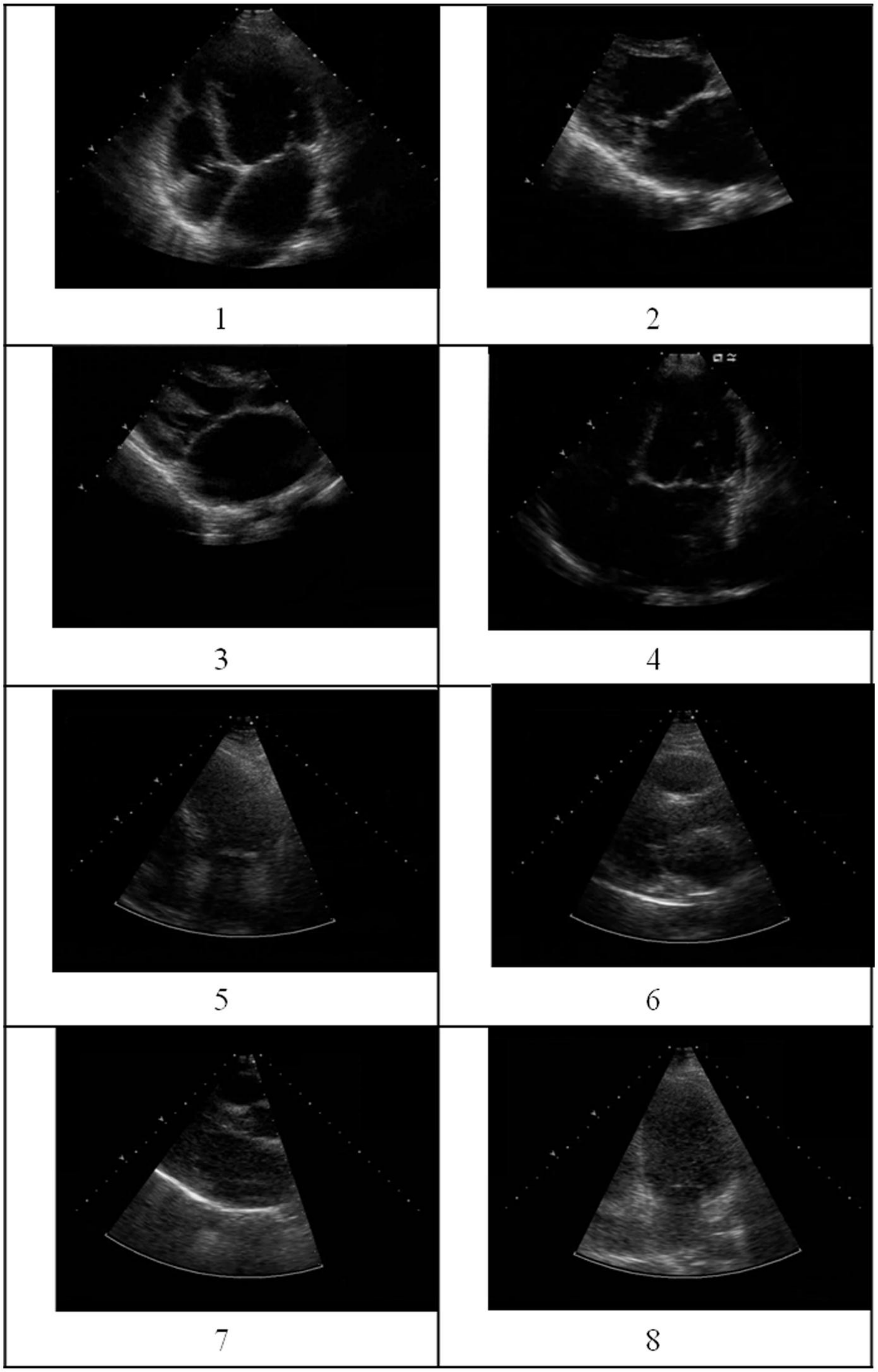

Figure 1. Original Images

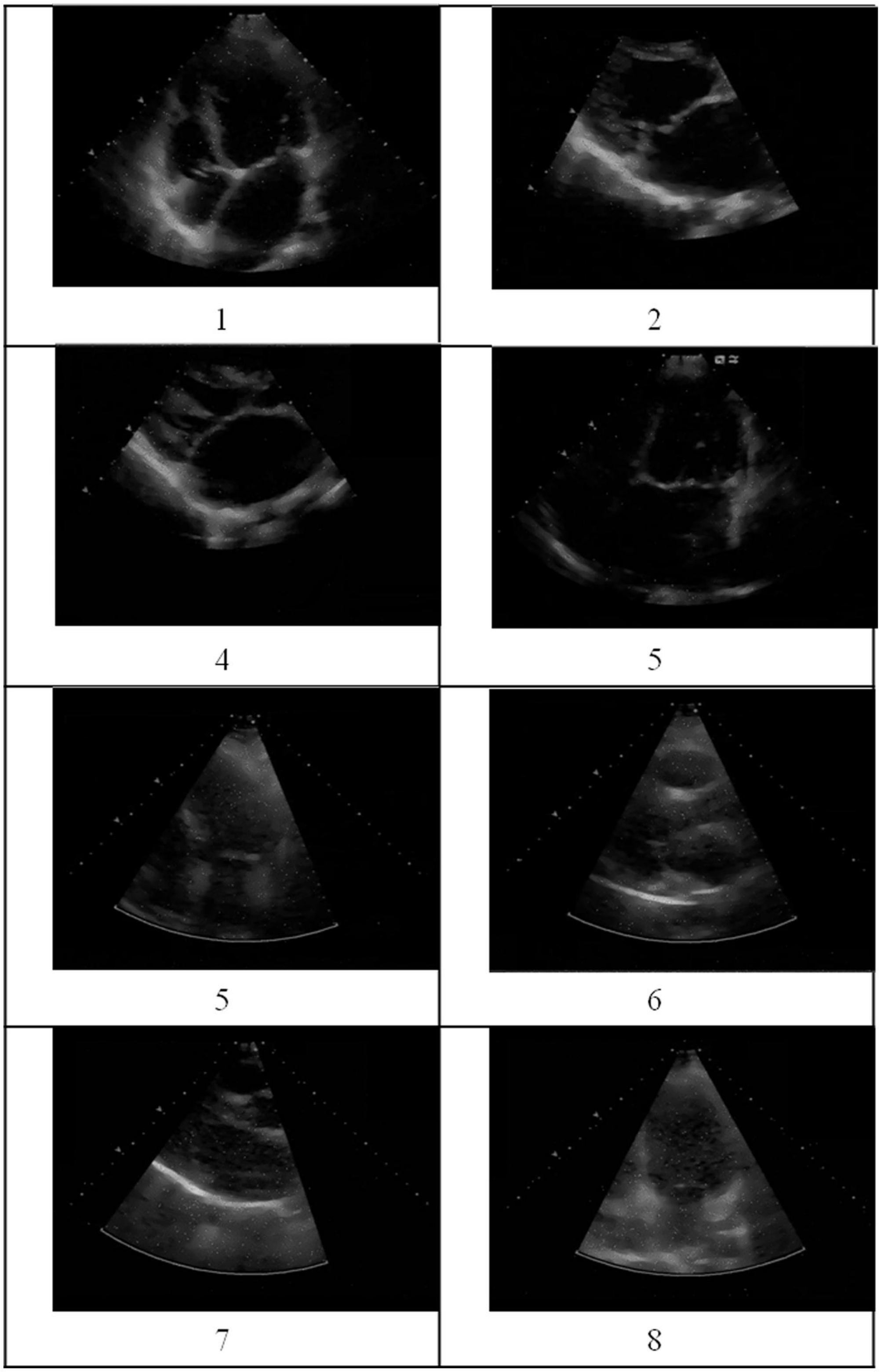

Figure 2. SRAD Filtered Image

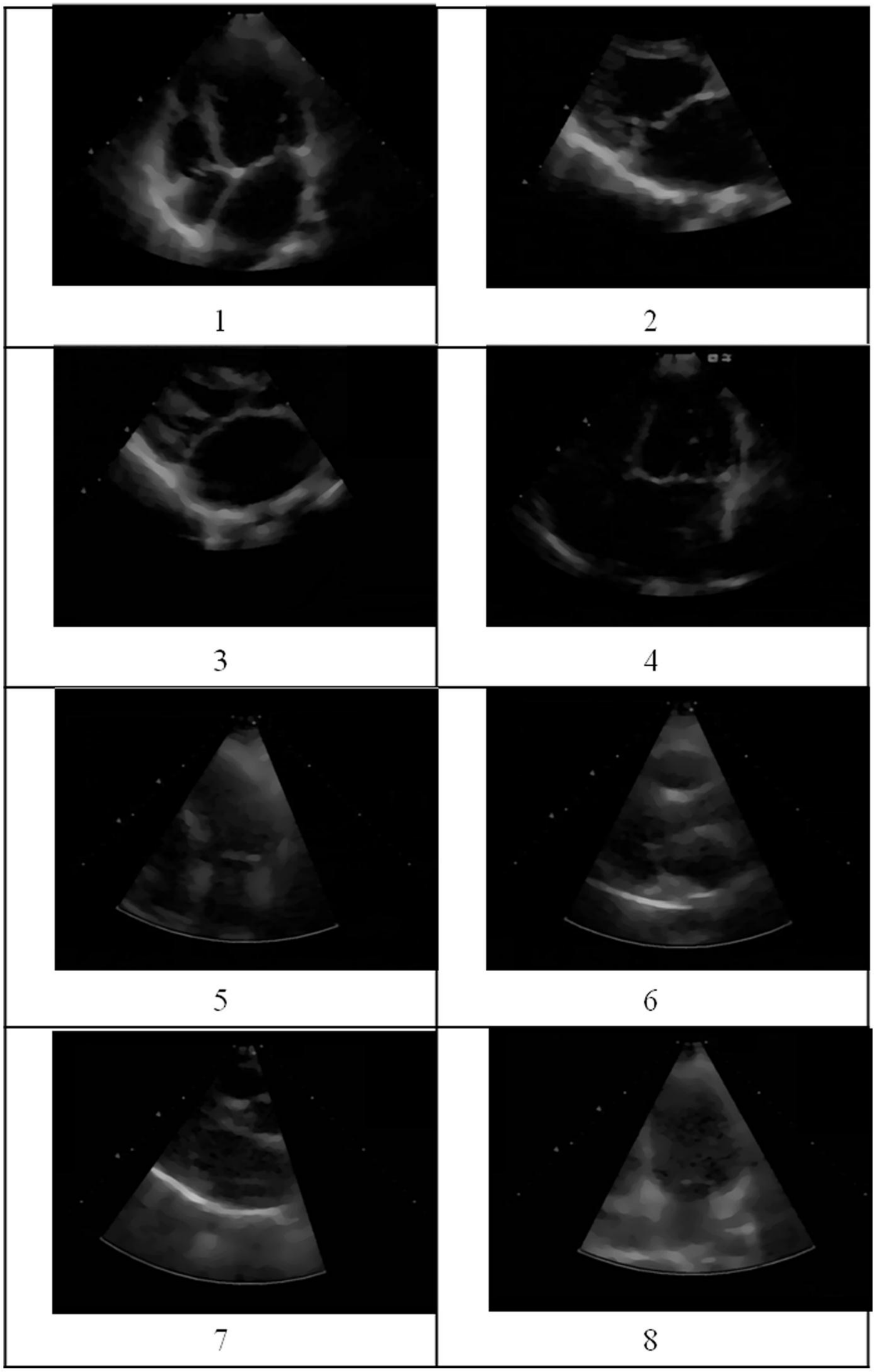

Figure 3. Despeckled Image after Applying Proposed Hybrid Filter

Table 1. Despeckled Image after Applying Proposed Hybrid Filter

Images	SRAD Method			Proposed Method		
	PSNR (dB)	MSE	RMSE	PSNR (dB)	MSE	RMSE
1	+37.83	10.7070	3.2722	+38.64	8.8847	2.9807
2	+39.94	6.5881	2.5667	+40.70	5.5337	2.3524
3	+39.56	7.2038	2.6840	+40.57	5.7077	2.3891
4	+41.74	4.3533	2.0865	+43.27	3.0653	1.7508
5	+40.11	6.3468	2.5193	+40.90	5.2892	2.2998
6	+38.20	9.8513	3.1387	+39.55	7.2064	2.6845
7	+38.45	9.2970	3.0491	+39.43	7.4220	2.7243
8	+37.16	12.5072	3.5366	+37.82	10.7328	3.2761

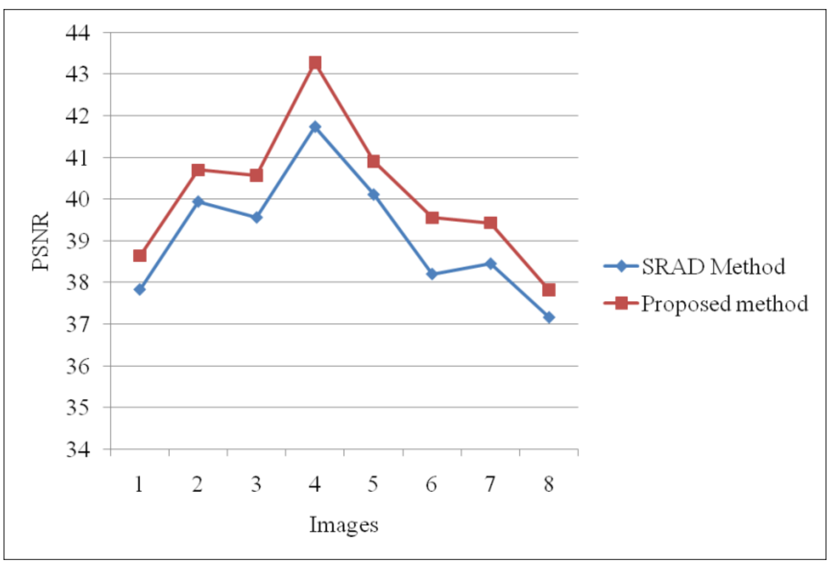

Figure 4. PSNR of Images in Case of SRAD and Proposed Method

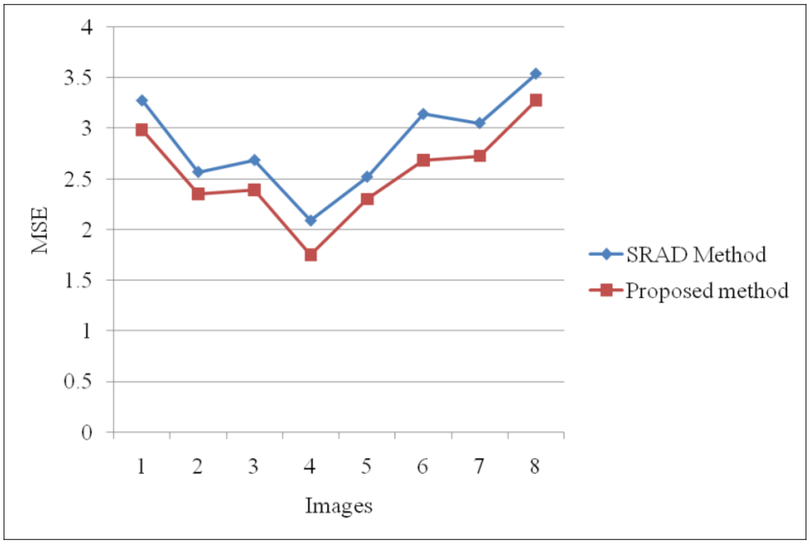

Figure 5. MSE of Images in Case of SRAD and Proposed Method

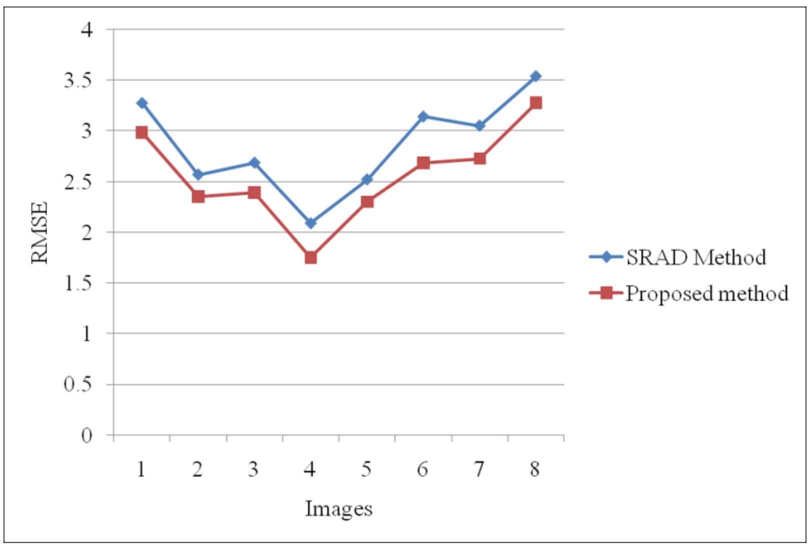

Figure 6. RMSE of Images in Case of SRAD and Proposed Method

5. Conclusions

Proposed method is an improvement over Yongjian Yu and Scott T. Acton's paper Speckle Reducing Anisotropic Diffusion by additional quality of relaxed median filter. Proposed method has been implemented on different echocardigraphic images and has resulted in giving spike free images. Statistical analysis has also been carried out for comparison between SRAD and the proposed filter. This analysis shows that proposed filter is better for echiocardiographic images. Here total 8 images have been taken for analysis and all images shows the improvement with proposed filter. However about 38 images taken for analysis and all images satisfy that PSNR in case proposed method is high and MSE and RMSE are low in comparison to SRAD method.

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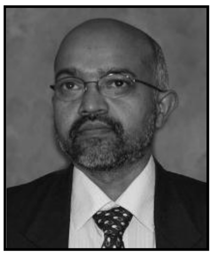

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