"Denoising" Of Mixed Noise in Ultrasound Images

Saraswathi Janaki samusarma[1], Mary Brinda[2]

[1] **Electronics and communication Engineering, Anna university, Easwari Engineering college**
Chennai, Tamilnadu 600 089, India

[2] **Electronics and communication Engineering, Anna university, Easwari Engineering college**
Chennai, Tamilnadu 600 089, India

Abstract

Medical images are affected by the mixed noise, which is the combination of speckle and Gaussian noise. This paper proposes an efficient algorithm for reducing the mixed noise in ultrasound images. The proposed method reduces the noise and also preserves edges effectively and hence the quality of the image is enhanced. Based on w avelet thresholding, ST-PCNN and Bayesian maximum a posteriori (MAP) are fused together to denoise the ultrasound images. Experimental results show a significant improvement in removing the mixed noise present in the ultrasound images and this method outperforms the other methods in terms of PSNR and MSE.

Keywords: *ST-PCNN, Bayesian Map estimator, PSNR, MSE, Spatially adaptive thresholding, soft-thresholding*

1. Introduction

Medical ultrasonography uses high frequency broadband sound waves in the megahertz range that are reflected by tissues to varying degrees to produce (up to 3D) images. It has several advantages which make it ideal in numerous situations, in particular it s tudies the function of moving structures in real-time, emits no ionizing radiation. The main advantage of ultrasonography is noninvasive imaging since it uses mechanical waves. The noise considered in this paper, is the mixed noise, which is the combination of speckle noise and Gaussian noise. The ultrasound images are badly degraded by the speckle noise, which is formally known as multiplicative noise. Due to the speckle noise, the detailed information in the ultrasound image is not easily identified. So the details of the image need to be preserved by removing the speckle noise. Thus the reduction of multiplicative noise becomes an important aspect in the application of the medical images. White Gaussian noise, comes from many natural sources, such as the thermal vibrations of atoms in conductors, shot noise, black body radiation from the earth and other warm objects, and from celestial sources such as the Sun.

The proposed method, the combined Bayesian MAP estimator and ST-PCNN method, attains better results, to reduce the mixed noise efficiently.

Yongqiu Tu & Shaofa Li Minqin Wang [4] proposed a Modified PCNN Model and Its Application to Mixed-noise Removal. In this method, a new approach named, L&A PCNN method is introduced to remove the mixed noise, in which this model has linear attenuated threshold and weighted-averaging-firing-pixel-intensity outputs. Initialize the parameters to determine the result matrix Y, followed by inversing the result of Y to denoise the low Gaussian noise, and again inverse the result to smooth the noisy pixel. Median filter is used to recover the original pixel values. The main drawback of this method is, since the parameters are set by using the heuristic method, this model is not good in adaptivity. So this method is restricted to the real-time applications.

Zhao Chunhong, et.al. [5] proposed "A new speckle reduction method of medical ultrasonic image". A robust method for de-noising the speckled image by wavelet transformation. The logarithmic transformation is applied to the noisy image and wavelet transformation is applied to reduce the speckle noise. The adaptive thresholding is used to identify the noisy co-efficients from the wavelet co-efficient and set the co-efficients to zero and remaining co-efficients are processed. Inverse wavelet transformation is applied to get the output and apply the exponential transformation to retrieve the original image. The main disadvantage of this method is edges are not preserved effectively and the noise is not much reduced.

M. I. H. Bhuiyan, et.al [6] proposed "New Spatially Adaptive Wavelet-based Method for the de-speckling of Medical Ultrasound Images" In this approach, log transformation is applied to the noisy image. Then the Discrete continuous wavelet transformation is applied to the log transformed co-efficients. The wavelet co-efficient is used to model the log transformed speckle co-efficients. Spatially adaptive thresholding method is used for

Denoising. Then the inverse discrete continuous wavelet transformation followed by the application of exponential transformation to retrieve back the denoised image. The major drawback of this approach is the complexity, as two prior models are used. Discrete continuous wavelet transformation causes the blurring and ringing noise.

Alin Achim [8] has proposed a " Novel Bayesian Multi-scale Method for Speckle Reduction" the logarithmic transform of the original image is analyzed into the multi-scale wavelet domain. Bayes MMAE estimator or Bayes MAP estimator and then inverse DWT is applied. The mean of the log-transformed image is considered in which Cauchy and Gaussian distribution is used to model the speckle noise. The main disadvantage of this method is, time taken for execution is large.

P.Badulescu and R. Zaciu [9] proposed "Removal Of Mixed-Noise Using Order Statistic Filter And Wavelet Domain Wiener Filter". In this paper, two methods are evaluated. First method is, using of order statistic prefilter and empirical weiner filtering, which is used to reduce the Gaussian noise. The disadvantage of this method is the higher time consumption. Second method is, order statistic filter for each decomposition level, where decomposition is carried out by the wavelet thresholding. The drawback of this method is, efficiency is less than the first method (about 1dB) in removing the mixed noise.

Zong X, et.al [10] proposed "Speckle reduction through multi-scale nonlinear processing" which presents an algorithm for speckle reduction. This speckle reduction method based on, soft-thresholding the wavelet coefficients of the logarithmically transformed medical ultrasound image. Shrinkage of wavelet coefficients through soft-thresholding in 1 and 2 scales, within finer levels of scale is carried out on coefficients of logarithmically transformed medical image. Then hard-thresholding of wavelet coefficients is applied within selected (mid-range) spatial-frequency levels of analysis is done in 3 and 4 scale to preserve the features to eliminate the noise. Then inverse discrete wavelet transformation is performed to reconstruct the de-noised image. And then exponential transformation is applied.

The main disadvantage of this method is that the parameters that are used for Wavelet shrinkage for de-noising were adjusted by the trial and error method. The computational time is high.

.

2. Proposed Algorithm

In order to increase the PSNR and MSE values, and to make the image noise-free and to preserve the edges, the following algorithm is used. Fig 1 explains the proposed method. The noise used is the mixed noise, which is the combination of speckle noise and Gaussian noise. The Log transformation is applied to the noisy image and the wavelet transformation is applied over the log transformed image. The combined Bayesian MAP estimator and ST-PCNN method is used to de-noise the image. The inverse wavelet transformation is applied and the exponential transformation is used to recover the original image.

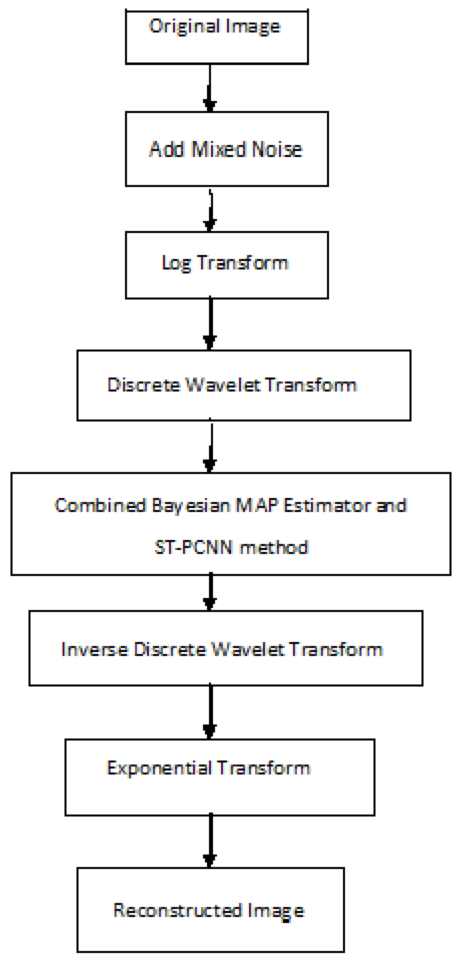


Fig. 1. Overview of the proposed method (Combined Bayesian MAP Estimator and ST-PCNN)

The noisy ultrasound image is given as

$$H(k, l) = i(k, l) * J(k, l) + £(k, l) \quad (1)$$

Where, i is the noise free original image, J is the speckle noise and £ is the additive Gaussian noise, (k,l) are the variables of spatial location (K represents the row and l represent the column).

2.1 Logarithmic Transformation

The dynamic range of an image can be compressed by replacing each pixel value with its logarithm. This has the effect that low intensity pixel values are enhanced. Applying a p ixel logarithm operator to an image can be useful in applications where the dynamic range may too large to be displayed on a s creen. Logarithmic transformation can be expressed as

Hl (k, l) = il(k, l) +Jl(k, l)

Since the speckle noise is formally known as multiplicative noise, 'J' is multiplied with the input image, 'I'. It can be converted into additive noise by applying the logarithmic transformation to the noisy ultrasound images.

2.2 Wavelet Transformation

Wavelet transformation is used for the reduction of mixed noise, because of its high energy concentration. After applying the Discrete wavelet transformation, the image is decomposed into four sub bands (LL, HL, LH and HH). where HL, LH, HH sub bands contain the detail components and LL sub band contain the low frequency components. Again the sub band LL is divided into four smaller sub bands for further filtration.

$$h_w(k,l) = i_w(k,l) + j_w \quad , \quad i=1,2,3$$

2.3 Bayesian Map Estimator

Bayesian MAP estimator, which is developed by Symmetric Normal Inverse Gaussian Probability density function (SNIG PDF) [1], is used to de-noise the ultrasound images. There are two types of thresholding.

1. Hard thresholding
2. Soft thresholding

Hard thresholding deletes all its coefficients that are smaller than the threshold, and retains the other co-efficients unchanged. On the other hand soft thresholding also deletes its coefficients under the threshold, but scales the ones that are left. Hard thresholding creates discontinuities in the reconstructed signal, while soft does not. In this method, adaptive thresholding is used, where different thresholds are used for different regions in the image. This may also be known as local or dynamic thresholding.

The Bayesian MAP estimator is obtained from the equation below:

$$y(h) = sign(h)\max(h - \sigma^2|L|,0)$$

Where, L is the SNIG PDF, which is given as,

$$L = \frac{2h}{\gamma^2} + \frac{\sum h}{\sqrt{\gamma^2 + h^2}} \frac{k_o(e^{\sqrt{\gamma^2+h^2}})}{k_1(e^{\sqrt{\gamma^2+h^2}})}$$

$\sigma^2|L|,0$ is used for thresholding function which is spatially adaptive.

$$x(h) = sign(h)\max(h - c\sigma^2|L|,0)$$

C is the tuning factor, which is used to control the smoothing effect.

$$\phi_y(\omega) = \exp(\gamma\varepsilon - \gamma\sqrt{\varepsilon^2 + \omega^2})$$

$$c_y(\omega) = \ln \phi_y(\omega)$$

The cumulate of the SNIG PDF can be obtained as

$$k_y{}^n = -j^n \frac{\partial c_y(\omega)}{\partial \omega}, \omega = 0$$

$$j = \sqrt{-1}$$

Using (1), the first four cumulate are obtained as

$$k_y{}^2 = \frac{\delta}{\varepsilon}$$
$$k_y{}^4 = \frac{3\delta}{\varepsilon^3} \qquad (2)$$
$$k_y{}^3 = 0$$
$$k_y{}^1 = 0$$

Using (2), expressions for the parameters ε and γ are obtained as

$$\varepsilon = \sqrt{3\frac{k_y{}^2}{k_y{}^4}}$$

$$\gamma = \varepsilon k_y{}^2$$

In order to make the Bayesian MAP estimator spatially adaptive, the cumulates are estimated from the local neighbors. For the (k, l)th coefficient, the second and fourth-order signal moments are denoted respectively as $p_y{}^2(k,l)$ and $p_y{}^4(k,l)$

$$p_y{}^4(k,l) = \max((p_h{}^4(k,l) - 6p_y{}^4(k,l)\sigma^2 - 3\sigma^4),0)$$
$$p_y{}^2(k,l) = \max((p_h{}^2(k,l) - \sigma^2),0)$$

The values of $p_y{}^2(k,l)$ and $p_y{}^4(k,l)$ are obtained using D x D square window, the corresponding second and fourth-order cumulates are obtained as

$$k_y{}^2 = h_y{}^2$$
$$k_y{}^4 = \max((p_y{}^4 - 3p^2y^2,0))$$

The value of 'σ' is obtained using the coefficients in the lowest subbands with diagonal orientation as,

$$\sigma = \frac{D_1 + D_2}{2}$$

where D1=Med (h(k,l))/0.6745), h(k,l) € HH1, and D2= Med(h(k,l))/0.6745), h(k,l) € HH2, and 'Med' denotes the median absolute.

2.4 ST-PCNN Method

In this method, Denoising is done by soft-thresholding the wavelet co-efficient. PCNN is used to determine the heavy tailed co-efficient in the wavelet domain. The neural model [2] ,for the PCNN is shown below.

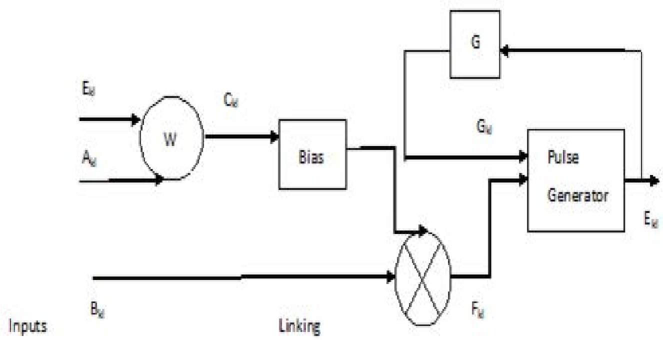


Fig. 2 PCNN Neural model

$$A_{k,l}[n] = B_{k,l}$$

$$c_{k,l}[n] = \sum D_{k,l} \times E_{k,l}[n-1]$$

$$F_{k,l}[n] = A_{k,l}[n](1 + \beta C_{k,l}[n-1])$$

$$G_{k,l}[n] = \exp(-\alpha) G_{k,l}[n-1] + V \times E_{k,l}[n-1] \ldots [3]$$

$$E_{k,l} = 0 if F \geq G$$

$$else = 1$$

Where $B_{k,l}$ - the input signal given to the PCNN model.
$A_{k,l}[n]$ - the feedback input.
$C_{k,l}[n]$ - the linking input.
$D_{k,l}$ - the weight matrix.
$F_{k,l}[N]$ - the pulse input.
$E_{k,l}[N]$ - the internal activity.
β - the linking constant.
α - the thresholding constant.
V is the amplitude constant of $G_{k,l}[N]$
n –number of iterations

ST-PCNN algorithm:

a) Initialize E,G, β=0.1, V= δ x 1.3499
b) Assign $D_{k,l}$=[0.5 1 0.5; 1 0 1; 0.5 1 0.5]
c) Using the above equations, determine the result value for E and G.
d) Based on the condition in equation (3), E can be found.

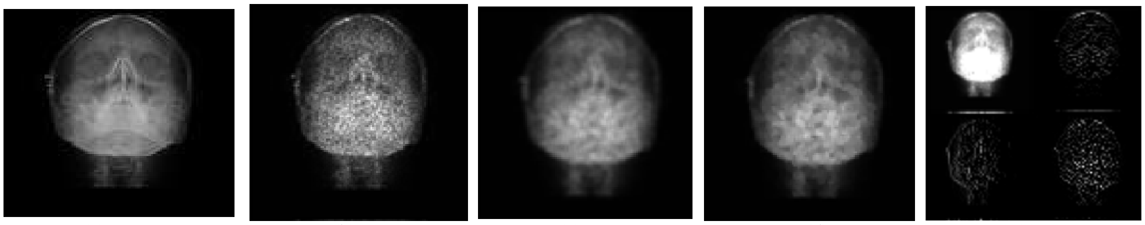
Inverse discrete wavelet transformation is applied to the output of the ST-PCNN. Exponential transformation is applied to output of IDWT to retrieve back the original image.

3. Experimental Results

The evaluation of parameters are made by PSNR andMSE. where PSNR=max size /mean (mean (original image-enhanced image) and MSE(Mean square error) =original image – corrupted image.

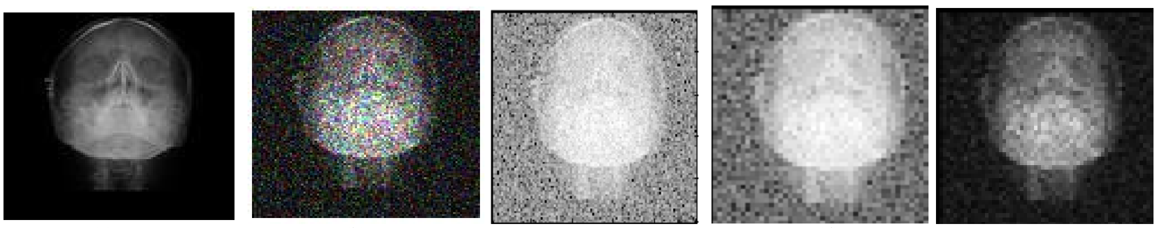
In this section, Mean, Median filters are compared with the wavelet filter, to determine the performance of the filter Gij in removing the speckle noise effectively. Experimental results are compared by means of PSNR, MSE .

By comparing the experimental results, the following conclusions are obtained: (a) Mean Filter can reduce the Gaussian noise effectively, whereas, median filter reduces the salt & pepper noise.(b) By using wavelet filter, a considerable amount of speckle noise is removed, than the mean and median filter. (c)The standard comprising method, combined ST- PCNN and Bayesian MAP estimator is superior to ST-PCNN and Bayesian MAP estimator. The performance of the proposed method is compared with the existing methods, which include ST-PCNN and Bayesian MAP estimator. From the results, it is observed that the proposed method outperforms the other methods in terms of PSNR, MSE, and MAE. From table 1 and 2, it is inferred that, as the speckle noise density is higher than the Gaussian noise density, the proposed method removes the speckle noise considerably than the gaussian noise that degrades the ultrasound images.In this case, the value of PSNR is higher than as it is for lower speckle noise density.From the results it is concluded that the proposed method removes higher speckle noise density than the higher density of Gaussian noise .



(a) (b) (c) (d) (e)

Fig. 3. (a) Face Ultrasound Image (b) Noisy image (c) Results of Mean Filter (d) Results of Median Filter (e) Results of Wavelet Filter.

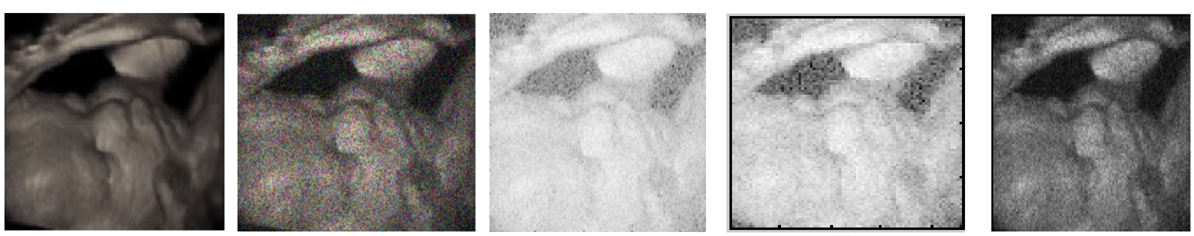


(a) (b) (c) (d) (e)

Fig. 4. (a) Face Ultrasound Image (b) Noisy image (c) Results of Lograthmic transformation (d) Results of Inverse Discrete Wavelet transformation (e) Results of Exponential transformation.

(a) (b) (c) (d) (e)

Fig. 5. (a) Pelvic Ultrasound (b) Noisy image (c) Results of Lograthmic transformation (d) Results of Inverse Discrete Wavelet transformation e) Results of Exponential transformation.



(a) (b) (c) (d) (e)

Fig. 6 (a) Baby Ultrasound image (b) Noisy image (c) Results of Lograthmic transformation (d) Results of Inverse Discrete Wavelet transformation e) Results of Exponential transformation.

Table 1: Comparative results between proposed method and ST-PCNN and Bayesian MAP Estimator

MIXED NOISE DENSITY (Variance)		ST-PCNN			BAYESIAN ESTIMATOR			COMBINED BAYESIAN ESTIMATOR AND ST-PCNN		
SPECKLE NOISE	GAUSSIAN NOISE	PSNR	MSE	MAE	PSNR	MSE	MAE	PSNR	MSE	MAE
0.1	0.01	21.30	480.94	131.81	20.80	540.49	148.75	21.32	479.94	131.17
0.1	0.04	20.78	543.65	149.73	21.30	481.55	131.45	20.79	544.28	149.35
0.1	0.08	20.152	627.78	176.86	20.17	624.68	176.24	20.16	627.02	176.58
0.1	0.1	19.938	659.47	190.14	19.94	658.74	189.95	19.93	660.99	190.35
0.1	0.4	19.138	795.79	419.24	19.12	795.84	419.03	19.12	795.81	419.61
0.1	0.8	19.11	795.90	689.64	19.12	795.90	690.23	19.12	795.90	689.71

Table 2: Comparative results between proposed method and ST-PCNN and Bayesian MAP Estimator

MIXED NOISE DENSITY (Variance)		ST-PCNN			BAYESIAN ESTIMATOR			COMBINED BAYESIAN ESTIMATOR AND ST-PCNN		
SPECKLE NOISE	GAUSSIAN NOISE	PSNR	MSE	MAE	PSNR	MSE	MAE	PSNR	MSE	MAE
0.01	0.1	19.9304	660.75	190.37	19.91	662.71	190.75	19.93	659.74	659.74
0.04	0.1	19.92	661.55	191.48	19.92	661.27	190.90	19.91	663.05	190.69
0.08	0.1	19.90	664.08	190.64	19.93	659.49	190.10	19.93	659.93	190.93
0.1	0.1	19.93	660.59	190.79	19.94	658.63	189.85	19.92	661.18	191.07
0.4	0.1	19.99	651.56	188.45	20.01	648.64	187.14	20.1	649.62	188.17
0.8	0.1	20.04	643.03	188.43	20.06	641.28	187.63	20.24	636.55	187.72

4. Conclusion.

In this paper an efficient technique for de-noising the medical ultrasound images has been proposed. Combined Bayesian MAP estimator and ST-PCNN method has been proposed for mixed noise reduction. This method is experimented on the test images like Lena, SAR and ultrasound images, where these images are corrupted by mixed noise at different densities. Experimental results show that the combined Bayesian MAP estimator and ST-PCNN method is more efficient in removing mixed noise while preserving edges.

References

[1] M.I.H.Bhuiyan, M.O.Ahmad and N.Swamy, "Spatially adaptive thresholding in wavelet domain for despeckling of ultrasound images", IET Image processing, Vol.3, 2009, pp. 147-162.

[2] Guo Ye-cai, He Long-qing and Wang Shao-bo, "Soft-Threshold De-noising Method of Medical Ultrasonic Image Based on PCNN", in International Conference on Artificial Intelligence and Computational Intelligence,2009, 554 - 558.

[3] S.Zhan and H.Jinglu, "Image Edge Detection Method Based On A Simplified PCNN Model With Anisotropic Linking Mechanism", in International Conference Intelligent Systems Design and Applications, 2010, pp.330-335.

[4] Yongqiu Tu, Shaofa Li and Minqin Wang, "Modified pcnn model and its application to mixed-noise removal," in International conference on Robotics and Biomimetices,2007,pp.1333-1338.

[5] Zhao Chunhong, Liu Mingyu and Ji Hongbing, "A new speckle reduction method of medical ultrasonic image", in International Conference on Bio informatics and Biomedical Engineering , 2007,pp. 1004 -1006.

Dr.S.Saraswathi Janaki obtained her Ph.D degree from Anna University, Chennai, Tamilnadu, India. She is currently working as a professor and Head in the department Electronics and communication Engineering in Easwari Engineering college, Chennai, Tamilnadu, India. Her areas of interest are signal and Image processing, Electronic circuits. She is a member of IEEE, ISTE, IACST.

Mary Brinda is pursuing masters degree in the department of Electronics and communication Engineering in Easwari Engineering college, Chennai, Tamilnadu, India.

[6] M. I. H. Bhuiyan, M. Omair Ahmad and M. N. S. Swamy, "New Spatially Adaptive Wavelet-based Method for the Despeckling of Medical Ultrasound Images", in International symposium on Circuits and Systems,2007,pp.2347-2350.

[7] S.Gupta, R. Chauhan and S. Saxena," Locally adaptive wavelet domain Bayesian processor for de-noising medical ultrasound images using speckle modeling", IEE Transactions on vision, Image and Signal processing, Vol.152,2005,pp. 129-135.

[8] A. Achim, P. Tsakalides and A. Bezarianos, "Novel Bayesian Multi-Scale Method For Speckle Removal In Medical Ultrasound Images", IEEE Transactions on Medical Imaging, Vol.20,No.8, 2001,pp. 772–783 .

[9] P.Badulescu and R. Zaciu, " Removal of mixed-noise using order statistic filter and wavelet domain wiener filter" , CAS,2009,Vol.1,pp.301-304.

[10] X.Zong,A.F.Laine and E.A Geiser, "Speckle reduction and contrast enhancement of echocardiograms via multiscale nonlinear processing", IEEE Transactions on Medical Imaging,Vol.17, 1998, pp. 532 -540.

[11] Raul C. Mure, "Pattern Recognition Using Pulse-coupled Neural Networks and Discrete Fourier Transforms", Transactions on Neurocomputing, Vol.51, 2003, pp.487-493.

[12] Yongqiu Tu, Shaofa Li and Minqin Wang,"Mixed-noise Removal for Color Images Using Modified PCNN Model", in International workshop on Intelligent Information Technology Applications, 2008,pp.347-351.