DESPECKLING OF POLYCYSTIC OVARY ULTRASOUND IMAGES BY IMPROVED TOTAL VARIATION METHOD

H Prasanna Kumar [#1], S Srinivasan [*2]

[# *] Department of Instrumentation Engineering, MIT Campus,
Anna University, Chennai-600044 Tamilnadu, India.
[1] uvcehpk@gmail.com
[2] srini@mitindia.edu

Abstract— Ultrasound imaging provides a non-invasive, low cost, real-time imaging that helps the clinician in diagnosis and planning of therapy. However, the usefulness of ultrasound imaging is degraded by the presence of signal depended noise known as speckle. Image denoising algorithms are challenging operation because the fine details are embedded in medical image and diagnostic information should not be destroyed during noise removal. This paper presents speckle reduction by an improved total variation filter (ITV) method. The performance of these filters is evaluated based on the parameters such as mean square error (MSE), peak signal-to–noise ratio (PSNR), similar structure index mean (SSIM) and feature structure index mean (FSIM). An experimental result shows that the speckle noise can be efficiently removed by the ITV method without affecting the structure of the object.

Keyword- FSIM, Improved total variation, PSNR, Speckle noise, Ultrasound imaging.

I. INTRODUCTION

In medical image processing, precise images are important to facilitate accurate observations for a given application. Low image quality is an obstacle for effective segmentation, feature extraction, analysis, recognition and quantitative measurements. Therefore, there is a fundamental need of noise reduction in medical images. There are currently a number of imaging modalities that are used in medical imaging. Among them ultrasound imaging [1] are potential for accurate measurement of organ anatomy namely liver, kidney, spleen, uterus, heart etc., in a minimal invasive way. The common problem with ultrasound image is speckle noise also known as multiplicative noise [2, 3].

When ultrasound pulses [4] passes through the tissues, a large number of discontinuities generate small echoes which travel back to the transducer. These detected echoes overlap and interfere both constructively or destructively to produce a fluctuating signal. The related electrical fluctuating signal produced by the transducer, present along each scan line. The display will appear as fine fluctuations in the gray shades and the whole image appears as a speckle pattern. In case of polycystic ovary syndrome (PCOS) [5], speckle noises are more because PCOS are fluid filled sacs and it will blur the boundaries of the PCOS, which is essential for despeckling the image. Despeckling is a trade-off between noise suppression and loss of information, something that experts are very concerned about. It is therefore required to retain as much of the important information as possible.

The despeckle filter originated from the synthetic aperture radar (SAR) community [6] and is applied to ultrasound image. The mean filtering technique [7, 8] successfully removes noise from the distorted image as pixel is replaced by the calculated mean, but the filtered image is blurred. The median filter was once the most popular nonlinear filter for removing noise, because of its good de-noising power and computational efficiency but small details tend to be lost. The adaptive filter uses a moving filter window and calculates the statistical information of all pixel gray value, such as the local mean and the variance. Lee filter [9], Frost filter [10], Kuan's filter [11] are some of the adaptive filters. Selection of the window size in adaptive filters mainly depends upon the local variations in image gradient. Window size becomes difficult as it is not uniform throughout the image.

Partial differential equations [12] based approaches like anisotropic diffusion filter [13] methods can preserve or even enhance prominent edges while removing the speckle. However the methods have limitations in retaining subtle features such as small cysts and lesions in images. In the homomorphic filtering [14] the image is denoised in Fast Fourier Transform (FFT) domain, and then the inverse FFT is calculated, this is a nonlinear filtering technique for simultaneously performing contrast enhancement and noise reduction by using the coefficient of variation. Thakur and Anand [15] introduced wavelet domain which gives a comparative study of various wavelet filters based denoising methods according to different thresolding values applied to images.

Oleg and Allen [16] attempted to modify the acquired radio frequencies of speckle noise into white Gaussian noise to remove the speckle. Nonlocal means filter [17] has been used for speckle reduction in ultrasound images. It removes the speckle while it requires more time. Proximity operator of the anisotropic total-variation [18] evaluated on a given noisy image, removes the speckle but edges become blurred. The total variation filter [19] has been successfully used to remove the Gaussian noise, the filter performance not good in the case speckle noise. In the case of adaptive maximum-likelihood (ML) technique [20], binary edge masks are first estimated to indicate the possible edges in the speckled image. An ML estimation approach is then utilized, whose shape parameter and window size are adaptively controlled by the edge mask. Fuzzy filters give [21] good performance of salt and pepper noise, which has a less signal to noise ratio.

This paper proposes an improved total variation (ITV) method to remove speckle noise from the PCOS image. It measures the local variations in the pixels, which exhibits different properties in the main structure and speckle texture. The ITV filter with the speckle noise model is described in section 2. The quantitative results for different filters are presented in section 3 and conclusions in section 4.

II. MATERIAL AND METHODS

A. Data collection

100 images of patients in the age group 25-35 years suffering from anovulatory infertility /PCOS were collected from JB Diagnostic Centre Bangalore. The ultrasound images were taken with a real time LOGIQ P3 (General Electricals, Milwaukee, USA) scanner with a 4.5-5.5MHz, curvilinear, broadband bandwidth transducer probe with the dynamic range set at 55dB.

B. Speckle noise model

To derive an efficient despeckle filter [22], a speckle noise model is needed. The speckle noise model for ultrasound images may be approximated as multiplicative [23]. The signal at the output of the receiver demodulation module of an ultrasound imaging system may be defined as

$$u_{(i,j)} = v_{(i,j)} \cdot n_{(i,j)} + m_{(i,j)} \tag{1}$$

Where $u_{(i,j)}$ represents the noisy pixel in the middle of the moving window, $v_{(i,j)}$ represents the noise free pixel, $n_{(i,j)}$ and $m_{(i,j)}$represent the multiplicative and additive noise, respectively, and *i, j* are the indices of the spatial locations that belong in the 2D space. Despeckling is based on estimating the true intensity $v_{(i,j)}$ as a function of the intensity of the pixel $u_{(i,j)}$ and local statistics (mean, variance) calculated from the neighbouring pixel. In Eq. (1), since the effect of the additive noise is considerably smaller compared with that of the multiplicative noise, it may be written as

$$u_{(i,j)} \cong v_{(i,j)} \cdot n_{(i,j)} \tag{2}$$

C. Method

It is observed that the speckle will be more at high frequencies and the images with spurious feature will have high total variation, i.e. the integral of the absolute gradient of those signals in the images are high. Based on these observations, it is proposed to reduce the intensity variation of an image by ITV method, which brings it close to the original image. ITV uses a quadratic penalty to enforce structural similarity between the input and output, and it can be written as,

$$\arg\max_{u} \sum_{b} \left\{ \left| \nabla u_{(i,j)_b} \right| + \frac{1}{2\lambda} (u_{(i,j)_b} - v_{(i,j)_b})^2 \right\} \tag{3}$$

Where $v_{(i,j)}$ intensity of the input image, $u_{(i,j)}$ is the resulting structure image, λ is the smoothing parameter and *b* is the image size. The term $(u_{(i,j)_b} - v_{(i,j)_b})^2$ is to make the extracted structures similar to those in the input image.

$\sum_b \left| \nabla u_{(i,j)_b} \right|$ Is the total variation regularized, can be written as

$$\sum_{b} \left| \nabla u_{(i,j)_b} \right| = \sum \left| \partial_x u_{(i,j)} \right| + \left| \partial_y u_{(i,j)} \right| \tag{4}$$

The terms ∂x and ∂y are the partial derivatives in x and y directions, the limitation of Eq. (4) is the inability to distinguish between the main structure and speckle. To overcome this a general pixel-wise windowed total variation measure is developed, and can written as

$$D_x(b) = \sum_{c \in r(b)} w_{b,c} \left| \partial_x u_{(i,j)_c} \right| \tag{5}$$

$$D_y(b) = \sum_{c \in r(b)} w_{b,c} \left| \partial_y u_{(i,j)_c} \right| \tag{6}$$

Where *r(b)* is the rectangular region centred at *b* pixel indexes. $D_x(b)$ is the windowed total variations in x directions for b pixels and $D_y(b)$ are windowed total variance in the y directions for b pixels, where x and y directions count the absolute spatial difference within the window r (b). The $w_{b,c}$ is a weighting function defined according to spatial affinity, expressed as,

$$w_{b,c} \alpha \exp\left(-\frac{[(x_b - x_c) + (y_b - y_c)]^2}{2\sigma^2}\right) \tag{7}$$

The term σ controls the spatial scale of the window. To distinguish prominent structures from the speckle elements besides windowed total variation, the method also contains a windowed inherent variation, expressed as

$$d_x(b) = \left| \sum_{c \in r(b)} w_{b,c} \left| \partial_x u_{(i,j)_c} \right| \right| \tag{8}$$

$$d_y(b) = \left| \sum_{c \in r(b)} w_{b,c} \left| \partial_y u_{(i,j)_c} \right| \right| \tag{9}$$

To further enhance the contrast between speckle and structure, especially for visually salient regions, we combine windowed total variation with windowed inherent variation to form new regularizer .The objective function is finally expressed as

$$\arg\max_u \sum_b (u_{(i,j)_b} - v_{(i,j)_b})^2 + \lambda\left(\frac{D_x(b)}{d_x(b)+\varepsilon} + \frac{D_y(b)}{d_y(b)+\varepsilon}\right) \tag{10}$$

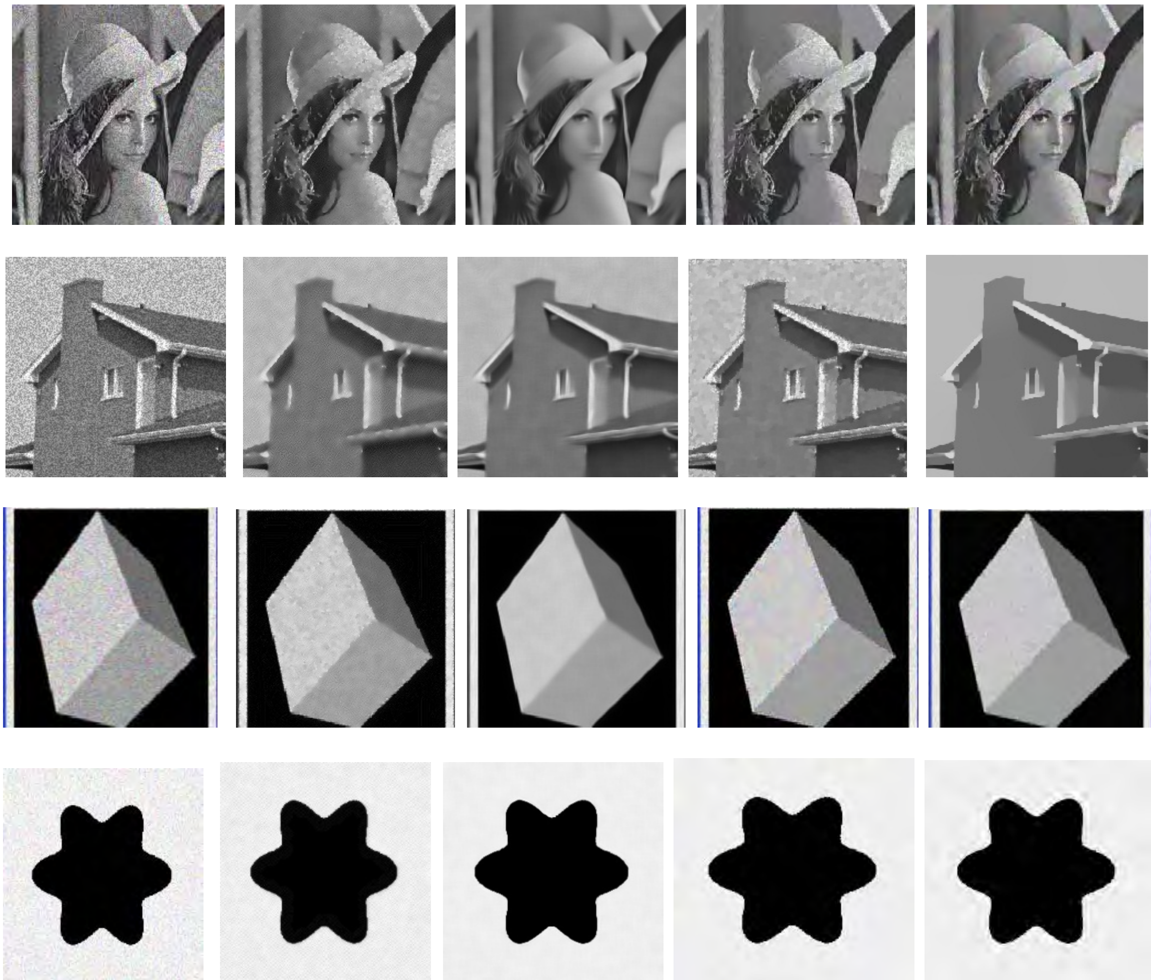
The term $(u(i,j)_b - v(i,j)_b)$ makes the result not to deviate widely. The effect of removing speckles texture from an image by the new regularizer as shown in Equation (10) is the improved total variation and ε is a small positive number to avoid division by zero.

III RESULTS AND DISCUSSION

In this part, we will report experimental results of our method on both synthetic images and real ultrasound images, and compare our experimental results with other speckle reduction methods. All experiments are implemented with MATLAB7.10 on a dual-core personal computer, 2.40 GHz, 2 GB RAM.

A. Performance on synthetic images

This section presents visual and numerical results obtained on four synthetic images corrupted by speckle noise. The corrupted images are obtained from four classical noise-free images: Lena, House, Square and Star. Fig. 1 presents the obtained denoised images with proposed method and with other conventional despeckling methods like the speckle reduction by anisotropic-diffusion (SRAD), non-local means (NLM), and total variation (TV). The images obtained with the ITV method seem to be smoothed with a better edge and shape preservation compared with the other method. Some noise is left in the case of SRAD and NLM filter which blurs the images. In TV method shapes are not preserved properly. To quantify the denoising qualities, Table 1 presents the numerical results for images corrupted by speckle noise. The performance criterion used is the Signal to Noise Ratio. We observe that SNR values are higher in the case of ITV method.



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

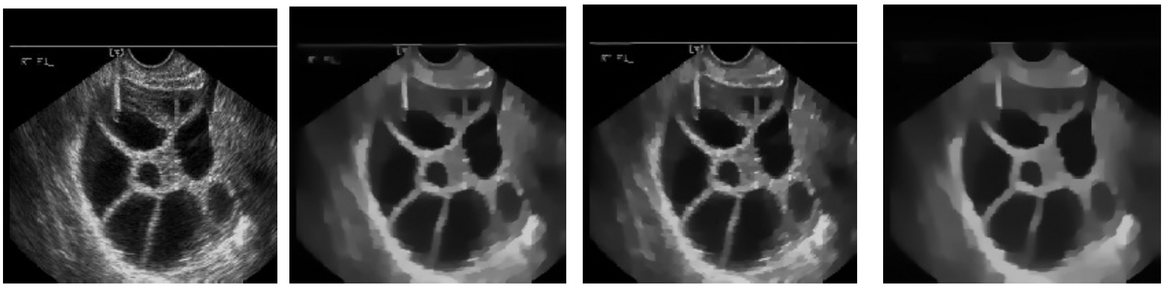
Fig. 1 (a) from top to bottom corrupted images of Lena, House, Square and Star. Denoised images using (b) SRAD, (c) NLM, (d) TV, and (e) ITV

TABLE 1 Signal to noise ratio measures obtained by different speckle removal methods.

Method / Images	SRAD	NLM	TV	ITV
Lena	39.46	39.89	43.68	49.89
House	46.90	48.90	53.45	59.86
Square	53.89	56.34	59.88	64.66
Star	51.67	61.80	62.99	69.88

B. Performance on ultrasound images

Further, we test the performance of the proposed method on ultrasound PCOS images and comparison with other three methods. To despeckle the image smoothing parameter λ is selected from Equation (10) whose value ranges between 0.01-0.03. Fig. 2 shows the filtered image for different λ values and it can be seen that for λ value 0.02 the filter removes the speckle and enhances the edges. As the λ values increases (0.04 and 0.09) significant information is lost and causes more blur. In order to quantify the performance of the filter, MSE and PSNR are determined. A better filter should have low MSE and high PSNR.The MSE and PSNR for different λ values are shown in Table 2. The MSE is low and PSNR is high for λ 0.02.In our work λ value of 0.02 is considered.



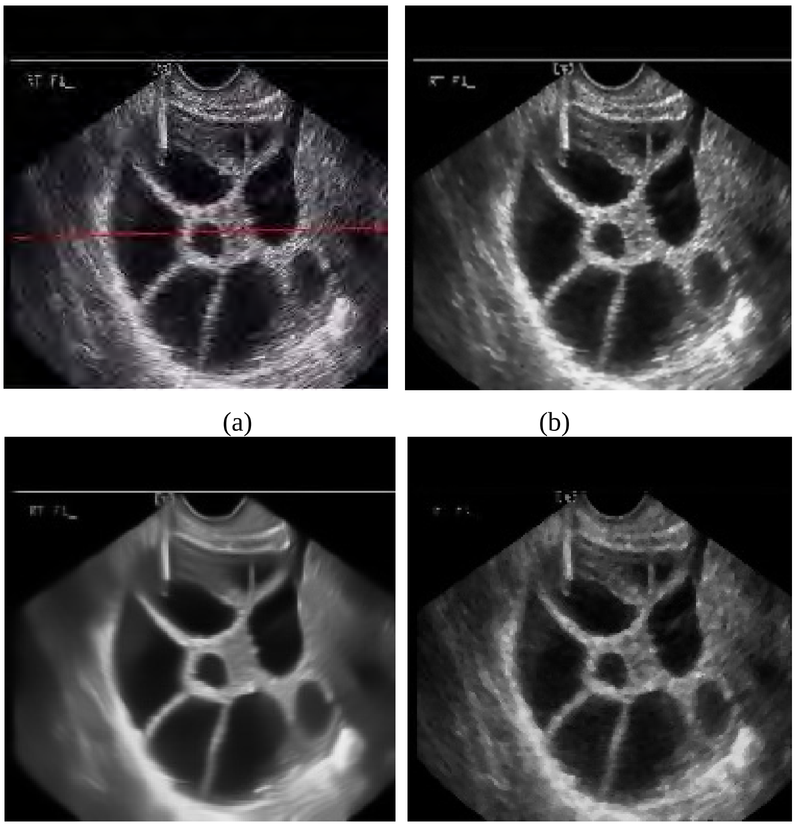
(a) (b) (c) (d)

Fig. 2 original and filtered images using different λ values (a) Original, (b) λ =0.02, (c) λ = 0.04, and (d) λ = 0.09

TABLE 2 MSE and PSNR for different λ values, where λ = 0.02 gives the better result.

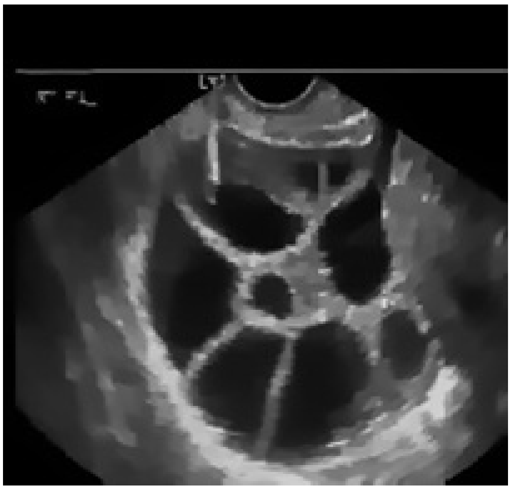
λ values	MSE	PSNR
0.02	28	37
0.04	32	29
0.09	41	24

Figure 3 shows the performance the improved total variation method is compared with a known speckle reduction filter such as SRAD (lambda = 0.225), NLM filter (smoothing parameter h = 1.7 and patch size alpha = 3), and TV filter (kappa value = 0.03).



(a) (b)

(c) (d)



(e)

Fig. 3 a) Original, (b) SRAD, (c) NLM, (e) TV, and (f) ITV with λ = 0.02

Table 3 summarizes the performance of SRAD, NLM, TV and ITV. A good filter will have low MSE, High PSNR and the values of SSIM and FSIM approaches to 1. From Table 3 it can be seen that for ITV method MSE is low, PSNR is high and SSIM, FSIM approaches to one. This can further be validated from Figure 4 where edges are sharped for ITV compared to other methods.

TABLE 3 summarizes quality Metrics of different filters.

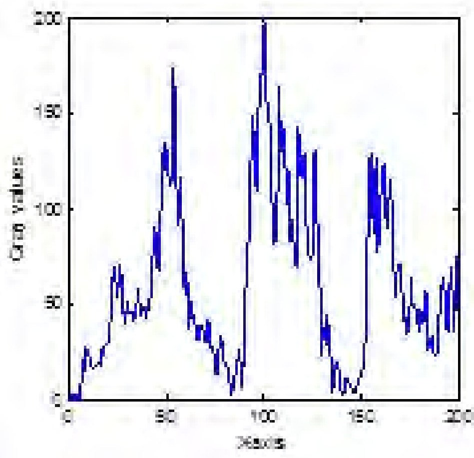
FILTERS	MSE	PSNR	SSIM	FSIM
SRAD	22.76	20.16	0.6612	0.7967
NLM	21.73	21.14	0.6403	0.7857
TV	24.86	19.85	0.6138	0.7238
ITV with λ = 0.02	19.59	32.35	0.8705	0.9190

The average processing time required for hundred images by ITV and other methods are presented in Table 4, it can be observed that the computation time required by the proposed method is less than the time required by conventional methods - SRAD, NLM, and TV.

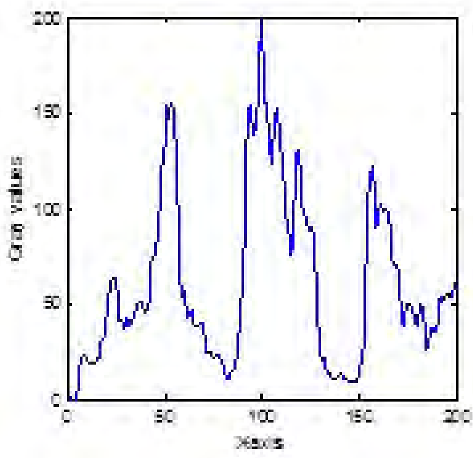
TABLE 3Average processing time required for different speckle removal methods

Method	Average processing time (in seconds)
SRAD	18.89
NLM	25.78
TV	13.90
ITV	11.87

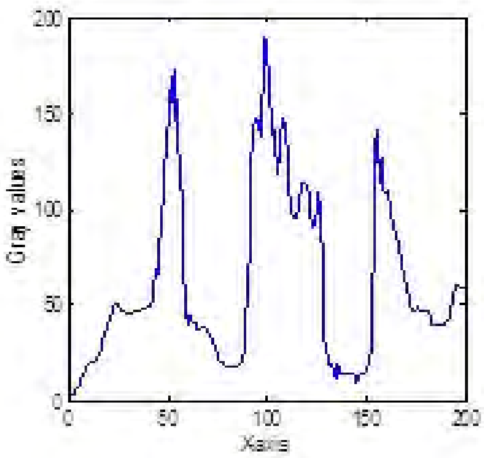
In order to evaluate the performance of the filter in terms of sharpness of the boundary, the intensity variation at 108^{th} column of Figure 3 (a) is considered. High intensity at Figure 4 (a) represents the ovaries boundaries of the original image and it can be seen that around 100^{th} instants the boundaries are not easily distinguishable. Using diffusion method SRAD removes the noise, but in the boundary more intensity diffused and some artifact left in 175^{th} to 190^{th} position. Adjusting the patches non-local means removes the noise, but reduces the intensity near edges.TV methods remove the noise but, some artifacts left in the low intensity area and the intensity distribution near the edges are unequal, due to this edge are not preserved properly. The ITV removes the noise and preserves th**e** edges with smooth distribution of intensity shown in Figure 4 (e).



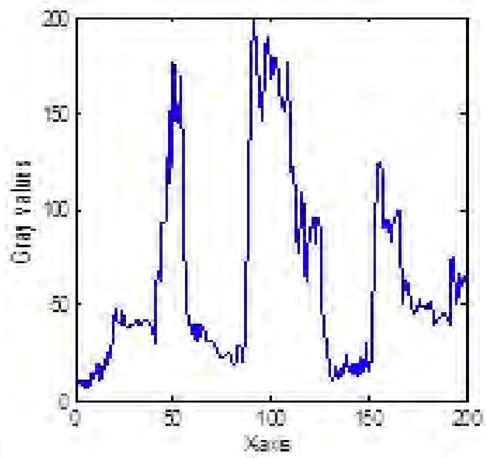
(a)



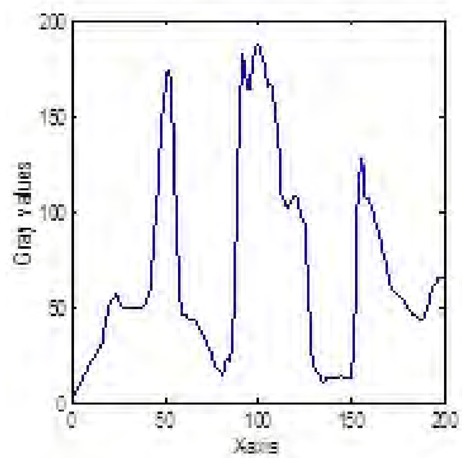
(b)



(c)



(d)



(e)

Fig. 4 presents the corresponding signal of 108th column (a) original signal, (b) SRAD signal, (c) NLM signal, (d) TV signal, and (e) ITV signal.

IV CONCLUSION

This paper, presents an ITV filter for ultrasound PCOS images. The method successfully reduces speckle noise by calculating the main structure and speckle pattern. Experiments were carried out on synthetic images. During the experiments, quantitative measures were used to compare with three denoising filters. Results showed that the improved total variance (ITV) filter proposes competitive performances compared to other state-of-the-art methods. Experiments on ultrasound images were conducted and showed that the ITV method is very efficient at smoothing homogeneous areas while preserving edges. The method is useful as a pre-processing step in segmentation or for visual interpretation.

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