FILTERS ANALYSIS FOR SPECKLE REDUCTION IN INTRAVASCULAR ULTRASOUND IMAGES

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Abstract

Speckle noise is an inherent property of intravascular ultrasound imaging (IVUS), and it generally tends to deteriorate the image quality (resolution and contrast), thereby reducing the diagnostic value of this medical imaging modality. As a result, the speckle reduction filtering is considered to be an important and essential procedure to be used, whenever IVUS images are used for atherosclerotic lesions assessment. Because next step of de-speckling is contour detection, it was necessary for the filter to be noise-reducing and edge-enhancer. The present study evaluates performances of three different denoising filters– Wiener filter, Anisotropic diffusion filter (Perona-Malik algorithm), Total variation filter – and demonstrates that in all these cases, the preprocessing procedure results in a dramatic improvement in the quality of filtered images. The results included a series of simulated and *in vivo* IVUS images.

Keywords: Intravascular Ultrasound Images, Speckle Noise, Wiener, Nonlinear Filters.

Presenting Author's biography

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1 Introduction

Intravascular ultrasound (IVUS) imaging [1] is a subject to transducer ring-down artifacts, missing vessel parts due to deep calcification shadowing or side-branches, heterogeneously plaques and ultrasonic speckle from blood. The main objective of image de-speckling techniques is necessary to remove such noises while retaining as much as possible the important image fine details and taking into account the nature of IVUS images. Intravascular ultrasound imaging is a widely used medical imaging procedure because it provides information on the lumen cross section area, the vessel wall thickness and on the length, volume and position of the atherosclerotic lesion. Though, one of its main limitations is the poor IVUS images quality due to speckle noise. The existence of ultrasound speckle is unattractive since it deteriorates image quality and it complicates the tasks of clinical interpretation and diagnosis. Consequently, speckle filtering is an essential pre-processing step for segmentation, analysis, and recognition from medical imagery assessments.

Several methods have been proposed in the literature for removing speckle. Among them, linear filters [2–4], temporal averaging [5], median filter [6], and Wiener filter. However, these filter approaches were developed mainly for additive random noise, and had little success in speckle noises suppression. Nonlinear methods [14–19] can be regarded as adaptive filters, whose smoothing direction and strength are controlled by an edge detection function. Though these adaptive methods are capable of efficiently suppressing the speckle pattern, they still seem to destruct small details being actually low-pass filters. The multiplicative nature of the speckle image formation was introduced in [13] via proposing a model, which first converts the multiplicative speckle noise to an additive noise after a logarithmic transformation to a received image. Subsequently, the Wiener filtering followed by the exponential transformation is used here to remove the resulted additive noise. The structure of the model turned out to be generic which implies further modification through replacing the classical Wiener filtering by other filtering schemes. Over the past decade, discovery of the wavelet transform and fast wavelet packet methods triggered the proposal of wavelet de-noising [21-24] as a powerful method of recovering signals from noisy data. By comparing the resultant images, obtained in a series of computer-based and in vivo experiments, the study demonstrates that the proposed preprocessing procedures are very efficient and result in dramatic improvement in the quality of de-speckled images. Furthermore, similar results were obtained for two alternative nonlinear de-speckling algorithms via replacing the wavelet de-noising procedure by total-variation filtering [14] and anisotropic diffusion [15].

This study demonstrates the applicability of alternative nonlinear filtering methods to the de-speckling problem in ultrasonic imaging.

The paper is organized as follow. Section II is devoted to discussion of properties of the speckle noise, and provides a brief overview of the nonlinear filters used in the present study. Experimental results are demonstrated in Section III, and are devoted to discussion in session IV. Some essential conclusions are summarized in Section V. The aim of this study is to validate the effectiveness and usefulness of some nonlinear filters that can improve the IVUS images diagnostic accuracy.

2 Methods

2.1 Speckle noise in IVUS image

Intravascular ultrasound (IVUS) is a new medical imaging modality that provides real-time, cross-sectional and high-resolution images of blood vessels. In contrast to angiography that only displays silhouette views of the vessel lumen and allows the definition of severe stages of coronary artery disease, IVUS imaging permits visualization of atherosclerotic lesion morphology and precise measurements of arterial cross-sectional dimensions. These unique capabilities have led to many important clinical studies including quantitative assessment of the severity of luminal stenosis, progression and regression of atherosclerosis, effectiveness of catheter-based therapeutic procedures and evaluation of the outcome of an intravascular pre- and post-intervention.

Like the progress of other clinical imaging modalities, the advent of IVUS technology has brought in new technical challenges in the field of medical image processing. Quantitative analysis of IVUS images requires the assessment of vascular wall such as the lumen and plaque composition. Manual contour tracing is laborious, time consuming and subjective. To overcome these problems, automatic contour detection methods may improve the reproducibility of quantitative IVUS and avoid a tedious manual procedure. However a high level of speckle noise may mask the intensity boundary, resulting in a rather poor definition of the object border. Moreover, drop-out of echo signals in parts of the object boundary also complicates border detection in intravascular ultrasound images. This work aims to suppress speckle in IVUS images.

Speckle in intravascular ultrasound images is seen as an inherent granular structure which is caused by the constructive and destructive coherent interference of back scattered echoes of tissue or blood. The acquired image is thus corrupted by a random granular pattern that delays the interpretation of the image content which affects the human ability to identify normal and pathological vessel tissue [16].

In medical imaging systems, speckle noise is referred as texture that may possibly contain useful information. The desired grade of speckle smoothing preferable depends on the clinicians' knowledge and on the application. For image segmentation procedure, estimating the size of the total cross-sectional area of the vessel and defining the interface between intima-media are usually preferred while smooth out the speckle texture.

2.2 Filtering Methods

Several techniques have been proposed for the despeckling of medical ultrasound images. In this section we present the theoretical overview of three de-speckling techniques; Wiener filter, anisotropic diffusion filter, and total variation filter.

2.2.1 Wiener Filter

One important classical technique for attempting to improve the quality of an image is the Wiener filter [17]. The Wiener filter is a global adaptive filter that produces an estimation of the uncorrupted image by minimizing the overall mean square error between the estimate and the uncorrupted image in a stochastic sense. The Wiener filter is mainly used to restore the corrupted images and remove the additive noise. It can be shown that the restoration linear filter that finds the optimum estimate in Fourier domain is given by

$$W = \frac{g * S_{ss}}{g . g * S_{ss} + S_{ww}} \tag{1}$$

where g is the filter convolve the original image, S_{ww} is the power spectrum of the additive noise and S_{ss} is the power spectrum of the original image. In this problem, we only assume the original image is only added with noise, so the filter g=1 in Fourier domain. The Wiener filtering is then simplified into

$$W = \frac{S_{ss}}{S_{ss} + S_{ww}} \tag{2}$$

The power spectra of the original image S_{ss} is unknown. A direct way is to model the power spectra of the original image as

$$S_{ss} = \frac{\sigma_s^2}{\left(\sqrt{\mu_x^2 + \mu_y^2}\right)^2} \tag{3}$$

where σ^2_s is the variance of the unknown original image S. However, we usually use the variance of the corrupted image σ^2_x to replace the σ^2_s. μ_x and μ_y are frequency coordinators.

The power spectrum of the additive noise S_{ww} is also unknown. Since the added noise is not Gaussian White Noise, we can't choose a relative uniform region in the corrupted image and calculate the power of this region.

2.2.2 Anisotropic Filter

Anisotropic diffusion filter is an efficient nonlinear technique that simultaneously performs contrast enhancement and noise reduction. It can smooth homogeneous image regions while retaining image edges. The main concept of anisotropic filter is the introduction of a function that preserves the image edges. This function, called diffusion coefficient, is chosen to encourage intra-region smoothing in preference to inter-region smoothing [18].

Perona and Malik [18] proposed a nonlinear partial differential equation to smooth corrupted image on a continuous domain, the diffusion is as follow

$$\begin{cases} \dfrac{\partial I}{\partial t} = div\left[c(|\nabla I|).\nabla I\right] \\ I(t=0) = I_0 \end{cases} \tag{4}$$

where I represents the image to be filtered, $c(x)$ is the diffusion coefficient and I_0 is the initial image. For $c(x)$, it has two coefficients options

$$c(x) = \frac{1}{1 + (x/k)^2} \tag{5}$$

or

$$c(x) = \exp[-(x/k)^2] \tag{6}$$

where k is the edge magnitude parameter.

It can be shown, that the equation (4) involving only first and second spatial derivatives of the corrupted image I defines the *affine geometric heat flow*. Moreover, such diffusion process has the desirable characteristics to preserve edges while exhibiting numerical stability [15]. Note that the time discretization step and the iteration number were used as parameters of the non-linear smoothing filter. Therefore, these parameters were adjusted to achieve the best visual results.

2.2.3 Total Variation Filter

Another class of de-noising methods consists in variational formulations, which transform an noise contaminated image J into an original image I that minimizes some energy functional E_λ (I) depending on J and on a parameter λ. Then a discrete version of the total variation (TV) filter, as originally specified by Rudin-Osher-Fatemi (ROF) model for image denoising [14], recovers I by solving

$$\min_I \left\{ E_\lambda(I) = \|J - I\|^2 + \lambda \sum_{n,m} |\nabla I(n,m)| \right\} \tag{7}$$

where $\|\cdot\|$ stands for the classical Euclidean norm on $\Re^2$. Note that the positive parameter λ controls the amount of de-noising and should be set then to the noise level.

The Total Variation filter is now considered to be among the most successful PDE based methods for image restoration and edge enhancement. The capability of filtering out the noise without blurring the most universal and crucial image features is behind its success. Note that the second term of the functional E_λ evaluates either the l^1-norm or l^2-norm of the solution's gradient. Because these norms are known to be minimized by image possessing sparse structure, the minimization of the ROF energy will prefer solutions having sparse gradient. Hence, the TV filtering is especially useful for recovering piece-wise constant images. It is worthwhile noting that the parameter λ controls the balance between de-noising and smoothing.

The TV filter was implemented by solving the ROF minimization problem (7) using the conjugate gradient algorithm [18]. It is shown in [19] that the TV-denoising can be alternatively implemented as a signal-dependent filter. Finally, it should be noted that the ROF functional E_λ, as defined by (7), is not smooth, and, therefore, it cannot be directly minimized by means of the conjugate gradient algorithm. In order to overcome this problem, a small positive number was added under the square-root in the second term of E_λ and, subsequently, the resulted regularized functional was minimized.

2.3 Performance Evaluation

In order to assess the performance improvements achieved by each speckle suppression method. The commonly used criterions are mean-square-error (MSE) and Peak Signal-to-MSE (PSNR). These two metrics were calculated for both the speckle-degraded and the restored images. These parameters are defined in equations (8) and (9), calculated over local ROI image windows

$$MSE = \frac{1}{N}\sum_{k=1}^{N}\left(\hat{S}_k - S_k\right)^2 \qquad (8)$$

and

$$PSNR = 10 \times \log_{10}\left(\frac{\max_S}{MSE}\right) \qquad (9)$$

where S is the original image , $\hat{S}$ is the despeckled image, and N is the total number of pixels in the current ROI window. The MSE value is a typical error measurement, while the PSNR is used instead of the classical SNR value in the case of additive noise.

3 Results

3.1 Simulated IVUS images

The synthetic image was despeckled using various filters and results were shown in the Fig. 1. The MSE and PSNR of the initial image and the filtered images were produced in table 1.

Tab. 1 MSE and PSNR for different filters: Simulated image

	Wiener	Anisotropic	Total variation
MSE	12.98	46.56	55.87
PSNR	16.27	18.22	23.45

3.2 In Vivo IVUS image

A real intravascular ultrasound image was despeckled using various filter approaches and results were shown in the Fig. 2. The MSE and PSNR of the initial image and the filtered images were produced in table 2.

Tab. 1 MSE and PSNR for different filters: Real image

	Wiener	Anisotropic	Total variation
MSE	10.54	40.51	51.71
PSNR	19.47	16.99	25.14

4 Discussion

Despeckle filtering is an important and essential issue in the enhancement of IVUS images, in this paper three different methods are implemented and evaluated 2 images both from simulation and real data. Wiener filter attempts an optimal speckle reduction given the noise power spectrum is known. However, the speckle power information is unknown in medical imaging situation. In such case, the power spectrum of the simulated noise can be used, and the results are also impressive comparing with the original IVUS images. Anisotropic diffusion method is easy to implement and the calculation is straightforward. The results obtained using this method are even better than Wiener filter. Thereby the restored images usually have more contrast, while details of vessel structures are kept well.

To compare the performance of the above mentioned 3 filters, we take the same small region with pixel size 64*64, and calculate the MSE and PSNR. The results are listed in the tables 1 and 2.

From the tables above we can see that the Wiener filter, anisotropic diffusion filter and total variation filter improve the PSNR. It is shown that these filters are suitable for removing the speckle in intravascular ultrasound images.

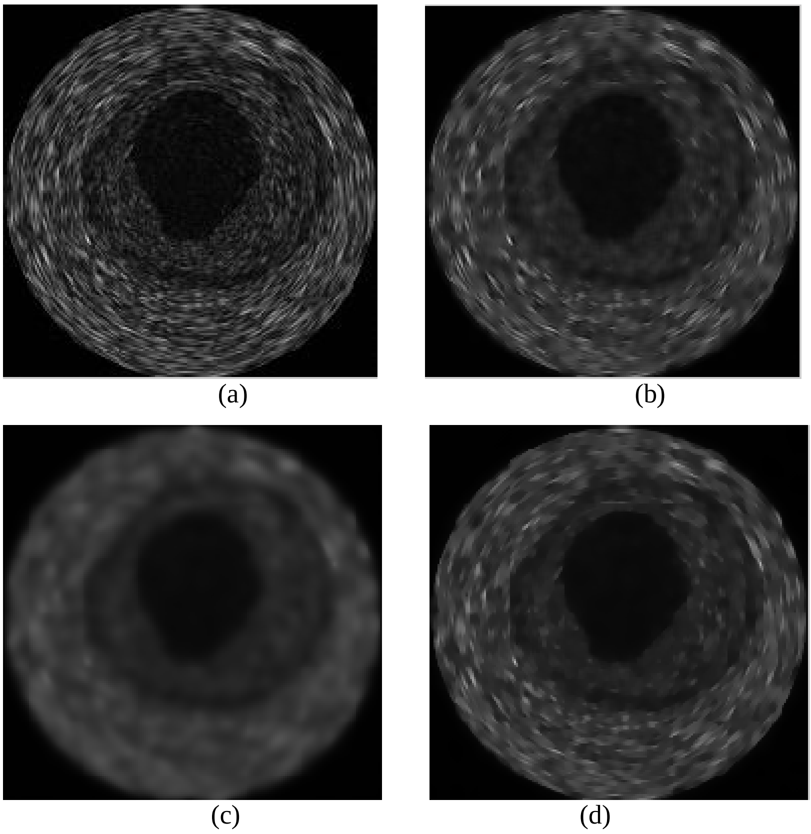

Fig. 1. Results of Simulated image: (a) Original image, (b) Wiener, (c) Anisotropic diffusion, (d) Total variation.

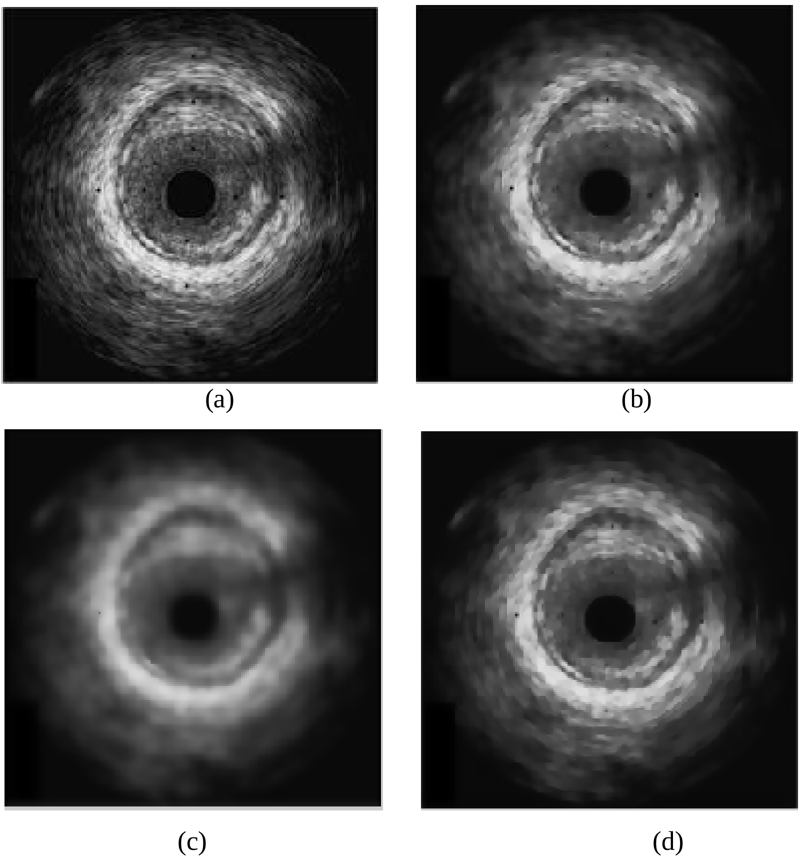

Fig. 2. Results of Real image: (a) Original image, (b) Wiener, (c) Anisotropic diffusion, (d) Total variation.

5 Conclusion

In this study, we implemented Wiener filter, anisotropic diffusion filter, and total variation filter to despeckle in medical intravascular ultrasound images. The Wiener filter can improve the IVUS images quality well and simulated power spectrum of speckle can be applied on many medical imaging situations.

The Anisotropic diffusion filter performed well on IVUS images with speckle as long as we choose reasonable parameters, and also it doesn't need extra information of noise pattern. The Total variation filter can improve the image quality (contrast and vessel wall details), the method is simple to implement and the statistics is easy to estimate and characterize.

Initial findings show promising results from these three filters, different clinical images are required to evaluate the performance and the effects of the filters on radiologists' diagnosis. Other filtering methods may also be studied and implemented to compare with these filters, for example, wavelet-based denoising methods.

6 References

[1] G.S. Mintz, S.E. Nissen, W.D. Anderson, S.R. Bailey, R. Erbel, P.J. Fitzgerald, F.J. Pinto, K. Rosenfield, R.J. Siegel, E.M. Tuzcu, P.G. Yock, American College of Cardiology clinical expert consensus document on standards for acquisition, measurement and reporting of intravascular ultrasound studies (IVUS). A report of the American College of Cardiology task force on clinical expert consensus documents, J. Am. Coll. Cardiol. 37 (2001) 1478–1492.

[2] Burckhardt CB. Speckle in ultrasound B-mode scans. IEEE Trans Son Ultrason 1978;25:1–6.

[3] Abbott JG, Thurstone FL. Acoustic speckle: theory and experimental analysis. Ultrason Imag 1979;1:303-24.

[4] Wagner RF, Smith SW, Sandrik JM, Lopez H. Statistics of speckle in ultrasound B-scans. IEEE Trans Son Ultrason 1983;30:156.

[5] Goodman JW. Some fundamental properties of speckle. Opt Soc Am J 1976; 66:1145–50.

[6] Ioannidis A, Kazakos D, Watson DD. Application of the median filter on nuclear medicine scintigram images. Proceedings of the 7th International Conference on pattern recognition 1984:33–6.

[7] J. W. Goodman, "Statistical properties of laser speckle patterns", in Laser Speckle and Related Phenomena, J.C. Dainty, Ed., No.9 in Topics in Applied Physics, Chapter 2, pp.9-77, Springer-Verlag, Berlin, 1977.

[8] C. B. Burckhardt, "Speckle in ultrasound B-mode scans, IEEE Trans. Sonic Ultrason., vol. SU-25, No 1, pp.1-6. Jan.1978.

[9] J. G. Abbott and F.L. Thurstone, "Acoustic speckle: Theory and experimental analysis", Ultrason. Imag., vol.1, pp.303-324, 1979.

[10] T. Loupas, W.N. McDicken, and P.L. Allan, "An adaptive weighted median filter for speckle suppression in medical ultrasound images", IEEE Trans. Circuits Syst., vol.36, No.1, pp.129-135, Jan.1989.

[11] M. Karaman, M.A. Kutay, and G. Bozdagi, "An adaptive speckle suppression filter for medical ultrasound imaging", IEEE Trans. Med. Imag., vol.14, pp.283-292, June 1995.

[12] J. T. M. Verhoeven and J. M. Thijssen, "Improvement of lesion detectability by speckle reduction filtering: A quantitative study", Ultrason. Imag., vol. 15, pp.181-204, 1993.

[13] A.K. Jain, Fundamental of Digital Image Processing, Englewood Cliffs, NJ: Prentice-Hall, 1989.

[14] L. Rudin, S. Osher, and E. Fatemi, "Nonlinear total variation based noise removal algorithms", Phys. D, vol. 60, pp. 259–268, 1992.

[15] G. Sapiro and A. Tannenbaum, "Image smoothing based on an affine invariant flow", in Proc. Of Conf. on Information Sciences and Systems, John Hopkins University, Baltimore, Maryland, pp.196-201, March 1993.

[16] M. Tur, K. C. Chin, and J. W. Goodman, "When is speckle noise is multiplicative?", Applied Optics, vol. 21, No.7, pp.1157-1159, April 1982

[17] E. Sekko, G. Thomas, and A. Boukrouche, "A deconvolution technique using optimal Wiener filtering and regularization", Signal processing, vol. 72, pp. 23-32, 1999.

[18] P. Perona and J. Malik, "Scale-space and edge detection using anisotropic diffusion", IEEE Trans.Pattern Anal. Mach. Intell., vol.12, No.7, pp.629-639, July 1990.

[19] D. Bertsekas, Nonlinear programming, Athena Scientific, Belmont, Massachusetts, 1999.

[20] T. Chan, S. Osher, and J. Shen, "The digital TV filter and nonlinear de-noising", IEEE Trans. ImageProcessing, vol.10, No.2, pp.231-241, Feb. 2001.

[21] I. Daubechies, Ten lectures on Wavelets. Philadelphia, PA: SIAM, 1992.

[22] S. G. Mallat, A Wavelet Tour of Signal Processing. New York: Academic, 1998.

[23] D. L. Donoho, "De-noising by Soft-Thresholding", IEEE Trans. Inform. Theory, vol. 41, No. 3, pp.613-627, May 1995.

[24] D. L. Donoho and I. Johnstone, "Adapting to Unknown Smoothness via Wavelet Shrinkage", J.American. Stat. Assoc., 90, pp.1200-1224, 1995.