A COMPARISON ON SPECKLE NOISE SUPPRESSION ALGORITHM FOR INTRAVASCULAR ULTRASOUND (IVUS) IMAGES

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Abstract

Accurate and reliable diagnosis of carotid artery stenosis depends on the quality of IVUS images. Especially in ultrasound images where coherent sources are involved, speckle noise causes blurring and loss of information. Thus, methods to eliminate speckle noise plays an essential part in the field of medical imaging. This paper compares various speckle noise suppression algorithms for carotid artery ultrasound images. Speckle noise reduction algorithms that are implemented includes Homomorphic Wavelet Level 1 and Level 2, Perona-Malik (PM) filter, Modified PM1, Modified PM2, Adaptive PM, Butterworth Filter, Doubly Degenerative Diffusion (DDD), Speckle Reducing Anisotropic Diffusion (SRAD) and Total Variance (TV) filter. A quantitative evaluation is carried out by estimating Signal to Noise Ratio (SNR), Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM), Beta Metric and Natural Image Quality Evaluator (NIQE). The performance metrics shows that Homomorphic Wavelet Level1, Modified PM 2, Adaptive PM and SRAD are robust in eliminating speckle noise from carotid artery ultrasound images, thereby increasing its diagnostic accuracy. Though DDD and TV approach have good SNR and PSNR values, their low Beta metric and high NIQE values have made them ineffective.

***Keywords*: Speckle noise reduction; intravascular ultrasound images; speckle reducing anisotropic diffusion; Perona-Malik filter.**

1. Introduction

Carotid arteries are major blood vessels that supply blood to head and brain. Narrowing of such arteries due to plaque formation is known as carotid artery stenosis. In some instances, it can advance to complete blockage leading to stroke. So, imaging of carotid artery plays a vital role in diagnosis of carotid artery stenosis and to quantitatively monitor carotid plaque progression during the course of treatment. Over some years, ultrasound imaging has been successfully utilized for arterial disease diagnosis due to its non-invasive nature and low cost. Speckle pattern often has negative effect on the quality of ultrasound images, which may cause poor diagnosis. Though speckle is considered as a noise, it carries some useful information. But still, it limits the contrast resolution of imaging modality and the efficiency of diagnosis. Therefore, speckle pattern should be suppressed without affecting important features of the image. The aim of this work is to give an extensive comparison on various algorithms used for despeckling carotid artery ultrasound images. This paper is structured as follows: Section 2 discusses some of the related works, Section 3 elaborates various despeckling algorithms to be compared, Section 4 gives the experimental results and Section 5 concludes the paper.

2. Related work

Speckle noise suppression technique is an essential pre-processing step because the presence of speckle pattern may disturb the feature extraction and analysis processes. Over past few years, numerous researchers have developed various algorithms ranging from simple filters to complicated algorithms to suppress speckle noise. Some commonly known spatial domain despeckling filters such as Lee, Kuan, Frost, median and Weiner are utilized in [1], [2] and [3]. In [4] and [5] Bilateral and Gaussian filters are implemented for speckle reduction in ultrasound. In recent years filtering in wavelet domain has become popular among researchers. Various kinds of wavelets such as Haar, Daubechies, Symlets, Coiflets and Biorthogonal are utilized for despeckling ultrasound images in [6], [7], and [8]. Some used thresholding in wavelet domain as in [9] [10] which proved to be effective. Recently, combination of algorithms is prevalently adopted in denoising ultrasound images. For example, an optimization algorithm cascaded with Weiner filter in [11], combination of wavelet and enhanced Kuan filter in [12], and combination of wavelet and bilateral filter in [13]. Most of the despeckling algorithms have certain demerits that has to be addressed. Some despeckling methods which use windows can have variation in its output for different window sizes [14]. Some methods require threshold values to be specified in the filtering process that should be estimated empirically. Wherein, inappropriate choice of threshold may lead to noisy boundaries. There are several papers which discusses about the despeckling algorithms for Synthetic Aperture Radar (SAR) images, satellite images, Optical Coherence Tomography (OCT) images and fetal ultrasound. But a comparison using carotid artery ultrasound is very limited. Table.1.1. summarizes works done on comparison of despeckling algorithms specifically for carotid artery ultrasound images in recent years.

Author/Paper	No. of algorithms compared	Comparison metrics
Rafati, M., et. al. [15]	3	10
Nieniewski, M., et. al. [16]	16	1
Loizou, C.P., et al. [17]	10	9
Yu, Y., [22]	3	3

Table 1. Summary of works comparing despeckling algorithms for carotid artery ultrasound

Although numerous despeckling algorithms have been proposed in the literature, a systematic comparison on the performance of these filters is still very beneficial to facilitate the selection of appropriate filter for clinical application. This work focuses on comparing the performance of ten filters for suppressing speckle noise in carotid artery ultrasound images.

3. Despeckling filters

3.1. *Butterworth filter*

Butterworth filters are more common in signal processing domain. In image processing applications, it is used for smoothing in frequency domain. As the speckle noise is present in high frequency, this filter removes high frequencies and preserves the low frequency components [14].

3.2. *DDD filter*

DDD algorithm was developed by Zhengyi Zhou et al in [19] and found to be inspired by non-linear diffusion models. This algorithm was noted to denoise rapidly due to implementation of slightly modified Fast Explicit Diffusion scheme. This framework is capable of boosting the overall efficiency by several times.

3.3. *Homomorphic wavelet filter*

In homomorphic wavelet filtering, input image undergoes logarithmic transform, followed by discrete wavelet transform. With the help of wavelet coefficients, inverse discrete wavelet transform is performed to get a reconstructed image. The exponential of this reconstructed image is the filtered output [18]. In this work, filtering is done in two levels. In level 1 filtering, input image is split into four sub bands as LL, LH, HL and HH. Since, most of the speckle noise is present in HH band, it is eliminated. In level 2 filtering, the entire process is repeated with level 1 filtered image as input.

3.4. *SRAD filter*

Speckle reducing anisotropic diffusion filter often known as SRAD is an extended version of anisotropic diffusion filter designed by Yu and Acton in [22]. SRAD distinguishes the edges in the images using instantaneous coefficient of variation, which provides high values for edges and low values in homogenous regions. The high values decrease the smoothing effect in edges; hence edges are preserved to a greater extent. Whereas speckle pattern is removed in homogenous regions [20].

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3.5. *PM filter*

It is a non-linear anisotropic diffusion method proposed by Perona and Malik in 1990 that uses techniques of partial differential equations. Later on, many variations and improvements have been made to this filtering process. In this work, four different versions of Perona Malik filter such as PM, Modified PM 1, Modified PM 2 and Adaptive PM proposed by Anthony Bua [21] are utilized whose equations are as follows.

3.5.1. PM Filter

$$\varepsilon_X = 1/(1 + ((abs\ (C_x))/K).\hat{}2) \tag{1}$$

$$\mathrm{PM} = \mathrm{I} + d_t * \left((\varepsilon_N * C_N + \varepsilon_S * C_S + \varepsilon_E * C_E + \varepsilon_W * C_W) - \mathrm{lambda} * (\mathrm{I})\right) \tag{2}$$

3.5.2. Modified PM1

$$\varepsilon_X = 1/(1 + ((abs\ (C_x))/K_1) + \left((abs(C_x))/K_2\right).\hat{}3 \tag{3}$$

$$\mathrm{Modified\ PM\ 1} = \mathrm{I} + d_t * \frac{\left((\varepsilon_N * C_N + \varepsilon_S * C_S + \varepsilon_E * C_E + \varepsilon_W * C_W) - \mathrm{lambda} * (\mathrm{I})\right)}{((abs(U).\hat{}\ (1/alpha + \ epsilon))} \tag{4}$$

3.5.3. Modified PM2

$$\varepsilon_X = 1/(sqrt(1 + ((abs\ (C_x))/K).\hat{}2)) \tag{5}$$

$$\mathrm{Modified\ PM\ 2} = \mathrm{I} + d_t * \left((\varepsilon_N * C_N + \varepsilon_S * C_S + \varepsilon_E * C_E + \varepsilon_W * C_W) - \mathrm{lambda} * (\mathrm{I})\right) \tag{6}$$

3.5.4. Adaptive PM

$$\varepsilon_X = 1/(1 + ((abs\ (C_x))/K_1).\hat{}(alpha)) \tag{7}$$

$$\mathrm{Adaptive\ PM} = \mathrm{I} + d_t * \left((\varepsilon_N * C_N + \varepsilon_S * C_S + \varepsilon_E * C_E + \varepsilon_W * C_W) - \mathrm{lambda} * (\mathrm{I})\right) \tag{8}$$

Where,

x denotes directions (North, East, West and South),
Cx denoted change in different directions;
K, K1 and K2 are the shape defining constant;
alpha and epsilon are constants;
dt is the time interval between space solutions and
lambda is the regularization constant;
I is the noisy image.

3.6. *TV model*

TV denoising approach is developed with an aim to preserve sharp edges while smoothing homogenous regions. The regularization parameter controls the degree of smoothing effect. Numerous TV based denoising algorithms have been developed. This work implements an algorithm proposed by Anthony Bua in [21]. The mathematical equation of Total Variance Regularization is given as:

$$T(u) = F(b/A_u) + \lambda\|\Delta u\| \tag{9}$$

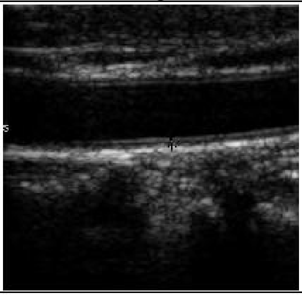
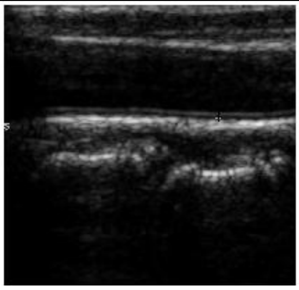
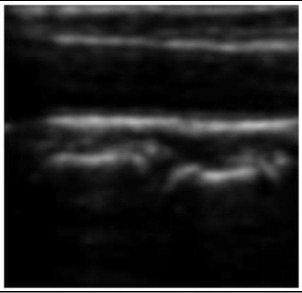
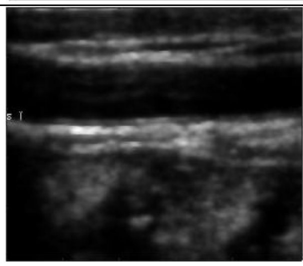
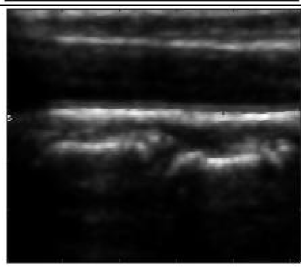
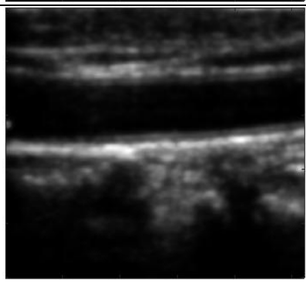
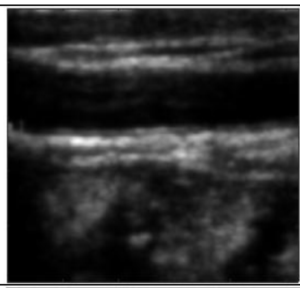
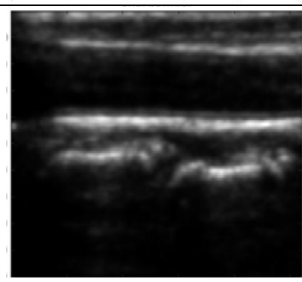
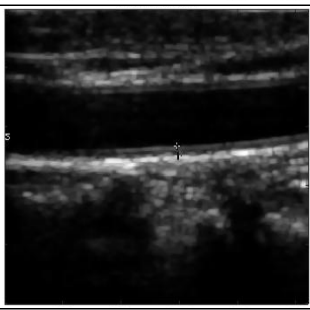
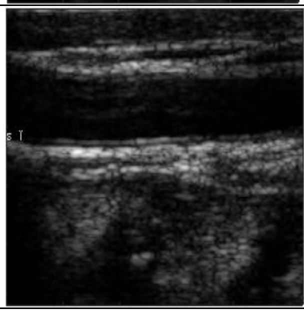
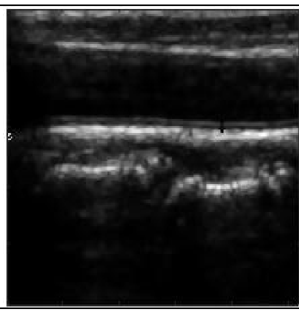
Where, F is the data fidelity term, which depends on the noise model and λ is the regularization parameter. The multiplicative model is represented as:

$$b = (A_u).\zeta \tag{10}$$

Where, A is the observation operator, u is the noise free data and ζ is the noise

4. Results

Ten despeckling algorithms are implemented on IVUS images and their output is shown in Fig.1.2.

	Image 1	**Image 2**	**Image 3**
Input image			
Butterworth			
PM			
Modified PM 1			
Modified PM 2			

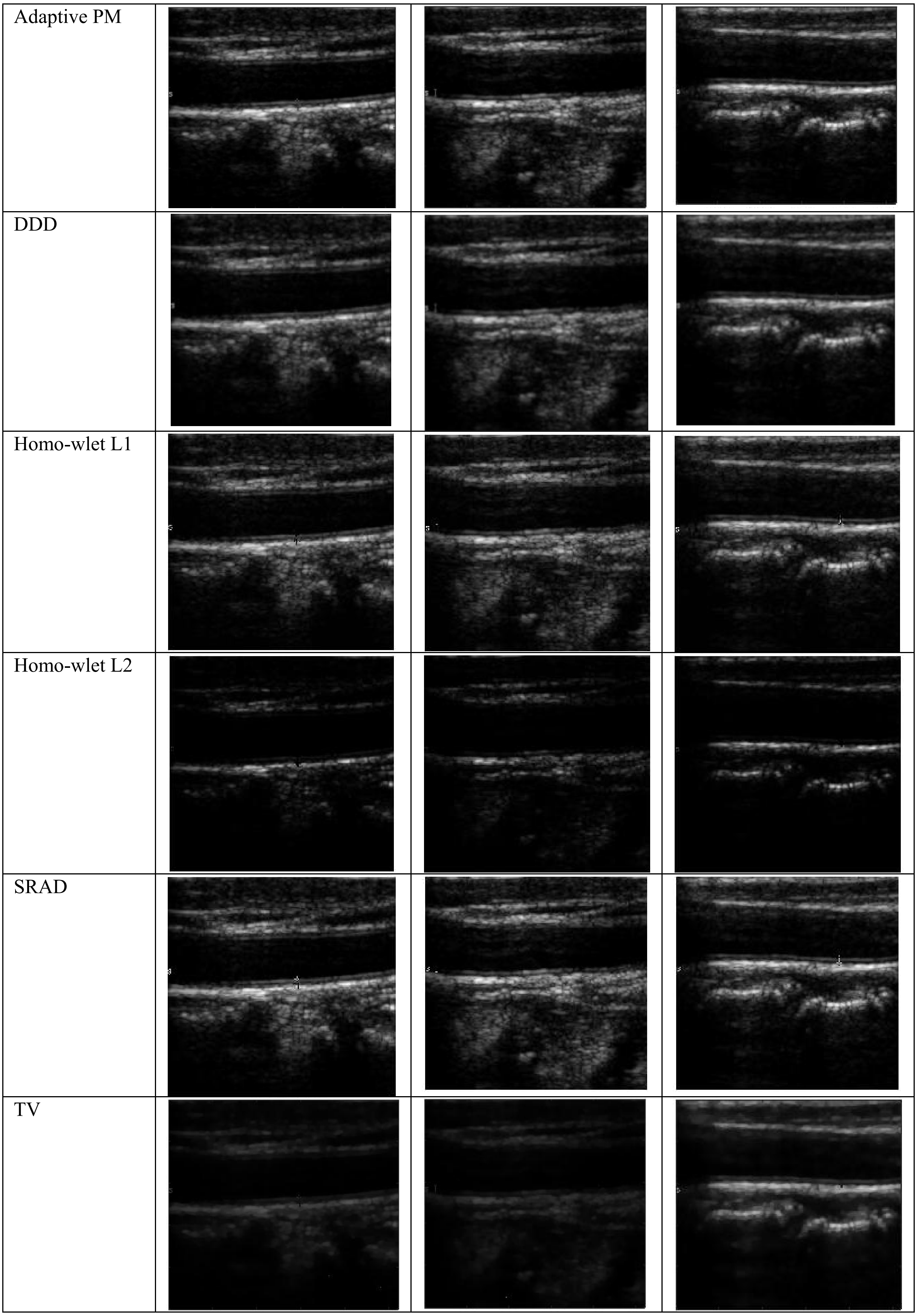


Figure.1.2. Resultant images of various despeckling algorithms

Despeckling algorithms are compared in terms of five image quality metrics such as Signal to Noise Ratio (SNR), Peak Signal to Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), Beta Metric and Natural Image Quality Evaluator (NIQE). PSNR expresses the ratio of maximum possible value of image and power of noise in range of decibels. SSIM provides comparison between two images based on luminance, contrast and structure. Therefore, this metric takes into account the factors of human visual system. NIQE is a completely blind image quality score which does not require any reference image. A lower NIQE score signifies or denotes better perceptual quality. Beta Metric value indicates the edge preserving condition in the image and its value ranges between -1 to +1. Table 2. Shows the values of the metrics that are calculated for all the ten filters.

Image 1					
	SNR (dB)	**PSNR (dB)**	**SSIM**	**Beta metric**	**NIQE**
Butterworth	17.0268	28.2049	0.7722	0.0581	5.4423
Homo-wavelet L1	22.4286	32.8915	0.9684	0.7062	4.5548
Homo-wavelet L2	12.2472	19.6408	0.4440	0.2125	6.4660
PM	17.3775	29.7711	0.8165	0.7269	5.2345
Modified PM1	16.9664	28.9839	0.8087	0.4784	5.4375
Modified PM2	19.2578	36.2369	0.9134	0.8865	4.6470
Adaptive PM	21. 2722	39.6659	0.9848	0.6512	4.2170
DDD	22.6201	32.2041	0.9492	0.2414	5.7471
SRAD	20.9932	31.7674	0.8960	0.9678	4.2345
TV	20.0979	33.4916	0.8682	0.4795	5.5907
Image 2					
	SNR	**PSNR**	**SSIM**	**Beta metric**	**NIQE**
Butterworth	16.8482	27.9927	0.7459	0.0703	5.7619
Homo-wavelet L1	22.9840	33.1328	0.9790	0.7363	4.5287
Homo-wavelet L2	11.8141	19.1700	0.3735	0.3053	5.7325
PM	17.0912	29.4471	0.7940	0.7640	5.3577
Modified PM1	16.0410	28.7110	0.7866	0.4987	5.2755
Modified PM2	19.9502	35.5860	0.9017	0.8454	4.7071
Adaptive PM	21.6993	40.0552	0.9832	0.6851	4.8266
DDD	23.8979	32.1440	0.9397	0.2489	5.6164
SRAD	21.0301	32.7303	0.7939	0.9538	4.9373
TV	19.9804	32.3363	0.8466	0.3228	4.7793
Image 3					
	SNR	**PSNR**	**SSIM**	**Beta metric**	**NIQE**
Butterworth	17.9540	28.4858	0.8048	0.0583	5.4984
Homo-wavelet L1	21.9564	32.1224	0.9492	0.7085	4.1570
Homo-wavelet L2	12.4526	19.5022	0.3456	0.3025	5.4028
PM	17. 1324	28.2473	0.7041	0.7242	6.4336
Modified PM1	16.0410	29.8052	0.8561	0.4673	5.2894
Modified PM2	19.6004	35.7642	0.9056	0.8341	5.0543
Adaptive PM	20.2577	39.1341	0.9723	0.6429	4.4003
DD	23.4903	32.5726	0.9557	0.2184	5.3332
SRAD	20.8342	31.2741	0.8242	0.9619	5.4302
TV	20.9804	32.4317	0.8904	0.3109	5.2967

Table 2. Performance metrics

5. Conclusion

This work presents a comparative analysis on different despeckling methods with an aim to suppress the speckle noise in carotid artery ultrasound in order to make the images suitable for further analysis. The experimental results show that Homomorphic Wavelet Level1, Modified PM 2, Adaptive PM, SRAD and DDD filtered images obtained higher SNR and PSNR values indicating successful despeckling. SSIM values are higher for Adaptive PM and Homomorphic Wavelet Level 1. Beta metric is higher for SRAD and Modified PM 2 which shows that edges are preserved. Whereas, Butterworth, Homomorphic Wavelet Level2 and DDD did not preserve the edges resulting in blurred image. Further, NIQE values indicate that Adaptive PM and SRAD maintained the perceptual quality of image successfully. Overall, this work gives a clear picture on performance of various despeckling algorithms which can be utilized in development of diagnostic systems. Future work will focus on critical analysis of deep learning methods for despeckling applications.

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