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Implementation of Proposed Threshold for Despeckling in Stationary Wavelet Domain

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Abstract— Medical images are prone to different types of noise. Such types of noise corrupted images leads to incorrect diagnosis. Hence, removal of noise is a prerequisite in medical imaging modality. Speckle noise is widely found in coherent medical images, like in Ultra Sound images and Optical Coherence Tomography images.In the preprocessing stage, the noise present in the medical image has to be removed while preserving the edge information and other structural details of the image. Relevant denoising technique has to be chosen based on the nature of the medical image. This research is focused on design of algorithms for speckle denoising of Ultra Sound images and Optical Coherence Tomography images in stationary wavelet domain. Standard speckle filters in wavelet domain were analyzed and compared with the proposed method. Results obtained proved that the proposed method was able to remove speckle noise while preserving better edges.

Index Terms—Despeckling, Stationary Wavelet Domain, Shrinkage methods, Edge preservation

1. INTRODUCTION

In image processing and computer vision, the techniques of image denoising from noise contaminated version of image to restore the originality of the image is a continuous research issue, aiming at arriving more better performance in the applications such as visual tracking, image classification, segmentation, registration etc. Usually a captured image gets contamination embedded into an image due to intrinsic and extrinsic causes[1]. The researchers has so far used a wide variety of methodology for the stated purpose, but the undertaken research has focused on spatial and transform domain techniques for image denoising.

Mostly the images captured through coherence illumination are formed with higher level of speckle noise. The success ratio of segmentation after the preprocessing of the image that involves denoising depends on the extent of the removal of noise from the image. Coherent Medical images and Satellite images are usually degraded with noise during image acquisition and transmission process[2]. Such types of images are corrupted by speckle noise. The researchers are making efforts to reduce speckle noise with highest possible level with the objective of retaining important features of the image. Synthetic Aperture Radar (SAR) imagery uses microwave radiation to illuminate the earth surface. Optical Coherence Tomography (OCT) and Ultra Sound (US) medical images are also affected due to speckle noise[3].

Image processing techniques have been widely used in medical imaging research. These techniques provides support in visualization, enhancements, segmentation and many more operations which are useful for processing medical images[4]. The main reason for utilization of these techniques is to detect any abnormality in the medical images. Few abnormalities to be mentioned are detection of tumors, finding blocked vessels and even detecting broken joints. Medical image analysis is performed in stages like removal of the noise, segmentation of the suspected parts of the image, feature extraction and its measurement.

2. REVIEW OF LITERATURE

Jyoti Sahu et al[5] proposed a multivariate thresholding technique for image denoising using multiwavelets. The proposed technique is based on the idea of restoring the spatial dependence of the noisy pixels in the subbands of wavelet decomposition. Coefficients with high correlation are considered for thresholding operation.

Yong Yue et.al[6] introduced a novel Multiscale Nonlinear Wavelet Diffusion (MNWD) method for denoising speckle in ultrasound images.

Wavelet diffusion is considered as an approximation to nonlinear diffusion within the framework of the dyadic wavelet transform. This idea is used in the design of a speckle suppression filter with an edge enhancement feature. MNWD takes advantage of the sparsity and multiresolution properties of wavelet, and the iterative edge preservation and enhancement feature of nonlinear diffusion.

David Donoho[7] proposed visushrink. It is also called as universal threshold. An estimate of the noise level σ was defined based on the median absolute deviation. VisuShrink does not deal with the minimization of mean squared error as a result it over smoothes the image, because it removes too many coefficients. VishuShrink performs well for additive noise but not for multiplicative noise.

Iman Elyasi et al[8] proposed Normal Shrink, following a generalized gaussian distribution model of the subband in wavelet domain. It produces best result of minimum MSE and maximum SNR only when the noise is low. Its performance is better than bayes shrink in terms of preserving the edges as well as in removing the noise.

Donoho et al[9] proposed Stein"s Unbiased Risk Estimator (SURE). It is referred as subband dependent threshold because it determines a threshold value for each resolution level in the wavelet transform. The main advantage of SureShrink is, it minimize the mean squared error, unlike VisuShrink, SureShrink reduces the noise by thresholding the empirical wavelet coefficients. It follows the soft thresholding rule and it is adaptive in nature.

Chang et al[10] proposed BayesShrink. The goal of this method is to minimize the Bayesian risk. It uses soft thresholding and it is also subband-dependent, like Sure Shrink, which means that threshold level is selected at each subband of resolution in the wavelet decomposition. The noise variance is obtained by median estimator in the HH1 subband.

2.1 Review Findings for Shrinkage Methods

- Linear filters causes blurring of edges whereas nonlinear filters preserves the edges with the drawback that these filters are sensitive to the size and shape of the filter window[11].
- Overall most of these techniques do not enhance edges, as these filters are not directional, and may not suppress noise near the edges[12].
- Drawback of discrete wavelet transformation is that it is not translation invariant. It loses lots of important pixel coefficients during reconstruction of the denoised signal to all most the original signal[13].
- In wavelet transform methods, the noise variance for threshold computation is obtained from coefficients of high frequency subband and the same threshold is used for all the resolution scales. The level of noise decreases as the scale of resolution increases. Therefore, noise variance should be estimated separately for each subbands[14].

3. MATHEMATICAL MODEL OF SPECKLE NOISE

Speckle Noise is multiplicative in nature. This type of noise is an inherent property of coherent imaging. It affects the diagnostic value of imaging modality, because of reduced image resolution and image contrast[15]. So, speckle noise reduction is an essential preprocessing step, in coherent medical images. Mathematically, the speckle noise is represented with the help of these equations below:

$$g(x,y) = f(x,y) * u(x,y) + \xi(x,y) \qquad (1)$$

Where, $g(x,y)$ is the observed image, $u(x,y)$ is the multiplicative component and $\xi(n,m)$ is the additive component of the speckle noise. Here 'x' and 'y' denotes the radial and angular indices of the image samples. As in coherent imaging, only multiplicative component of the noise is to be considered and additive component of the noise has to be ignored. Hence, equation (1) can be modified as;

$$g(x,y) = f(x,y) * u(x,y) + \xi(x,y) - \xi(x,y) \qquad (2)$$

Therefore,

$$g(x,y) = f(x,y) * u(x,y) \qquad (3)$$

4. PROBLEM FORMULATION

The proposed work focuses on the wavelet transform filtering method. This method is chosen because; most of the signal energy is contained in a few large wavelet coefficients, whereas a small portion of the energy is spread across a large number of small wavelet coefficient. These coefficients represent details as well as high frequency noise in the image. By appropriately thresholding these wavelet coefficients, image denoising is achieved while preserving fine structures in the image[16]. All wavelet transform denoising algorithms involve the following three steps in general.

1. Forward Wavelet Transform: Wavelet coefficients are obtained by applying the wavelet transform.

2. Estimation: Clean coefficients are estimated from the noisy ones.
3. Inverse Wavelet Transform: A clean image is obtained by applying the inverse wavelet transform.

Discrete Wavelet Transform (DWT) does not provide shift invariance. This leads to small shifts in the input waveform which makes major changes in the wavelet coefficients[17]. To overcome the problem of DWT, Stationary Wavelet Transform (SWT) of two dimensions is used in the proposed work. SWT2 performs a multilevel wavelet decomposition using orthogonal wavelet filters.

The noisy image is read as input. As discrete stationary wavelet domain is used the size of the image must be strictly a positive integer. The value 2^N must equally divide the row value and column value of the input image before performing 2D stationary wavelet transform. But all the input images will not be having the size which is strictly a positive integer value. In such cases the image has to be extended symmetrically to overcome this problem[18].

After the input image is symmetrically extended, the next step is to decompose the input image upto 3 levels using "bior 3.1" wavelet filter. The decomposition results in subdivision of the input image into four subbands namely LL, LH, HL and HH. The size of the input image in all the four subbands will be the same. The proposed threshold function is applied separately to all the subbands except for LL subband. The proposed threshold is as follows.

In the proposed threshold technique, in each subband median and absolute difference between the median and the pixel is calculated. This calculation is used to measure the variability between noisy pixel and the noiseless pixel. In the next step the threshold (th2) is calculated using tukey's biweight function[19]. This function helps in determining the outlier. Next the threshold value is compared with the MD*(x,y)* to determine whether the pixel lies inside the outlier value or not. If the variable measure of the pixel is above the threshold, then the pixel is removed using soft thresholding technique else the pixel is not a noisy pixel and hence it is retained.

4.1 Proposed Algorithm

Step-1: Start
Step-2: Read the noisy image.
Step-3: Extend the noisy image. The noisy image will be extended using symmetric extension in order to improve the boundary problem.
Step-4: Set the level of wavelet decomposition to 3.
Step-5: Choose bior3.1 wavelet filter.
Step-6: Perform decomposition of the input image using swt2() upto 3 levels.
Step-7: Perform thresholding in LH, HL, HH subband
Step-7.1: Calculate the median M value of each subband image.
Step-7.2: Calculate $MD(x,y) = median(\sum_{i,j}^{n} |x_{i,j} - M|$. It is a measure to indicate the variability of the pixel.
Step-7.3: Formulate the threshold (th1) using tukey's biweight function

$$th1 = I(x,y) * \left(\left(1 - \left(\frac{I(x,y)}{f}\right)^2\right) \wedge 2\right) * 0.5$$

Step- 7.4: If th1 > MD*(x,y)*
Perform Soft thresholding of the subband image.
else
Retain the pixel
Step-8: Perform inverse stationary wavelet transform using ISWT2().
Step-9: Calculate PSNR, RMSE, IQI, SSIM, MSD, DR, ENL, FOM, CC.
Step-10: Stop

5. IMAGE METRICS

5.1 Peak Signal to Noise Ratio

Peak Signal to Noise Ratio (PSNR)[20] is one of the most essential statistical parameter for quality measurement of an image or signal. It is used as an estimate to measure the quality of objective difference between the noisy and the denoised image. The basic idea is to compute a single number that reflects the quality of the reconstructed image. Higher PSNR value provides higher image quality. It is calculated as;

$$PSNR = 10 * log10\left(\frac{1}{MSE}\right) \quad (4)$$

5.2 Root Mean Square Error

Root Mean Square Error (RMSE)[21], is an estimator in to quantify the amount by which a noisy image differs from noiseless image. RMSE is computed by averaging the squared intensity of the noisy image and the denoised image, where error is the difference between desire quantity and estimated quantity. Having a RMSE value of zero is ideal.

$$RMSE = \sqrt{\frac{\sum_{x=1}^{m}\sum_{y=1}^{n}\left(\bar{f}(x,y) - f(x,y)\right)^2}{m*n}} \quad (5)$$

5.3 Image Quality Index

The Image Quality Index (IQI)[20] is a measure of comparison between original and distorted image. It is divided into three parts: luminance $l(x, y)$, contrast $c(x, y)$, and structural comparisons $s(x, y)$ as mentioned in equation (6),(7) and (8). The dynamic range for *IOI(x, y)* is [-1, 1].

$$l(x,y) = \frac{2\mu_x\mu_y}{\mu_X^2 + \mu_y^2} \quad (6)$$

$$c(x,y) = \frac{2\,\sigma_x\,\sigma_y}{\sigma_x^2+\sigma_y^2} \quad (7)$$

$$s(x,y) = \frac{2\sigma_{xy}}{\sigma_x+\sigma_y} \quad (8)$$

$$IQI(x,y) = l(x,y).c(x,y).s(x,y) = \frac{4\mu_x\mu_y\mu_{xy}}{(\mu_X^2 + \mu_y^2)(\sigma_x^2+\sigma_y^2)} \quad (9)$$

5.4 Structural Similarity Index

The Structural Similarity Index (SSIM)[20] measures the similarity between two images which is more consistent with human perception than conventional techniques. The range of values for the SSIM lies between −1, for a bad and 1 for a good similarity between the original and despeckled images, respectively.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y+c1)(2\sigma_{xy}+c2)}{(\mu_X^2 + \mu_y^2+c1)(\sigma_x^2+\sigma_y^2+c2)} \quad (10)$$

5.5 Noise Mean Value (NMV), Noise Standard Deviation (NSD)

Noise Variance determines the contents of the speckle in an image. A lower variance gives a "cleaner" image as more speckle is reduced, it is not necessarily that it should depend on the intensity of the image. The formulas for the NMV and NSD calculation are as follows[22].

$$NMV = \frac{\sum_{r,c} f_d(r,c)}{r*c} \quad (11)$$

$$NSD = \sqrt{\frac{\sum_{r,c}\,(f_d(r,c)-NMV)^2}{r*c}} \quad (12)$$

5.6 Pratt's Figure of Merit (FOM)

It measures edge pixel displacement between each filtered image I_{filt} and the original image $I_{orig.}$ It is defined as[23]:

$$\text{FOM} = \frac{1}{\max\,(N_{filt},\ N_{orig}),} \sum_{i=1}^{n} \frac{1}{1+d_i^2\alpha} \quad (13)$$

where N_{filt} and N_{orig} are the number edge pixels in edge maps of I_{filt} and I_{orig}. Parameter α is set to a constant 1/9, and d_i is the euclidean distance between the detected edge pixel and the nearest ideal edge pixel. The FOM metric measures how well the edges are preserved throughout the filtering process. This metric has a significant relationship with the overall quality score at 1% significance level.

5.7 Equivalent Number of Looks

Equivalent Numbers of Looks (ENL)[24] is a measure to estimate the speckle noise level in the image. The value of ENL depends on the size of the tested region; theoretically a larger region will produces a higher ENL value than a smaller region. The formula for the ENL is

$$ENL = \frac{NMV^2}{NSD^2} \quad (14)$$

5.8 Deflection Ratio (DR)

The formula for the deflection ratio[25] calculation is;

$$DR = \frac{1}{R*C}\sum_{r,c}\frac{(f_d(r,c)-NMV)}{NSD} \quad (15)$$

After speckle reduction the deflection ratio should be higher at pixels with stronger reflector points and lower elsewhere.

5.9 Correlation Coefficient (CC)

For digital images, correlation[26] is a measure of the strength and direction of a linear relationship between two variable. A correlation of 1 indicates a perfect one-to-one linear relationship and -1 indicates a negative relationship. The square of the correlation coefficient describes the variance between two variables in a linear fit. The Pearson's correlation coefficient is defined as;

$$r = \frac{\sum_i(f_i - f_m)(\bar{f}_i - \bar{f}_m)}{\sqrt{\sum_i(f_i - f_m)^2}\,\sqrt{\sum_i(\bar{f}_i-\bar{f}_m)^2}} \quad (16)$$

where, f_i and $\bar{f}_i$ are intensity values of ith pixel in noisy and denoised image respectively. Also, f_m and

$\bar{f}_m$ are mean intensity values of noisy and denoised image respectively.

5.10 Execution Time

Execution Time(ET) [27]of a denoising filter, is defined as the time taken by a processor to execute an algorithm when no other software, except the operating system (OS), runs on it. Execution time is referred with respect to the system's clock time-period. The execution time taken by a filtering algorithm should be low for real-time image processing applications. Hence, when all metrics give the identical values then a filter with lower execution time is better than a filter having higher execution time.

6. Results and Discussions

An objective evaluation of the existing thresholding techniques and the proposed threshold techniques is listed in Table 1. The PSNR value is very high for the proposed threshold technique. The next highest PSNR value is generated by proposed threshold technique. The proposed threshold has a very low RMSE value compared with other thresholding techniques. It also indicates that the proposed threshold is capable of removing more speckle noise equally maintaining low error between the original and denoised image.

High image quality index is exhibited by Vishu shrink, indicating that the denoised image has a better variation between the original and denoised image. If the structural similarity index is equal to one, then it is an indication that the structural detail of the original image is preserved even after denoising. Hence proposed threshold has produced a value which is very close to one.

The NMV value and NSD values of the proposed threshold has produced the same value, comparatively less than other thresholding techniques. It indicates that the speckle noise content of the denoised images is very less.

ENL value and DR values of both the proposed threshold are same and less. When compared with other thresholding techniques Bayes Shrink has produced a higher ENL value indicating that the original and denoised image has more similar features. But the proposed threshold as exhibited a higher DR value indicating that there is more deflection along the edges in the denoised image.

The FOM value is high in proposed threshold whereas the existing threshold shrinkages were not evaluated using this parameter. Similarly, the CC value is high in proposed threshold. The execution time for the proposed algorithm is 4.173seconds

Table 1. Comparison Of Existing Denoising Filters With Proposed Threshold

	Existing Denoising Filters				
Assessment Parameters	Visu Shrink	Normal Shrink	Bayes Shrink	Sure Shrink	**Proposed**
PSNR	31.65	29.28	38.70	29.60	68.2510
RMSE	11.68	10.23	12.67	10.81	0.0098
IQI	0.5902	0.3812	0.3938	0.4645	0.1823
SSIM	0.7882	0.8214	0.8532	0.8953	0.9997
NMV	11.56	9.61	21.72	13.48	0.2205
NSD	3.30	2.01	6.75	4.23	0.2164
ENL	1.2685	3.6853	7.6893	3.5742	1.0378
DR	0.0031	0.0381	0.0610	0.0461	0.8023
FOM	NA	NA	NA	NA	0.2498
CC	NA	NA	NA	NA	0.5847

7. CONCLUSION

As a prerequisite, Ultrasound images and Optical Coherence Tomography images should undergo denoising before being interpreted by the medical expert, as an objective to be achieved. The proposed work was tested with Ultrasound images and Optical Coherence Tomography images. The images were obtained from online database and the database of Optical Coherence Tomography images were collected from hospital.The proposed algorithms were evaluated with several parameters and the best proposed algorithm was identified. The proposed threshold gave good results both objectively and subjectively.The proposed threshold gave good results for ultra sound image than for optical coherence tomography images.

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