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SPECKLE REDUCTION BASED ON OPTIMUM MUTIRESOLUTION LEVEL

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ABSTRACT

Sonar images are highly affected by speckle noise which reduces spatial resolution. Denoising is required in sonar images to distinguish a number of different regions by analyzing the image. Sparsity of the wavelet representation of the images is exploited in speckle denoising in sonar images. The proposed technique enhances the denoising property of the classical thresholding and the Bayes soft thresholding technique by proper selection of time scale level. The optimum mutiresolution level for speckle reduction is found to be the maximum level of decomposition possible for the image of size S to be denoised and the chosen basic wavelet function. The proposed denoising method is compared and evaluated based on the Peak Signal to Noise Ratio (PSNR). Simulation results revealed that an improvement was achieved by implementing the proposed method.

KEYWORDS: Denoising, Mutiresolution, Speckle, Wavelet Transform

INTRODUCTION

Sonar images [1] are highly unreliable due to the presence of speckle noise which reduces spatial resolution by giving a variance to the intensity of each pixel. The speckle noise produced due to the coherent nature of scattering phenomenon is of multiplicative nature. Sonar image of an object will closely resemble the optical image of the same but have less resolution than the optical image. The Signal to Noise Ratio (SNR) of such signals can be very low depending on the acquisition conditions and they contain almost homogeneous and textured regions with relatively rare edges. The spatial resolution of the sidescan sonar image will be the limiting factor in its performance. The nominal resolution corresponds to the minimum distance between two objects that can still be distinguished on the sonar image.

Classical wiener filter [2] is designed primarily for additive noise suppression. A homomorphic approach [3] is suggested for addressing the multiplicative speckle noise. The multiplicative speckle noise that disturbs the sonar images can be transformed into an additive noise by obtaining the logarithm of the image and consequently applying the wiener filter. To obtain the denoising result, the logarithm inversion is performed at the end of the process.

In this paper a wavelet decomposition based denoising algorithm is proposed in order to remove the speckle noise from sonar images. The multi-resolution analysis [4] represents the signals in different scales efficiently and helps images to be approximated from coarse to fine resolution. The method gives the optimum multiresolution level for speckle reduction. The experimental justification for this improvement is shown in the paper. During this process, the sonar image quality is enhanced in terms of SNR and resolution. First speckle deterioration of the image model is introduced. Then different wavelet shrinkage rules are briefed and the results and discussions of the proposed methodology applied on different thresholding schemes is detailed.

SPECKLE NOISE AND WAVELET SHRINKAGE

Speckle [5] is a high-frequency noise commonly observed in side scan sonar imagery that affects all coherent imaging systems. It is in fact common to all types of remote sensing using coherent radiations as a source of illumination.

After interaction with the seafloor, the acoustic waves are no longer in phase and positive or destructive interferences may occur, producing anomalously high or low returns. The acquired image is thus corrupted by a random granular pattern, called speckle that hinders the interpretation of the image content. Because speckle is difficult to distinguish from the real signals at the limit of resolution of the sonar, it proves hard to remove without affecting significantly the image. The mean filter averages the speckle in the data but lowers the resolution.

Some of the best known standard despeckling filters are the methods of Kuan (an MMSE filter), Frost (an adaptive wiener filter) and Lee (a particular case of Kuan filter with linear approximation made for the multiplicative noise model). These filters use the second-order sample statistics within a minimum mean squared error estimation approach.

A kind of model for the speckle noise is

$$h(m,n) = g(m,n)\,\eta_m(m,n) + \eta_a(m,n) \quad (1)$$

Where $g(m,n)$ is a noise-free original image, to be recovered, $h(m,n)$ is a noisy observation of $g(m,n)$, $\eta_m(m,n)$ and $\eta_a(m,n)$ are multiplicative and additive noise respectively. Since the effect of additive noise is considerably small compared to that of multiplicative noise (coherent interfering) in acoustic imaging, the model is approximated as

$$h(m,n) = g(m,n)\,\eta_m(m,n) \quad (2)$$

Transform the multiplicative noise model into an additive one by taking the logarithm of the original speckled data.

$$\log h(m,n) = \log g(m,n) + \log \eta_m(m,n) \quad (3)$$

This equation can also be rewritten as

$$h'(m,n) = g'(m,n) + \eta'_m(m,n) \quad (4)$$

Now the problem of de-speckling is rejecting an additive noise. Various noise shrinkage techniques could be adopted in order to perform this task.

In the wavelet domain [6], the additive noise is uniformly spread throughout the coefficients, while most of the image information is concentrated in the few largest ones. The sparsity or the decorrelation capacity of the wavelet representation of the images is exploited in speckle denoising. The most straightforward way of distinguishing information from noise in the wavelet domain consists of thresholding the wavelet coefficients.

Perform the DWT of the noisy image up to n levels

$$W[h'(m,n)] = W[g'(m,n)] + W[\eta'_m(m,n)] \quad (5)$$

Since speckle noise lies in high spatial frequency, it will reduce to near zero after a finite number of repeated smoothing operations. Then perform the inverse DWT $W^{-1}(.)$, and take the exponent to reconstruct the denoised image.

METHODOLOGY

The different wavelet denoising approaches differ in the selection of the threshold, time scale levels, and basic wavelet function. The signal denoising via wavelet thresholding or shrinkage [7] have shown that various wavelet thresholding schemes for denoising have near-optimal properties in the minimax sense. The proposed method gives the optimum time scale level for the speckle reduction in sonar images for different wavelet shrinkage rules. Instead of blindly assuming a multiresolution level, give the last level for which at least one coefficient is correct. This maximum level decomposition of image varies with the size of the image and the basic wavelet function chosen.

The methods for finding the threshold value for denoising is the classical approach and the Bayesian approach. As the reconstructed image quality will change with the threshold value changes, finding an optimum threshold value T is a key problem. A small threshold value will pass all the noisy coefficients and image will be less smoothing. As the threshold value increases, more number of coefficients becomes zero which leads to smooth signal and destroys details. An efficient method for finding the threshold value for denoising is by analyzing the statistical parameters of the wavelet coefficients.

The basic shrinking is thresholding [8],[9], where the wavelet coefficient with small magnitudes is set to zero ("hard-thresholding") while keeping or shrinking in magnitude ("soft-thresholding") the remaining ones.

The soft-threshold function (also called the shrinkage function)

$$\Psi_T(x) = sgn(x).\max(|x| - T, 0) \tag{6}$$

Takes the argument and shrinks it toward zero by the threshold T.

The hard-threshold function

$$\Psi_T(x) = x.1\{|x|>T\} \tag{7}$$

Which keeps the input if it is larger than the threshold; otherwise, it is set to zero. An advantage of soft thresholding is that it provides smoothness while hard thresholding preserves features.

In BayesShrink rule [10], the threshold is determined for each subband by assuming a Generalized Gaussian Distribution (GGD). The threshold T is obtained by minimizing the Bayesian Risk, i.e, the expected value of the mean square error.

To estimate the noise variance σ^2 from the noisy wavelet coefficients [11], [12], a robust median estimator is used from the finest scale wavelet coefficients. It is the median absolute deviation (MAD) of the highest-frequency subband coefficients divided by 0.6745.

$$\sigma = \{MAD(|w_{HH}(m,n)\}/0.6745 \tag{8}$$

Where $w_{HH} \in$ wavelet sub-band HH

It is observed that the threshold value set by

$$T = \sigma^2/\sigma_X \tag{9}$$

Is very close to the optimum threshold. Here σ_X is the estimate of image information of the sub-band. The Bayesian risk minimization is subband-dependent.

When σ/σ_X<<1, the signal is much stronger than the noise, the normalized threshold is chosen to be small in order to preserve most of the signal and remove some of the noise; when σ/σ_X>>1, the noise dominates and the normalized threshold is chosen to be large to remove the noise which has overwhelmed the signal. Thus, this threshold choice adapts to both the signal and the noise characteristics as reflected in the parameters σ and σ_X.

The proposed method when applied on the above three wavelet shrinkages yields for natural images the best results both in terms of mean squared error and visual quality.

RESULTS AND DISCUSSIONS

This section depicts the results of the image-denoising algorithm, which achieves near optimal performance in the wavelet domain for recovering original signal from the noisy one. For the chosen image of size, S and the selected wavelet, the optimum multiresolution levels for any of the thresholding method is obtained as the maximum level decomposition of image. As the level is decreased or increased, the performance degradation is observed.

The performance of the wavelet thresholding method that has been proposed in this paper is investigated with simulations. The level of decomposition is calculated based on the size of the selected image. Different basic wavelets were chosen separately for the proposed de-noising algorithm for the restoration of image containing speckle noise.

For objective evaluation of the denoised image, the Peak Signal to Noise Ratio (PSNR) has been calculated using

$$PSNR = 10\log_{10}255^2/MSE\ (dB) \tag{10}$$

Where

$$MSE = \left(\sum_{i,j}[g(m,n) - f(m,n)]^2\right)/MN \tag{11}$$

M is the width of image and *N* is the height of image, *g*(m,*n*) is the gray scale value of original image, and *f*(m ,*n*) is the gray scale value of the de-noised image.

The PSNR values were observed for different levels of decomposition of the image. The Table 1 portrays the PSNR values in dB for three different wavelets using the Bayes thresholding method. Maximum PSNR values for Haar, Daubechies, and Coiflets were obtained at levels of decomposition 8, 5, and 3 respectively. This is the maximum level of decomposition of the selected image for the chosen basic wavelet function and is called the optimum multiresolution level.

Table 1: PSNR Values for Bayes Thresholding

N	2	3	4	5	6	7	8	9
Haar	27.5396	27.5642	27.5617	27.5591	27.5649	27.5593	**27.577**	27.5727
dB4	29.5658	29.5872	29.5917	**29.604**	29.5627	29.5927	29.5687	29.6011
Coif5	30.0146	**30.095**	30.0096	29.8978	29.8274	29.812	29.7529	29.7363

Method Applied on Classical Approach

The wavelet thresholding procedure removes noise by thresholding only the wavelet coefficients of the detail subbands, while keeping the low resolution coefficients unaltered. The Figure 1 shows the PSNR values observed at different levels of decomposition for three different wavelets haar, db4, and coif5 using the soft thresholding method. The maximum PSNR values were observed at the optimum multiresolution level for three wavelets which were 8, 5, and 3 respectively.

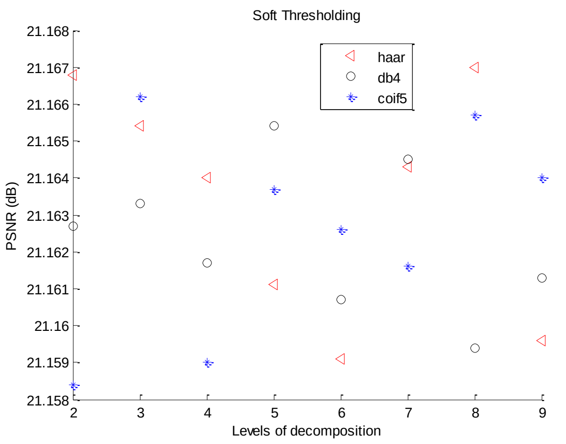

Figure 1: Performance at Different Decomposition Levels for Three Different Wavelets Using Soft Thresholding

In Figure 2 the PSNR values observed at different levels of decomposition for three different wavelets haar, db4, and coif5 using the hard thresholding method. The maximum PSNR values were observed at the optimum multiresolution level for three wavelets which were 8, 5, and 3 respectively.

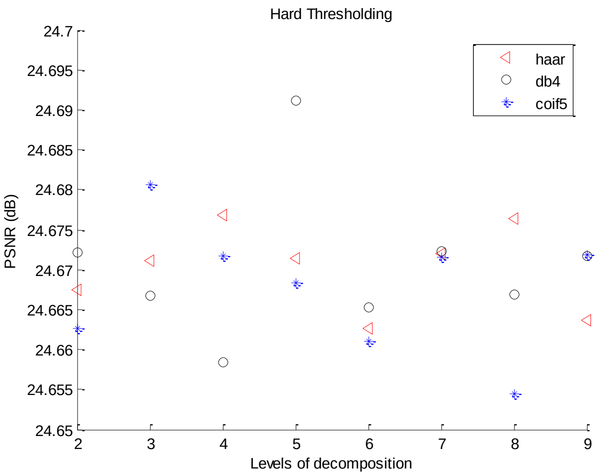

Figure 2: Performance at Different Decomposition Levels for Three Different Wavelets Using Hard Thresholding

For the chosen image of size, S and the selected wavelet, the optimum multiresolution levels for the soft thresholding and hard thresholding method is obtained as the maximum level decomposition of image. As the level is decreased or increased, the performance degradation is observed.

Method Applied on Bayesian Approach

Bayes threshold choice adapts to both the signal and the noise characteristics. Simulation results show that the Bayesian soft thresholding method has the maximum PSNR compared to the other thresholding methods. The PSNR for the noisy image is found to be 24.6756. For the chosen image of size, S and the selected wavelet, the optimum multiresolution levels for the Bayesian method is obtained as the maximum level decomposition of image.

The PSNR value for this method is 30.0954. As the level is decreased or increased, the performance degradation is observed in Bayes thresholding method also. Figure 3 depicts the results. The optimum multiresolution level for three different wavelets haar, db4, and coif5 using the Bayes thresholding method were 8, 5, and 3 respectively.

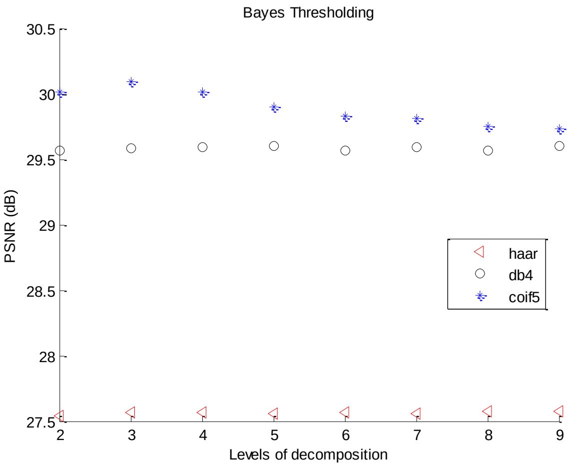

Figure 3: Performance at Different Decomposition Levels for Three Different Wavelets Using Bayes Thresholding

The results demonstrate the variation in denoising effectiveness with the choice of basic wavelet function, the wavelet shrinkage used and the multiresolution level. The new approach can achieve fairly desired de-noising effectiveness.

The Figure 4 depicts a noisy image with speckle noise and Figure 5, the denoised image. This example uses the coiflets wavelet function.

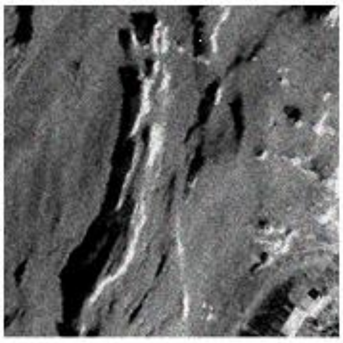

Figure 4: Noisy Image

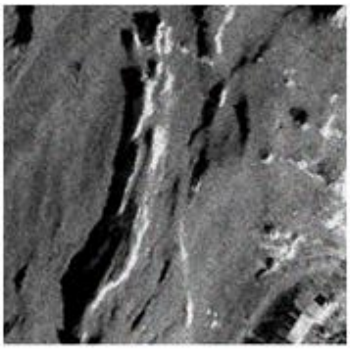

Figure 5: Denoised Image Using Coiflets Wavelet Function

CONCLUSIONS

This paper presents a novel method for finding optimum multiresolution level based on PSNR values and visual quality, as an improvement on the classical thresholding approaches and the Bayesian thresholding method. For all the thresolding methods, the optimum multiresolution level for speckle reduction is the maximum level of decomposition possible for the image of size S to be denoised and the chosen basic wavelet function. This method fine tunes the existing denoising methods by optimizing the level of decomposition. The above method can be applied to other denoising architecture with proper modifications.

The maximum level of decomposition possible for the particular image and the chosen basic wavelet function is determined after a series of simulations. It was found that this maximum level is the optimum level of decomposition based on the PSNR values and visual quality. The denoising performance may be further improved by choosing the optimum wavelet shrinkage rule for the image.

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