

RESEARCH ARTICLE

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An Effective Image Denoising Using Adaptive Thresholding In Wavelet Domain

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ABSTRACT

This paper deals with denoising of images using threshold estimation in wavelet domain. Image denoising in wavelet domain is estimated by using Gaussian distribution modeling of subband coefficients or any shrink techniques such as bayes shrink, Normal shrink. Normal shrink is computationally more efficient and adaptive. A near optimal threshold estimation is done using subband technique. Image denoising algorithm uses soft thresholding to provide smoothness and better edge preservation at the same time. In this paper, we analyzed several methods of noise removal from degraded images with Gaussian noise by using adaptive wavelet threshold (Bayes Shrink and Normal Shrink) and compare the results in terms of MSE.

Keywords: Wavelet thresholding, Image denoising, Discrete wavelet threshold, subband.

I. INTRODUCTION

An image is often corrupted by noise during its acquisition or transmission. The denoising process is to remove the noise while retaining and not distorting the quality of processed image.

The traditional way of image denoising is filtering. These methods are mainly based on thresholding the discrete wavelet transform (DWT) coefficients, which have been affected by additive white Gaussian noise[1].

Simple denoising algorithms that used DWT consists of three steps:

1. Discrete wavelet transform is adopted to decompose the noisy image and get the wavelet coefficients.
2. These wavelet coefficients are denoised with wavelet threshold.
3. Inverse transform is applied to the modified coefficients and get denoised image.

The second step known as thresholding is a simple non-linear technique ,which operates on one wavelet coefficients as a time .in its most basic form,each coefficient is threshold by comparing threshold ,if the coefficient is smaller than threshold ,set to zero ;otherwise it kept as it is or it is modified[5] .replacing the small noise coefficient by zero and inverse wavelet transform on the resulted coefficient[2].

II. WAVELET BASED IMAGE DENOISING:

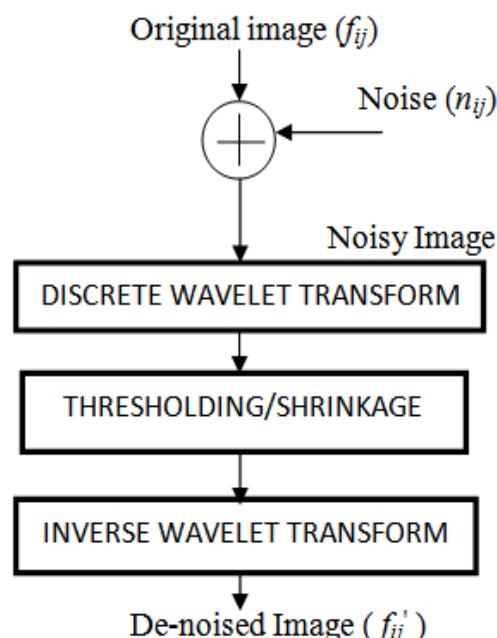


Fig: The basic frame work of the wavelet transform based image de-noising

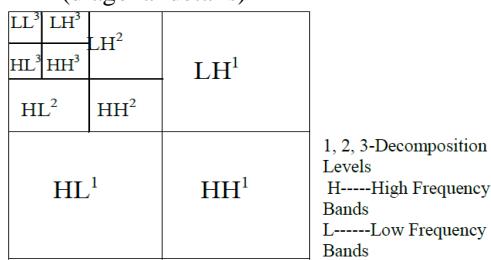
III. DISCRETE WAVELET TRANSFORM

The Discrete Wavelet Transform (DWT) of image signals produces a non-redundant image

representation, which provides better spatial and spectral localization of image formation, compared with other multi scale representations such as Gaussian and Laplacian pyramid. Recently, Discrete Wavelet Transform has attracted more and more interest in image de-noising. The DWT[3] can be interpreted as signal decomposition in a set of independent, spatially oriented frequency channels.

The mathematical manipulation, which implies analysis and synthesis, is called discrete wavelet transform and inverse discrete wavelet transform. Another consideration of the wavelets is the sub-band coding theory or multi resolution analysis In case of a 2D image, an N level decomposition can be performed resulting in $3N+1$ different frequency bands namely,

- LL (low frequency or approximation coefficients),
- LH (vertical details)
- HL (horizontal details)
- HH (diagonal details)



IV. WAVELET THRESHOLDING

Let the signal be $\{f_{ij}\}$ $i=1,..,M$, $j=1,..,N$, where M,N is some integer power of 2. It has been corrupted by additive noise and one observes

$$g_{ij} = f_{ij} + \sigma n_{ij}, \quad i=1,..,M, j=1,..,N$$

where $\{n_{ij}\}$ are independent and identically distributed (*iid*) zero mean, white Gaussian Noise with standard deviation σ i.e. as normal $n_{ij} \sim N(0, \sigma^2)$.

Mean Squared Error (MSE) is minimum, that is given by

$$\text{MSE} = \frac{1}{MN} \sum_{j=1}^M \sum_{i=1}^N [\{f'_{ij}\} - \{f_{ij}\}]^2$$

Here, the threshold plays an important role in the de-noising process. There are two thresholding methods frequently used. The *soft-threshold*[7] function (also called the shrinkage function).

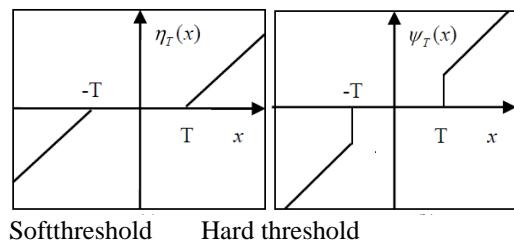
$$\eta_T(x) = \text{sgn}(x) \cdot \max(|x| - T, 0)$$

takes the argument and shrinks it towards zero by the threshold T . The other popular alternative is the *hard thresholding* function.

$$\psi_T(x) = x \cdot \mathbf{1}\{|x| > T\}$$

which keeps the input if it is larger than the threshold; otherwise, it is set to zero. The wavelet thresholding procedure removes noise by thresholding only the wavelet coefficients of the detail sub-bands, while keeping the low resolution

coefficients unaltered.



V. WAVELET THRESHOLDING METHODS

The following are the methods of threshold selection for image de-noising[4] based on wavelet transform

1. Bayes shrink (BS)
2. Normal shrink (N)

Method 1: Bayes shrink (BS):

The Bayes shrink[6] method is for images including Gaussian noise. The observation model is expressed as follows:

$$Y = X + V$$

Here Y is the wavelet transform of the degraded image, X is wavelet transform of the original image, and V denotes the wavelet transform of the noise components following the Gaussian distribution $N(0, \sigma_v^2)$.

Here, since X and V are mutually independent, the variances σ_y^2 , σ_x^2 and σ_v^2 of y , x and v are given by:

$$\sigma_y^2 = \sigma_x^2 + \sigma_v^2$$

$$\sigma_v^2 = \left[\frac{\text{median}(|HH_1|)}{0.6745} \right]^2$$

The variance of the sub-band of degraded image can be estimated as:

$$\sigma_y^2 = \frac{1}{M} \sum_{m=1}^M A_m^2$$

Where A_m are the wavelet coefficients of sub-band underconsideration, M is the total number of wavelet coefficient in thatsub-band. The bayes shrink thresholding technique performs softthresholding, with adaptive data driven, sub-band and leveldependent near optimal threshold given by

$$T_{BS} = \begin{cases} \frac{\sigma_v^2}{\sigma_x} & \text{if } \sigma_v^2 < \sigma_y^2 \\ \max\{|A_m|\} & \text{otherwise} \end{cases}$$

$$\text{Where } \sigma_x = \sqrt{\max(\sigma_y^2 - \sigma_v^2, 0)}$$

In the case, where $\sigma_v^2 > \sigma_y^2$, σ_x is taken to be zero, i.e. $T_{BS} \rightarrow \infty$, or, in practice, $T_{BS} = \max(|A_m|)$, and all coefficients are set to zero.

Method 2: Normal Shrink (N)

The optimum threshold value for the Normal

Shrink (T_N) [6] is given by

$$T_N = \frac{\lambda \sigma_v^2}{\sigma_v}$$

L_k is the length of the sub-band at k_{th} scale. And J is the total number of decomposition.

VI. RESULTS

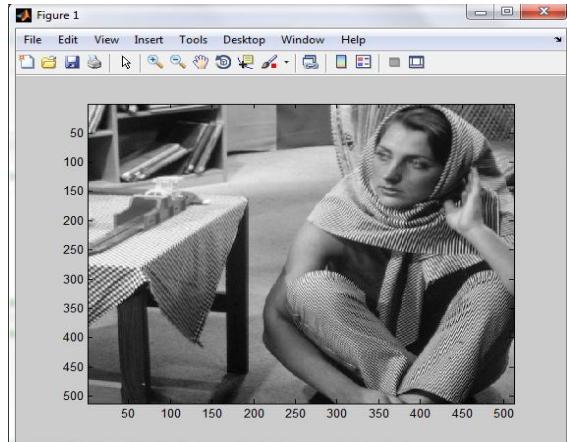


Fig 1: Original image

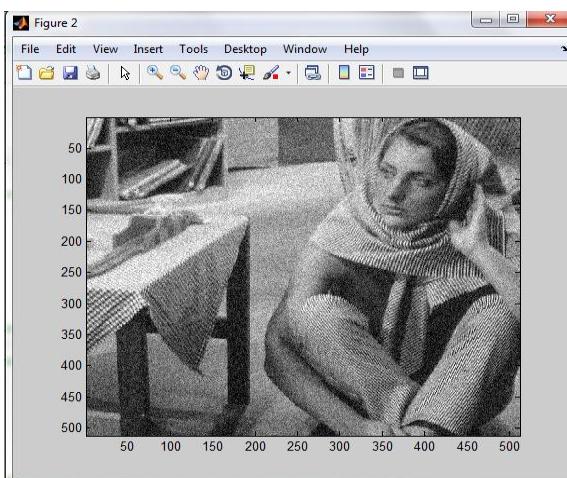


Fig2:Noisyimage

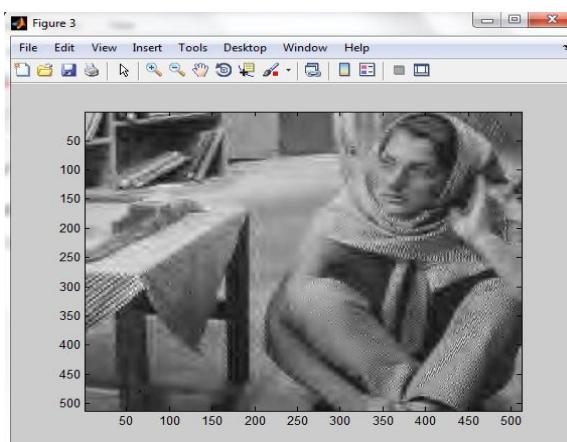


Fig3:Denoised image using Hard thresholding

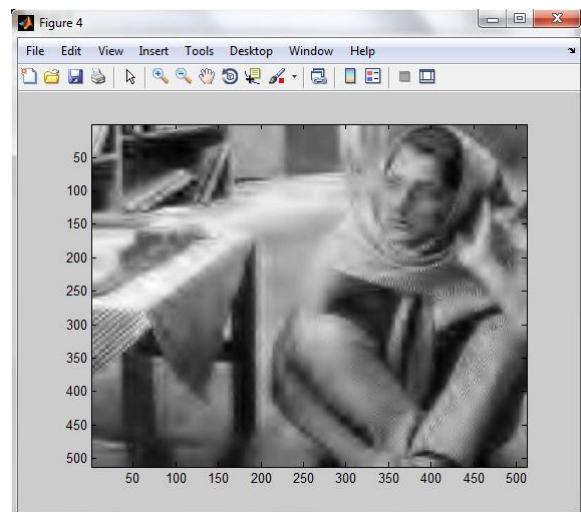


Fig4: Denoised image using Soft thresholding

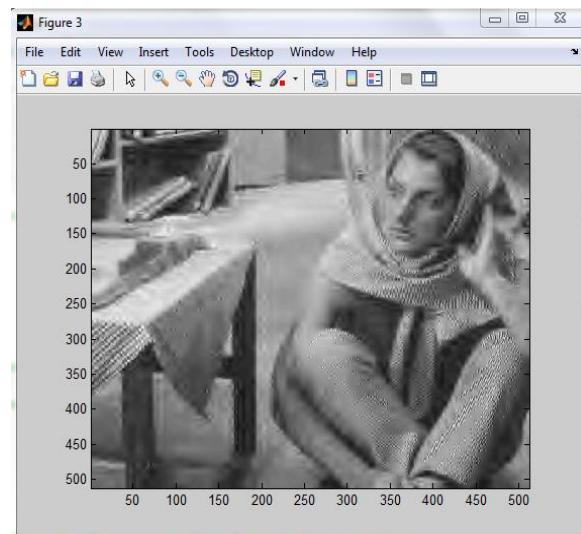


Fig5: Denoised image using Normal Shrink

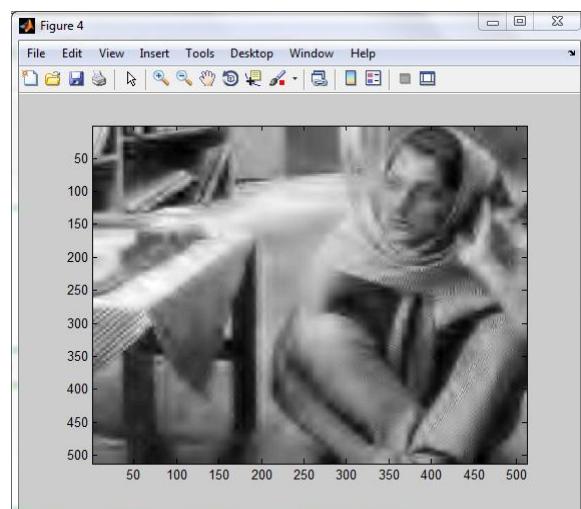


Fig6:Denoised using Bayes Shrink

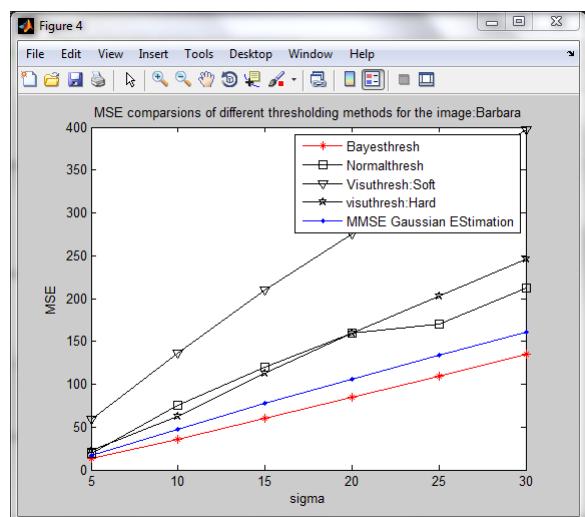


Fig7: MSE for different thresholding methods

VII. CONCLUSION

In this paper, the image de-noising using discrete wavelet transform is analyzed. The experiments were conducted to study the suitability of different wavelet bases and also the different methods of threshold or shrinkage. Results show in low noise, the normal shrink gives better denoising and in high noise, the modified bayes shrink yields the best results for denoising because they have maximum Signal to Noise Ratio (SNR) and minimum Mean Square Error (MSE).

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