



# Image Denoising Based on PSNR and MSE Values Calculation Using Adaptive Wavelet Thresholding by Various Shrinkage Methods under Three Noise Condition

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## ARTICLE INFO

### Article history:

Received: 6 January 2013;

Received in revised form:

17 June 2013;

Accepted: 27 June 2013;

### Keywords

De-noising,  
Spatial domain methods,  
Wavelet shrinkage,  
Optimal threshold selection.

## ABSTRACT

Wavelet transforms enable us to represent signals with a high degree of sparsity. Wavelet thresholding is a signal estimation technique that exploits the capabilities of wavelet transform for signal denoising. The aim of this paper is to study various thresholding techniques such as Sure Shrink, Visu-Shrink and Bayes Shrink and determine the best one for image denoising. This paper presents an overview of various threshold methods for image denoising. Wavelet transform based denoising techniques are of greater interest because of their performance over Fourier and other spatial domain techniques. Selection of optimal threshold is crucial since threshold value governs the performance of denoising algorithms. Hence it is required to tune the threshold parameter for better PSNR values. In this paper, we present various wavelet based shrinkage methods for optimal threshold selection for noise removal.

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## Introduction

An image may be contaminated by noise during acquiring and transmission. The noise present in the images may appear as additive or multiplicative components which have been modelled in a number of ways in the literature [1],[17] such as Gaussian noise, Speckle noise, Salt & Pepper noise, Impulse noise etc... As the occurrence of noisy pixels in the image is random in nature, their distributions are modelled using probabilistic methods [20] [24]. In most of the real time applications such as medical imaging, satellite image data analysis, remote applications etc., the noisy components have to be removed to ensure faithful information retrieval from the images. A common defect in the imaging system is unwanted non linearity in the sensor and display system. Post processing correction of sensor signals and pre-processing correction of display signals can reduce degradations substantially [1]. Hence pre-processing is essential in any information analysis and retrieval system. Denoising is one of the pre-processing techniques which have drawn much attention of the researchers over a few decades. In this paper, present a detailed survey of various noise removal techniques, with a focus on threshold computing methods is presented since choosing the threshold is crucial in the process of denoising. This paper is organized as follows. Section 2 presents denoising procedure and classification of denoising methods. Section 3 discusses about the wavelet based denoising techniques. Various threshold methods and the tradeoffs involved in selecting an optimal threshold are presented in Section 4. Finally, discussions on observations and conclusion are presented in Section 5.

## Methods of Denoising

If  $f(x,y)$  be the uncorrupted image of size  $N \times N$  and  $n(x,y)$  be the noise function, then the noisy image observation  $g(x,y)$  with additive noise. The process of denoising is nothing but the estimation of the information from noisy observation. With this

background, the state of art denoising methods can be categorized as follows.

### Spatial Filtering Techniques

Spatial filtering is the method of choice in situations when only additive noise is present. This category consists of mean filter and the order statistics filter such as Median filter, Maximum and Minimum filter, Midpoint and Alpha trimmed median filter. Arithmetic and Geometric mean filters are well suited for random noise like Gaussian or uniform noise. The Contra-harmonic filter is well suited for impulse noise, but it requires the prior knowledge about the noise (light or dark). As found in the literature [1],[17], median filter can perform well in removing impulse noise while the number of passes of the median filter has to be kept as low as possible, since larger number of passes may result in blurred images. The process of spatial filtering consists of moving the filter mask (Fig: 1) from point to point in an image. At each point  $(x,y)$  the response of filter at that point is calculated. The mask may be of any size of interest (3X3, 5X5, 7X7 etc...). Also, it has to be noted that size of the filter mask affects the performance of the filter [15].

Another class of filters which fall under spatial filters is adaptive filter, whose behaviour changes based on the statistical characteristics of the image inside the filter region defined by  $m \times n$  rectangular window. These filters can offer superior denoising performance with the cost of increased complexity [17] [24].

Adaptive median filter is the prime variant of adaptive filter. Filter mask size is altered according to the parameters calculated in the mask area considered originally. It performs well for the impulse noise with low spatial density and seeks to preserve details while smoothing non-impulse noise too. Researchers have shown interest to evolve adaptive iterative median filter which outperforms even for high density noises [26].

### Frequency domain filtering

Frequency domain filtering can be used for periodic noise reduction and removal. This category of filters include band pass filter, band stop filter, Notch (Reject/Pass) filters. The appropriate filter can be chosen with the prior knowledge of noise distribution. The various Fourier domain filtering techniques such as Inverse filter, Wiener filter and least square filter are found in literature. A simple method of removing multiplicative noise like speckle noise too has been proposed namely homomorphic filtering [1] [17]. Fourier transform has been found to be an important image processing tool for image processing and analysis. The major advantage of Fourier domain analysis is that, it can explore the geometric characteristics of a spatial domain image [2]. It has been used for the removal of additive noises from the images. Unlike Fourier transform, Wavelet transform shows localization in both time and frequency and hence it has proved itself to be an efficient tool for a number of image processing applications including noise removal [19]. Fourier transform based methods are less useful because, they cannot work on non-stationary signals and they can capture only global features. But in the real scenario, as the images are only piecewise smooth and the noise distributions are random in nature, Fourier transform cannot perform well for the stochastic noise, but wavelets can do. Hence wavelet based noise removal has attracted much attention of the researchers for several years [4], [6]. A detailed study on wavelet based Denoising techniques is presented in the next section

### Wavelet Denoising

Wavelet transform is the mathematical tool used for various image processing applications such as noise removal, feature extraction, compression and image analysis. The general method of wavelet based denoising is that, the noisy image may first be transformed to wavelet domain [2] [6].

The transformed image appears as four sub-bands (A, V, H, and D) as shown in Fig 1 based on the level of decomposition 'j'. 2D discrete wavelet transform leads to decomposition of approximate coefficients at level 'j' into four components i.e. the approximation at level 'j+1' and details in three orientations (Horizontally, Vertically and Diagonally) [25]. Since the noisy components are of high frequency, the three higher bands may contain the noisy components [25], and proper threshold may be applied to smooth the noisy wavelet coefficients followed by the inverse 2D-DWT may be applied to reconstruct the denoised image. Selection of optimal threshold is crucial for the performance of denoising algorithm. Threshold is selected based on the image and noise priors such as mean and variance [10] [23]. Selection of optimal threshold along with various types of wavelet threshold methods is presented in the next section.

### Wavelet Based Threshold Methods

#### Visu Shrink

Visu Shrink is thresholding by applying the Universal threshold proposed by Donoho and Johnstone]. This threshold is given by  $\sigma \sqrt{2 \log M}$  where  $\sigma$  is the noise variance and  $M$  is the number of pixels in the image. It is proved in [2] that the maximum of any  $M$  values is as  $N(0, \sigma^2)$  will be smaller than the universal threshold with high probability, with the probability approaching 1 as  $M$  increases. Thus, with high probability, a pure noise signal is estimated as being identically zero. However, for denoising images, Visu Shrink is found to yield an overly smoothed. This is because the universal threshold (UT) is derived under the constraint that with high probability, the estimate should be at least as smooth as the

signal. So the UT tends to be high for large values of  $M$ , killing many signal coefficients along with the noise. Thus, the threshold does not adapt well to discontinuities in the signal.

#### Bayes Shrink

Bayes Shrink has attracted much attention since it sets different thresholds for every subband. Here sub-bands are frequency bands that differ from each other in level and direction. The relationship between the wavelet transform of the degraded image, uncorrupted image and generalized Gaussian noise with distribution

$N(0, \sigma^2)$  ( $Y$ ,  $X$  and  $V$  respectively),

can be modeled as:

$$Y = X + V.$$

Since huge information about the noise is available at the diagonal coefficients of first level wavelet decomposition (HH1) the noise variance ' $\sigma$ ' is calculated using the robust estimator.  $W_m$  are the wavelet coefficients in each scale and  $M$  is the total number of wavelet coefficients. With this background, the threshold using Bayes shrink is calculated.

The Bayes shrink method is effective for images corrupted by Gaussian noise. Bayes shrink is less sensitive to the presence of noise in the areas around the edges [9] [11]. However, the presence of noise in flat regions of the image is perceptually more noticeable by the human visual system. Bayes shrink performs little Denoising in high activity sub-regions to preserve the sharpness of edges but completely denoised the flat sub-parts of the image.

#### Sure shrink:

Sure Shrink is more explicitly adaptive to unknown smoothness and has better large-sample MSE properties. This method is a subband adaptive threshold scheme, based on Stein's unbiased estimator for risk (SURE) (quadratic loss function) [6-8]. One gets an estimate of the risk for a particular threshold value  $t$ . minimizing the risks in ' $t$ ' gives a selection of the threshold value. Sure Shrink is a thresholding by applying subband adaptive threshold, a separate threshold is computed for each detail subband based upon SURE (Stein's unbiased estimator for risk), a method for estimating the loss  $2 \mu^{\hat{}} - \mu$  in an unbiased fashion. In our case let wavelet coefficients in the  $j$ th subband be  $\{X_i : i=1, \dots, d\}$ ,  $\mu^{\hat{}}$  is the soft threshold. applied to the image data, resulting in an estimate of the mean vector. This estimate is sparse and much less noisy than the raw image data [14]. The SURE principle just described has a serious drawback in situations of extreme sparsity of the wavelet coefficients. In such cases the noise contributed to the SURE profile by the many coordinates at which the signal is zero, swamps the information contributed to the SURE profile by the few coordinates where the signal is nonzero. Consequently, Sure Shrink uses a Hybrid scheme [16].

The risk function values are equal to the risk in coefficient values. A mere least square estimate does not denoise the original image [21].

#### Trade off between Threshold, PSNR and Complexity

Selection of optimal threshold determines the efficiency of the Denoising algorithm [10]. The common measure of quality in images in peak signal to noise ratio are defined as :

$$\text{PSNR} = 10 \log_{10} (255)^2 / \text{MSE} \text{ (db)}$$

Here MSE is the mean square error whose magnitude quantifies the presence of noise and the performance of Denoising algorithm. As discussed in section - IV wavelet based shrinkage algorithms give better estimate of the noise priors and hence the threshold with the expense of high computational

complexity. It is very crucial to select the threshold value with less computational complexity and with significant improvements in PSNR.

**Evaluation Criteria**

The above said methods are evaluated using the quality measure Peak Signal to Noise ratio which is calculated using the formula:

$$PSNR = 10 \log_{10} (255^2 / MSE) \text{ (db)}$$

where MSE is the mean squared error between the original image and the reconstructed de-noised image. It is used to evaluate the different de-noising scheme like Neighshrink and Modified Neigh shrink.

**Figure: My\_Image**

| NOISE TYPE: GAUSSIAN        |            |           |
|-----------------------------|------------|-----------|
| DENOISING METHOD            | PSNR VALUE | MSE VALUE |
| SURE SHRINK                 | 27.073     | 94.9615   |
| BIVARIATE SHRINK            | 75.7106    | 0.0017459 |
| NOISE TYPE: SALT AND PEPPER |            |           |
| DENOISING METHOD            | PSNR VALUE | MSE VALUE |
| SURE SHRINK                 | 18.4253    | 695.528   |
| BIVARIATE SHRINK            | 75.6832    | 0.0017569 |
| NOISE TYPE: SPECKLE         |            |           |
| DENOISING METHOD            | PSNR VALUE | MSE VALUE |
| SURE SHRINK                 | 19.55      | 536.8392  |
| BIVARIATE SHRINK            | 75.7009    | 0.0017498 |

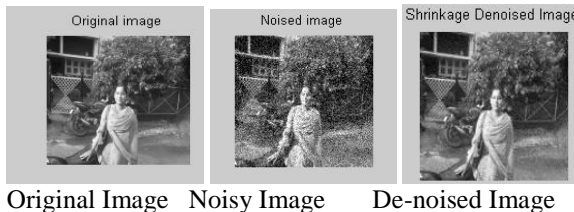
**Experiments**

Quantitatively assessing the performance in practical application is complicated issue because the ideal image is normally unknown at the receiver end. So this paper uses the following method for experiments. One original image is applied with Gaussian noise with different variance. The methods proposed for implementing image de-noising using wavelet transform take the following form in general. The image is transformed into the orthogonal domain by taking the wavelet transform. The detail wavelet coefficients are modified according to the shrinkage algorithm. Finally, inverse wavelet is taken to reconstruct the de-noised image. In this paper, different wavelet bases are used in all methods. For taking the wavelet transform of the image, readily available MATLAB routines are taken. In each sub-band, individual pixels of the image are shrunk based on the threshold selection. A de-noised wavelet transform is created by shrinking pixels. The inverse wavelet transform is the de-noised image.

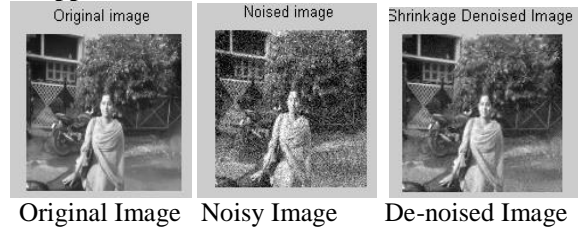
**Results and Discussions**

For the above mentioned three methods, image de-noising is performed using wavelets from the second level to fourth level decomposition and the results are shown in figure (3) and table if formulated for second level decomposition for different noise variance as follows. It was found that three level decomposition and fourth level decomposition gave optimum results. However, third and fourth level decomposition resulted in more blurring. The experiments were done using a window size of 3X3, 5X5 and 7X7. The neighborhood window of 3X3 and 5X5 are good choices.

**Gaussian Noise with Sure Shrink Method**



**Salt & Pepper Noise with Sure Shrink Method**



**Speckle Noise with Sure Shrink Method**



**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 different window sizes. Among all discrete wavelet bases, coif let performs well in image de-noising. Experimental results show that Bivariate Shrink Method gives better result than Sure Shrink, Bayes Shrink and Neigh Shrink methods..

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