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Wavelet Transform Based Image Denoise Using Threshold Approaches

Akhilesh Bijalwan, Aditya Goyal, Nidhi Sethi

Abstract:- This paper deals with the threshold estimation method for image denoising in the wavelet transform domain. The proposed technique is based upon the discrete wavelet transform analysis where the algorithm of wavelet threshold is used to calculate the value of threshold. The proposed method is more efficient and adaptive because the parameter required for calculating the threshold based on sub band data. The threshold value is computed by $x\sigma^2_{w0}/\sigma$ where x is the scale parameter which depends upon the sub band size and number of decomposition and σ_{w0} is the noise variance estimation. σ are the wavelet coefficient variance estimation in various sub bands. Experimental results on several test images are compared with popular denoise technique from three aspects (PSNR, RMSE and CoC).

Keywords: Wavelet Thresholding, Image Denoising, Discrete Wavelet Transform.

INTRODUCTION.

An image is a two dimension function f(x,y), where x and y are plane coordinates, and the amplitude off at any pair of coordinates(x, y) is called the gray level or intensity of the Image at that point. There are two types of images i.e. gray scale image and RGB image. An image is often corrupted by noise in its acquition and transmission. Basically image noise is unwanted fluctuations. There are different types of image noise present in the image like Gaussian noise, salt and pepper noise, speckle noise, shot noise, white noise [1]. Image denoise is used to remove the additive noise while retaining as much as possible the important signal features. There is various noise reduction techniques which are used for removing the noise. Most of the standard algorithm used to denoise the noisy image and perform the individual filtering process. Denoise generally reduce the noise level but the image is either blurred or over smoothed due to losses like edges or lines. In the recent years there has been a fair amount of research on wavelet thresholding and threshold section for image denoising [3], because wavelet provides an appropriate basis for seprating noisy signal from the image signal. Wavelet transform is good at energy compaction, the small coefficient are more likely due to noise and large coefficient due to important signal feature [8]. These small coefficients can be thresholded without affecting the significant features of the image.

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***** Correspondence Author (s)
Akhilesh Bijalwan*, Computer Science and Engineering, Uttarakhand Technical University/ Dehradun Institute of Technology / Dehradun, India.
Aditya Goyal, Computer Science and Engineering, Uttarakhand Technical University/ Dehradun Institute of Technology / Dehradun, India.
Mrs. Nidhi Sethi, Computer Science and Engineering, Uttarakhand Technical University/ Dehradun Institute of Technology / Dehradun, India.

The wavelet transform (WT) is a powerful tool of signal processing for its multiresolutional possibilities. Unlike the Fourier transform, the wavelet transform is suitable for application to non-stationary signals with transitory phenomena, where frequency response varies in time [2].
The wavelet coefficient represents a measure of similarity in the frequency content between a signal and a chosen wavelet function [2]. These coefficient are computed as a convolution of the signal and the scaled wavelet function, which can be interpreted as a dilated band pass filter because of its band pass like spectrum [5]. By wavelet analysis from a signal at high scales, extracted global information called approximations, and at two scales, extracted fine information called details.
The discrete wavelet transform (DWT) requires less space utilizing the space saving coding based on the fact that wavelet families are orthogonal or biorthogonal bases, and thus do not produce redundant analysis. The discrete wavelet transform corresponds to its continuous version sampled usually on a dyadic grid, which means that the scales and translations are power of two [5].
Thresholding is a simple non-linear technique, which operates on one wavelet coefficient at a time. In its most basic form, each coefficient is thresholded by comparing against threshold. If the coefficient is smaller than threshold then it set to be zero; otherwise it is kept or modified. We replace the small noisy coefficient by zero and inverse wavelet transform on the result may lead to reconstruction with the essential signal characteristics and with less noise. Since the work of Donoho and Johnstone [4], [9], [10], there has been much research on finding thresholds, however few are specifically designed for images.

I. IMAGE DENOISING

In image processing, wavelets are used for instance for edges detection, watermarking, texture detection, compression, denoising, and coding of interesting features for subsequent classification.

A. Wavelet Denoising Principle

Image denosing based on the wavelet transform is mainly completed by wavelet thresholding in wavelet domain [12]. The processing of image denosing in wavelet domain can be considered as an optimal estimation to the input image with noise data using the threshold.
The wavelet thresholding for image denoising involves the following steps [6]:

1. The wavelet coefficients can be obtained by using the wavelet decomposition on the input image with noise.
   w = W (X + N)

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Where w are the wavelet coefficients; W is the wavelet transform; X is the ideal input data; N is the noise data.

2. The optimal estimations are acquired by modifying the wavelet coefficients based on a rule of wavelet threshold.

$$W` = \delta_\lambda(w)$$

where W` is the optimal estimation of the wavelet coefficients; $\delta_\lambda(w)$ is a wavelet threshold function; λ is the threshold.

3. The denoised image can be got by wavelet inverse transform on the modified wavelet coefficients.

$$X` = W^{-1}w`$$

Based on the above analysis, obviously, there are two problems existing in this research of the wavelet thresholding denoising on image:

a: The choice of the wavelet thresholding function
b: The choice of the wavelet threshold
Our research revolves around the above two main questions. To compute the two-dimensional DWT of an image, we decompose the approximations at level j to obtain four matrixes of coefficients at level j +1.

III. SOFT AND HARD THRESHOLDING

Signal denoising using the DWT consists of the three successive procedures, namely, signal decomposition, thresholding of the DWT coefficients, and signal reconstruction. Firstly, we carry out the wavelet analysis of a noisy signal up to a chosen level N. Secondly, we perform thresholding of the detail coefficients from level 1 to N. Lastly, we synthesize the signal using the altered detail coefficients from level 1 to N and approximation coefficients of level N [2]. However, it is generally impossible to remove all the noise without corrupting the signal.

As for thresholding, we can settle either a level-dependent threshold vector of length N or a global threshold of a constant value for all levels. According to D. Donoho's method, the threshold estimate δ for denoising with an orthonormal basis is given by

$$\delta = \sigma\sqrt{2\log N}$$

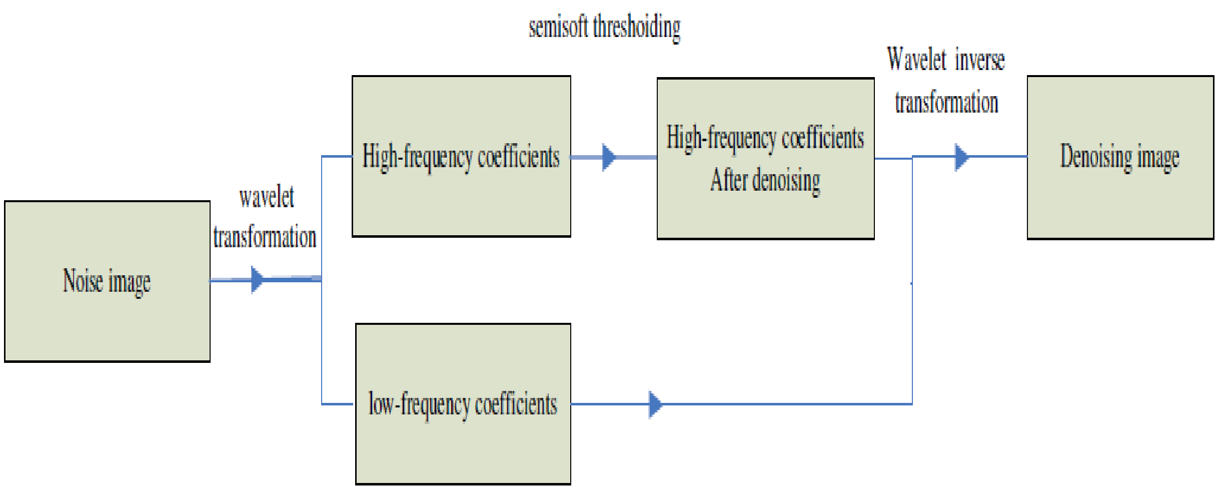
where the noise is Gaussian with standard deviation σ of the DWT coefficients and L is the number of samples or pixels of the processed signal or image. This estimation concept is used by Matlab.
From another point of view, thresholding can be either soft or hard. Hard thresholding zeroes out all the signal values smaller than δ. Soft thresholding does the same thing, and apart form that, subtracts δ from the values larger than δ. In contrast to hard thresholding, soft thresholding causes no discontinuities in the resulting signal. In Matlab, by default, soft thresholding is used for denoising and hard thresholding for compression [2].

IV. WAVELET THRESHOLD

The traditional wavelet threshold is Donoho wavelet threshold which is shown as formula

$$\lambda = \sqrt{2\sigma^2 \log N}$$

Where s is the estimate variance, N is the number of the wavelet coefficients. However, this wavelet threshold has a fatal shortcoming. Because this threshold value is proportional with the signal size logarithm's square root, therefore, when N is big, the threshold value will tend to reset the while wavelet coefficients, as a result, the wavelet filter will degenerate as the degradation of low-pass filter. And there is a serious "overkill" wavelet coefficients tendency.



Due to the above deficiency of Donoho's threshold, the more effective Bayes wavelet threshold is used to optimize the performance of the wavelet threshold denoising algorithm in this study with assumption of the wavelet coefficients obeying a distribution. The threshold According to the Bayes Rule is shown formula:-

$$\lambda_s = \frac{\sigma_D{}^2}{\sigma}$$

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where λ_s are various thresholds in various sub bands. σ_D is the noise variance estimation. s are the wavelet coefficients variance estimations in various sub-bands. Because the main information of the noise images concentrates on the wavelet high-frequency (low-scale) sub band, the median of the magnitudes of the all diagonal details coefficients in the wavelet low-scale sub-band is used to calculate the value of the noise variance estimation, which is showed as formula

$$\sigma_D = \frac{\text{median}(|w|)}{0.6745}$$

Where w are the wavelet high-frequency diagonal coefficients.

The wavelet coefficients variance estimations in various sub-bands can be calculated as formula:-

$$\sum \sigma = \sqrt{\max\left(\sigma_n^2 - \sigma_D^2,\ 0\right)}$$

$$\sigma_n^2 = \frac{1}{m \times n} \sum_{i,j=1}^{m,n} w_n^2$$

Where σ_n are the variance estimations of the coefficients in various sub-bands. mxn is the number of the corresponding coefficient w_n in different sub-bands.

The wavelet bayes threshold considers the distribution characteristics of the wavelet coefficients, hence the properties of this threshold is more excellent than the traditional wavelet threshold.

Based on the above section the improved method based on the wavelet thresholding function has many advantages and can obtain the great result.

V. IMAGE DENOISE ALGORITHM

This section describes the image denoising algorithm, which achieves near optimal semi soft threshholding in the wavelet domain for recovering original signal from the noisy one.

The algorithm is very simple to implement and computationally more efficient. It has following steps:

1. Perform multiscale decomposition of the image corrupted by guassian noise using wavelet transform.
2. Estimate the noise variance σ^2
3. For each level, compute the scale parameter
4. Compute the standard deviation
5. Compute threshold λ
6. Apply semi soft thresholding to the noisy coefficients.
7. denoise high frequency coefficient
8. merge low frequency coefficient with denoise high frequency coefficient
9. Invert the multiscale decomposition to reconstruct the denoised image .

VI. PARAMETRIC DESCRIPTION

A. Algorithm for Peak Signal to Noise ratio (PSNR)

Step1: Difference of noisy image and noiseless image is calculated using imsubract Command.

Step2: Size of the matrix obtains in step 1 is calculated.

Step3: Each of the pixels in the matrix obtained in step is squared.

Step4: Sum of all the pixels in the matrix obtained in Step3 is calculated.

Step5: (MSE) is obtained by taking the ratio of value obtained in step 4 to the value obtained in the Step2

Step6: (RMSE) is calculated by taking square root to the value obtained in Step5.

Step7: Dividing 255 with RMSE, taking 1log base 10 and multiplying with 20 gives the value of PSNR.

B. Algorithm for Correlation of Coefficient (Coc)

Step1: Mean of the noiseless image and noisy image are calculated.

Step2: Mean of the noiseless image is subtracted from each of the pixel in the noiseless image resulting in a matrix.

Step3: Similarly the mean of noisy image is subtracted from each of the pixels in the noise image resulting in a matrix.

Step4: Values obtained in Step2 and Step3 are multiplied.

Step5: Sum of all the elements in the matrix obtained in Step4 is calculated.

Step6: Square of all the elements of the matrix obtained in Step2 is calculated and sum of this squared matrix is determined.

Step7: Similarly square of all the elements of the matrix obtained in Step3 is calculated and sum of the elements of this squared matrix is also determined.

Step8: Values obtained in Step6 and Step7 are multiplied and its square root is taken.

Step9: Ratio of the value obtained in Step5 to the value obtained in Step8 is calculated.

C. Algorithm for Root Mean Square Error (RMSE)

Step1: Difference of noisy image and noiseless image is calculated using imsubract command.

Step2: Size of the matrix obtains in Step1 is calculated.

Step3: Each of the pixels in the matrix obtained in step is squared.

Step4: Sum of all the pixels in the matrix obtained in step 3 is calculated.

Step5: (MSE) is obtained by taking the ratio of value obtained in Step4 to the value obtained in the step 2.

Step6: RMSE) is calculated by taking square root to the value obtained in Step5.

VII EXPERIMENTAL RESULTS AND DISCUSSIONS

In this section we present some results to demonstrate the performance of our algorithm. The experiments are conducted on Lena image of size 512x512 which is corrupted by Gaussian white noise of standard deviation 0.05. experiment 1 using wavelet hard threshold noise filter, wavelet soft threshold noise filter, wavelet bayesShrink threshold noise filter, and wavelet semisoft threshold noise filter eliminate image noise, and the results which are shown in fig.1, show that the proposed filter is significantly effective than the other in quality.

In experiment 2 we use lena image which is corrupted by Gaussian noise. And the result in table 1 shown that psnr rmse and coc value. This table show that the our method is more effective.

Table 1: Gaussian noise with mean = 0.005 and variance = 0.005

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	PSNR	RMSE	CORR.
Noisy image	23.0120	13.8750	9.540
Gaussian filter	29.4530	10.0765	9.62
Wavelet Transform	38.1730	4.0154	9.534

The experiment shows that the traditional image denoise methods are difficult to preserves the details of the image effectively while removing the noise. So, compared with the above several methods, the proposed methods in this paper can preserves most satisfying image details.

VIII. CONCLUSION

In this paper, a simple and sub band semi soft threshold method is proposed to address the issue of image recovery from its noisy counterpart.it is based on the discrete wavelet transform and Gaussian distribution modeling of subband coefficients. The image denoise algorithm uses semi thresholding to provide smoothness and better image details preservation. The wavelet semi soft thresholding denoise algorithm produce overall better psnr msnr and coc result compared with other traditional denoise approaches.

Wavelet BayesShrink

Result of wavelet hard threshold denoising method

Lena (Standard deviation 0.05)

Result of wavelet soft threshold denoising method

The proposed algorithm

Fig. 1(comparisons with various method)

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