Comparative Study of Different Wavelet based Image De-noising Methods

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ABSTRACT

The de-noising is a challenging task in the field of signal and image processing. Any natural image corrupted by gussian noise can be de-noised using wavelet method. Wavelet-based image de-noising is an important technique in the area of image noise reduction. Wavelets have their natural ability to represent images in a very sparse form which is the foundation of wavelet-based de-noising through thresholding. The wavelet de-noising method gives various coefficients arising from discrete wavelet transform then thresholds the coefficients using proper thresholding techniques. This paper explores properties of several thresholding techniques in wavelets denoising, such as VisuShrink, SureShrink, BayesShrink.

Keywords: Discrete wavelet transform, image denoising, thresholding techniques.

1. INTRODUCTION

Image processing is any form of signal processing for which the input is an image, such as photographs or frames of video and the output of image processing can be either an image or a set of characteristics or parameters related to the image. Most of the image processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it. An image is corrupted by noise during transmission. The de-noising process is to remove the noise without effecting quality of the processed image. There are many non-linear method of de-noising has been employed these methods are mainly based on thresholding. coefficients which has been affected by gaussian noise by Discrete Wavelet Transform (DWT). The DWT algorithm consists three steps.
Decompose the noisy image and get wavelet coefficient.

Wavelet coefficients are denoised with wavelet threshold.

Inverse transform is applied to the coefficient and get denoised image.

The nature of the wavelet transforms both in time and space result in denoising with edge preservation. DWT decompose the image into series coefficients. Small coefficient are dominated by noise, large coefficient carry more information than noise. The second step, known as thresholding, is a simple non linear technique, which operates on one wavelet coefficient at a time. It means replacing noisy coefficient below a certain threshold value by zero may gives noiseless coefficient. The inverse wavelet transform may lead to reconstruction with essential information with less noise.

In this paper, properties of several thresholding techniques are explored; those techniques are vishusrink, sureshrink, bayesShrinkage. The performance of these techniques has studied in different level of decomposition at different noise level. The paper organized as fallows. Section 2 introduces the discrete wavelet transform. Section 3 tells about decomposition method. The several thresholding techniques explain in section 4. Experimental and results are given in section 5. Finally conclusion is discussed in section 6.

2. THE DISCRETE WAVELET TRANSFORM

The Wavelet Series is just a sampled version of CWT and its computation may consume significant amount of time and resources, depending on the resolution required. The Discrete Wavelet Transform (DWT), which is based on sub-band coding, is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required.

The foundations of DWT techniques to decompose discrete time signals were devised. Similar work was done in speech signal coding which was named as sub-band coding. In 1983, a technique similar to sub-band coding was developed which was named pyramidal coding. Later many improvements were made to these coding schemes which resulted in efficient multi-resolution analysis schemes. By passes an image successive through series of low pass and high pass filters and down sampling by two, the analysis filters which produce the transform coefficients. In case of a 2D image, an N level decomposition can be perfumed resulting in 3N+1 different frequency band namely, LL(low frequency or approximation coefficients), LH(vertical details), HL(horizontal details) and HH(diagonal details). The next level transform applied to the LL only.

3. DWT DECOMPOSITION

With DWT we can decompose an image more than once. Decomposition can be continued until the signal has been entirely decomposed or can be stopped before by the application at hand. Mostly two ways of decomposition are used they are:

- Pyramidal decomposition
- Packet decomposition
In this paper explains about only pyramidal decomposition. Pyramidal decomposition is the simplest and common form of decomposition here applying decomposition only to the LL sub band as shows in a fig 1.

![Figure 1: Three decomposition steps of an image using Pyramidal Decomposition](image1)

![Figure 2](image2)

![Figure 3](image3)

Figure 1: Three decomposition steps of an image using Pyramidal Decomposition

Figure 2 a) single level decomposition b) Two level decomposition c) Three level decomposition.

Figure 3: Sub-bands of the 2-D orthogonal wavelet transform
At each level the detail sub band are the final results and only the approximation sub band is further decomposed.

The figure 2, shows the different level of decomposition. The pyramidal structures obtain from this decomposition. At the lowest level there is one approximation sub band there are nine detail sub bands obtained. After decomposition, a total of $D(N)= 3N+1$ sub band obtained as shows in the figure 2.3.

**RECONSTRUCTING APPROXIMATION AND DETAILS**

This is process of obtaining original signal without loss of information. The mathematical manipulation to achieve this is called the inverse discrete wavelet transform (IDWT). Both the decomposition and composition process is as shows in the figure (4).

![Figure 3.4: a) Decomposition b) Reconstruction](image)

**4. THRESHOLD SELECTION**

Thresholding plays an important role in the denoising process there are two main thresholding techniques are there hard and soft thresholding.

Hard thresholding keeps the input if it is larger than the threshold; otherwise, it is set to zero. This procedure removes the noise by thresholding only the wavelet coefficient of the detail sub band.

Signal is $X$ if $|X|>T$, 0 if $|X|<0$  \( (1) \)

Soft threshold function (also called shrinkage function) it takes the argument shrink towards zero by threshold T

$$\text{Sign}(X)(|X|-T) \text{ if } |X|>T, \ 0 \text{ if } |X|<0 \quad (2)$$

There are many threshold method exist, but In this paper focus on some methods like visuShrink, SURE, byersShrink method.

1. **VisuShrink**

VisuShrink 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 pixel in the image. For denoising image, VisuShrink is found to yield an overly smoothed estimate.

2. SURE Shrink

SUREShrink is a thresholding by applying subband adaptive threshold. It is based on Stein’s Unbiased Estimator for Risk (SURE), a method for estimating the loss in an unbiased fashion. Let wavelet coefficients in the \( j \)th subband.

\[ \{ \Xi_i : i = 1, \ldots, d \} \]

For the soft threshold estimator

\[ \hat{X}_i = \eta_i(X_i) \]

\[ SURE(t; X) = d - 2 \sum_{i=1}^{d} \min(\|X_i\|, t)^2 \]

Select threshold \( t^S \) by

\[ t^S = \arg \min SURE(t; X) \]

3. BayerShrink

The bayersShrink rule uses a bayesian mathematical framework for images to produce subband dependent threshold which nearly optimal for soft thresholding. The variation in terms of wavelet transform is given by \( \Delta_{x}^2 = \) original signal, \( \Delta_{y}^2 = \) degrade signal, \( \Delta_{z}^2 = \) original signal. Here \( \Delta_{x}^2 \) can be estimated from the first decomposition level diagonal sub-bands HH1 by the robust and accurate median estimator.

\[ \Delta_{x}^2 = \left[ \frac{\text{median}(|HH1|)}{0.6745} \right]^2 \]  
(5)

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

\[ \Delta^2_y = \frac{1}{M} \sum_{M=1}^{M} Am^2 \]

where \( Am \) are the wavelet coefficients of sub-band under consideration, \( M \) is the total number of wavelet coefficient in that sub-band.

Where

\[ \Delta^2_x = \sqrt{\max(\Delta^2_y - \Delta^2_x, 0)} \]  
(7)

This method has been proposed for use with soft thresholding.

5. EXPERIEMENTS AND RESULT

The experiment conducted on gray scale test image Barbara of size 512x512. A Gaussian noise of different variation \( \sigma = 10, 20, 30, 40 \) added to the original image. By applying wavelet transformation obtain the wavelet coefficients those coefficients are modified according to the thresholding or shrinkage algorithms finally; denoised image is obtained by inverse wavelet transformation. In this paper explore the general study of different thresholding technique applied to the each wavelet decomposition and studied its performance.

For taking the wavelet and inverse wavelet transform of the image, available MATLAB commands are used. Its performance are judged by taking Peak Signal to Noise Ratio, which is calculated using the formula

\[ \text{PSNR}(\text{db}) = 10 \log_{10} \left( \frac{255^2}{\text{MSE}} \right) \]  
(8)

Where MSE is the mean squared error between the original image and the reconstructed denoised image calculated by the equation
Experimental results are tabulated on the table shown below. Result are compared by PSNR value obtained.

Table 1: PSNR comparative results of different denoising algorithms at different level of decomposition.

<table>
<thead>
<tr>
<th>σ</th>
<th>Hard</th>
<th>VisuShrink</th>
<th>SURE Shrink</th>
<th>BayerShrink</th>
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6. CONCLUSION

In this paper, several thresholding method in image denoising evaluated. Image corrupted with gaussian noise. Here decomposed images into three level of decomposition at each level applied respective thresholding technique. Based on experiment BayerShrink are the best denoising method. It produces less MSE and higher PSNR value. Further decomposition causing bluring the image after reconstruction.

7. REFERENCES