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Comparative Analysis of Thresholding Techniques using DWT for Denoising Image

Ana Rahmat, Sugandha Agarwal and O.P. Singh
Amity School of Engineering and Technology, Amity University, Lucknow, India

Key words: Wavelet thresholding, DWT (Discrete Wavelet Transform), denoising, wavelet coefficient, Root Mean Square Error (RMSE) and Peak Signal-to-Noise Ratio (PSNR)

Corresponding Author:
Ana Rahmat
Amity School of Engineering and Technology, Amity University, Lucknow, India

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Abstract: The process of reconstructing the original image which is corrupted by noise is called de-noising. Discrete wavelet transform is superior over other transforms in terms of image denoising as its functions are localized both in frequency and time domain. The denoising of image has three major steps decomposition, thresholding and reconstruction. In this study, the qualitative and quantitative assessment of the denoised image is done on the basis of different noise variance and further analytic result shows that soft threshold is superior over hard threshold in terms of matrices such as Root Mean Square Error (RMSE) and Peak Signal-to-Noise Ratio (PSNR).

INTRODUCTION

In the present scenario the digital image plays a vital role in day to day applications like Digital cameras, satellite TV, Medical field and magnetic resonance imaging, etc. The digital images received at the receiver output are usually degraded by noise due to atmospheric hindrance, sensor location, light levels at receivers, etc.[1]. In order to enhance the quality of degraded image, the concept of image denoising was introduced. In the past two decades the wavelet transforms has gained popularity in image de-noising and has widespread application in image and signal processing. Wavelet transform is widely used because of its simple and effective algorithm, fast calculation speed, accuracy, edge detection, etc.[2]. Its increased popularity is because it can process data in terms of scaling and resolution and have good multiresolution, multiscaling analysis[3]. The concept of wavelet based de-noising techniques was first proposed by Donoho and Johnstone[4] and Donoho[5] by reconstructing the image from the noisy data using wavelet transform. By Gunawan[6] presented a modified Donoho's thresholding techniques for de-nosing image and results a higher PSNR value as compared with previous one. In 2001 researchers approached efficient de-noising techniques and concluded that PSNR gain is strictly dependent on noise variance, windowsize. Later on in 2016 researchers has proposed a method of total variation to suppress the very heavy noise and thus, improve the PSNR[7]. By using various de-noising techniques it is concluded that wavelet transform techniques is improved and advanced version over traditional one and combination of wavelet filters and spatial domain filters gives a better result[8]. In this study, we have compared the thresholding techniques, i.e., hard threshold and soft threshold on the basis of PSNR and RMSE values. The original image is followed by Gaussian and salt and pepper noises with varying amount of variances and then DWT is applied both with soft threshold and hard threshold and experimental result shows that soft threshold has better image denoising effect than hard threshold.

MATERIALS AND METHODS

Wavelet transform: Wavelets are defined as basis function which has the ability to decompose an image data into its subsequent wavelet coefficients. These wavelet coefficients can be represented in the form low frequencies and high frequencies. The basis function is represented by the Wavelet Transform (WT) and classified as continuous wavelet transform and Discrete Wavelet Transform (DWT)[1]. The wavelet transform is linear in nature in order to get noisy image, we add Gaussian noise and salt pepper noise to original image[9]:

$$g(i, j) = f(i, j)+n(i, j) \tag{1}$$

Where:

f(i, j) = The original image signal of size M×N
n(i, j) = Added noise signal
g(i, j) = The resultant signal

The denoising of image by wavelet transform is divided in to three steps:

- Applying the discrete wavelet transform for decomposition
- Threshold selection
- Reconstruction of the original signal by inverse wavelet transform

The first step decomposition of the signal is explained in Fig. 1 where the input image is divided into approximated, horizontal, vertical and diagonal wavelet coefficients. Figure 1 shows two level decomposition of DWT where HH2, HL2, LH2, LL2 are coefficient of second level and HH1, HL1, LH1 describes the details of first level decomposition and to obtain the three level decomposition the LL2 (approximated coefficient) is decomposed alone.

Overview of discrete wavelet thresholding: In the process of discrete wavelet transform when the noisy image is decomposed into subsequent coefficient the next thing is thresholding. The threshold value T plays a vital role in wavelet threshold denoising method and has to be chosen appropriately. Threshold selection is very important as small threshold will pass noisy data and results noise in the image and large threshold introduces artifacts and blur which degrades the quality of image[10]. The threshold selection is based on two techniques, adaptive thresholding and non-adaptive thresholding[11]. BayesShrink and SureShrink comes under adaptive thresholding. VisuShrink comes under non adaptive threshold.

Non-adaptive threshold: VisuShrink is anon-adaptive universal threshold which is proposed by Donoho and Johnstone[4] and is represented as[1]:

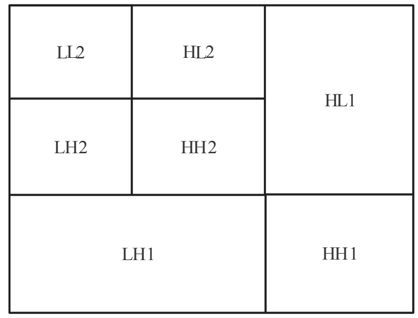

Fig. 1: Two level decomposition of DWT

$$T = \sigma\sqrt{2\log N} \tag{2}$$

Where:

σ = The noise variance or noise levels
N = The number of pixels values

The VisuShrink totally depends on data points for large value of N, T tends to be high which leads to kill more numbers of signal coefficient along with noise. Universal threshold method used to remove noise efficiently and effectively however it fails to remove speckle noise. It only deals with additive noise this is one of the drawback of it.

Adaptive threshold

SureShrink: SureShrink is a level dependent thresholding scheme. For each detailed subband a separate threshold is computed based upon SURE (Stein's Unbiased Estimator for Risk), for minimizing MSE in an unbiased fashion. Sure Shrink is a subband adaptive it minimizes noise by thresholding the empirical wavelet coefficients. The SURE threshold T is given by:

$$T = \text{argminSURE}(t{:}x) \tag{3}$$

The SURE(t:x) is the estimation of risk and it is minimized by the SURE threshold T.

BayesShrink: BayesShrink is an adaptive threshold which is Generated by Gaussian Distribution (GGD) for wavelet coefficient and hence, tries to find the threshold value T which minimizes Bayesian risk[2] it is useful for the signal degraded by Gaussian noise. In terms of calculating MSE Bayes Shrink performs better than SureShrink that's why it is more widely used in image denoising. The threshold value for BayesShrink is given by:

$$T_{bayes} = \begin{cases} \dfrac{\sigma y^2}{\sigma_s}, & \text{if } \sigma^2 g<\sigma^2 y \\ \max A_m, & \text{otherwise} \end{cases} \tag{4}$$

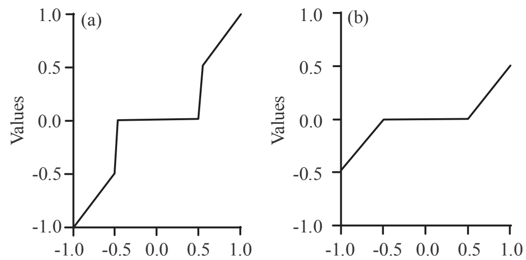

Fig. 2(a, b): Threshold types (a) Hard threshold and (b) Soft threshold

Here, σ^2_y, σ^2_g, σ^2_s is the noise variances of the noisy signal, noise followed by Gaussian distribution and noise variance of original signal, respectively. A_m is the wavelet coefficient of level M:

$$\sigma_y^2 = \sigma_s^2 + \sigma_g^2 \tag{5}$$

The noise variance σ_g^2 can be stated as:

$$\sigma_g^2 = ([\text{median}(|a(n)|)] / 0.06745^2 \tag{6}$$

and the variance of noisy signal can be estimated as:

$$\sigma_y^2 = \frac{1}{N} \sum_{m=1}^{M} A_m^2 \tag{7}$$

Here, N is the total number of wavelet coefficient.

Thresholding techniques: There are various types of thresholding techniques basics are hard thresholding and soft thresholding[10]. The soft thresholding techniques is used more over hard thresholding as it possess abrupt changes and are not discontinuous at threshold points and yields to give more visually pleasant image[6, 8] (Fig. 2). In a hard threshold if the input amplitude is smaller than the assigned threshold value T then it will set to zero otherwise it is kept unchanged whereas in soft threshold its shrinks the nonzero coefficients towards zero. Mathematically it can be represented[12] as:

$$\text{Hard threshold:} \begin{cases} y = x \text{ if} |x| > T \\ 0 \text{ if} |x| < T \end{cases} \tag{8}$$

$$\text{Soft threshold} = \text{sign}(x)\ (|x| - T) \tag{9}$$

Where:

x = The input signal
y = The output signal
T = Threshold levels

RESULTS AND DISCUSSION

We have taken a lifting body image of size 512×512 and performs our experiment for Gaussian and salt and pepper noise at three different noise variance, i.e., 0.1, 0.2, 0.5[13]. In order to get better result it's not a need to select suitable wavelet function but also suitable decomposition level. Here, we have used Haar wavelet transform and second decomposition level. For the threshold selection, we have used universal threshold method. The quality of denoised image is calculated by Peak Signal to Noise Ratio (PSNR) and Root Mean Square Error (RMSE) and is measured as[12]:

$$\text{PSNR} = 10\log_{10} \frac{255^2}{\text{mse}} \tag{10}$$

$$\text{RMSE} = \sqrt{\frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} [x(i, j) - x'(i, j)]^2} \tag{11}$$

M×N is the size of the image and RMSE is the root mean square error between original image (x) and denoised image (x'). It may be noted that the following conditions must be satisfied for a good fusion of images[8]:

- The smallest possible RMSE
- The highest possible PSNR

Analysis of lifting body image corrupted with salt and pepper noise for different noise variances. Analysis of lifting body image corrupted with Gaussian noise for different noise variances.

With reference to Fig. 3 and 4, it is observed that the de-noised images generated by soft threshold technique (Fig. 3(e, g, i) and Fig. 4(e, g, i), for different noise variances exhibit good geometric details when compared to the hard thresholding techniques (Fig. 3f, h, j) and Fig. 4(f, h, j).

Quantitative analysis: The quantitative analysis of results obtained from different thresholding techniques have been carried out using indicators as mentioned in Table 1. The de-noised image which will best preserve the spectral, spatial and structural similarity information of the original image is the one that has low RMSE and high PSNR. Lower value of RMSE represents a greater accuracy measure in terms of image fidelity and higher values of PSNR are an indication of less image distortion.

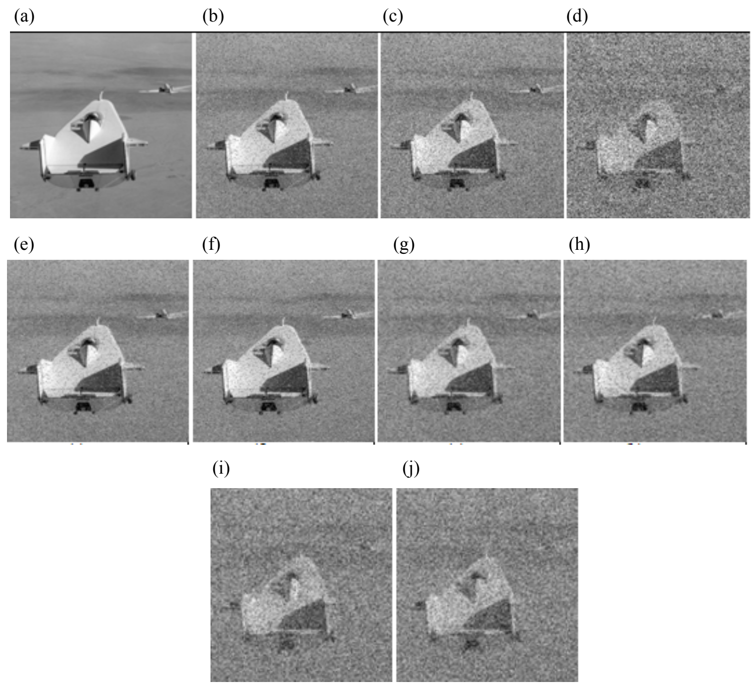

Fig. 3(a-j): De-noised images generated by hard and soft threshold techniques for image corrupted with salt and pepper noise, (a) Original image (b-d), Noise variance = (0.1), (0.2), (0.5) (e, f), Denoising by soft and hard threshold, variance = 0.1, (g, h), Denoising by soft and hard threshold, variance = 0.2, (i, j), Denoising by soft and hard threshold, variance = 0.5

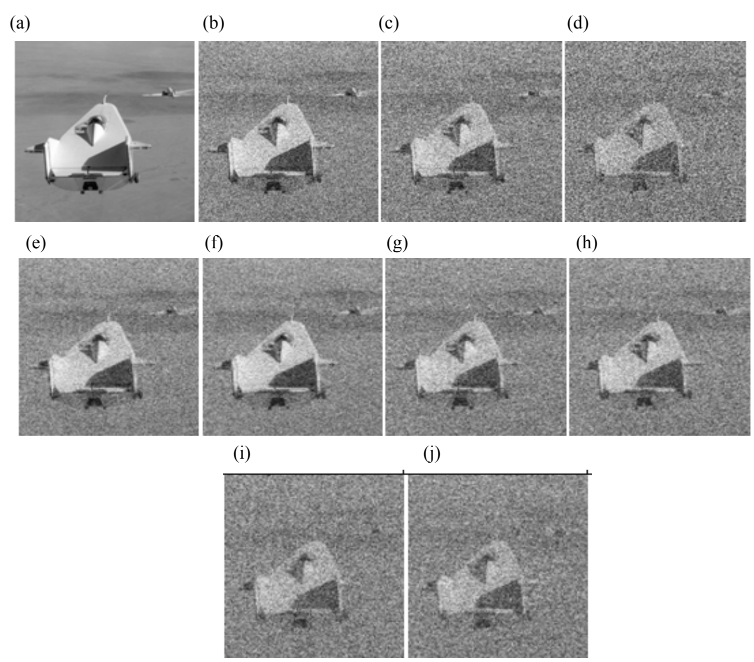

Fig. 4(a-j): De-noised images generated by hard and soft threshold techniques for image corrupted with Gaussian noise, (a) Original image, (b-d) Noise variance = (0.1), (0.2), (0.5), (e, f) Denoising by soft and hard threshold, variance = 0.1, (g, h) Denoising by soft and hard threshold, variance = 0.2, (i, j) Denoising by soft and hard threshold, variance = 0.5

Table 1: Denoised numerical results PSNR (dB) and RMSE for image corrupted by salt and pepper noise and Gaussian noise

Denoising techniques	Types of noise	Noise variance	Soft threshold PSNR	Hard threshold PSNR	Soft threshold RMSE	Hard threshold RMSE
DWT	Salt and pepper noise	0.1	31.8049	30.6376	07.08	07.68
		0.2	29.8779	29.7805	11.55	11.50
		0.5	25.2304	25.2612	12.72	16.35
	Gaussian noise	0.1	28.8518	28.8007	07.94	08.00
		0.2	26.9157	26.7304	09.74	09.93
		0.5	24.8071	24.7250	12.17	12.25

CONCLUSION

In this study, comparative analysis of thresholding techniques for image denoising using discrete wavelet transform is done. The 512×512 image is taken with different noise level, the denoised image results that soft threshold outperforms over hard threshold in terms of PSNR and RMSE. As soft threshold results a larger vale of PSNR and low RMSE when compared to hard threshold, higher PSNR and low RMSE is subject to indicate higher accuracy and less image distortion and suggests that DWT based de-nosing technique yields the highest performance in terms of preservation of spectral and spatial information.

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