International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 1 Issue 10, December- 2012

Wavelet Based Noise Reduction using a New Threshold Model

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Abstract

Emerging innovation of denoising stems out due to the need in improvement of pictorial information during acquisition & transmission. This problem is considered and a new thresholding technique is framed which is based on scale-base decomposition in which noises are represented as wavelet coefficients. Discarding these coefficients results in a threshold transform coefficients (TTC), inverse wavelet of TTC is the noise suppressed image. Experimental results are compared with the existing universal and visushrink threshold using PSNR values for various images shows that proposed algorithm is better in preserving the details and edges of the image.

1. Introduction

In real world an image is often contaminated by undesired information during transmission (or) acquisition called noise, which has to be processed by engineers and scientists. In order to process the image it should be noise free [5]. This led to the development of various image denoising techniques in spatial domain and as well as in frequency domain. Among them wavelet transform has attain a dramatic progress in image denoising.

The success of wavelet transform is because it can localize signals in time and scale compared to other transforms. Wavelet denoising by Donoho is a non-linear thresholding of wavelet coefficient depending upon the noise power and image size [1][2][3]. Visushrink is done by applying soft-thresholding operator with the help of universal threshold. It fails to adapt to the various structural and statistical properties of wavelet tree [2]. Even though many shrinkaging techniques have been developed yet there is no best method for determining the threshold.

This paper deals with a new approach for removing the speckle noise which increases the mean gray value of the local area .Speckle noise is also called as multiplicative noise modeled by multiplying the random values by pixel values .This noise is a major problem in radar application [9]. The proposed technique is based on non-linear orthogonal thresholding the detail wavelet coefficients. Here two threshold values are calculated to threshold the image and inverse operation produce a restored image from noise.

2. Discrete wavelet transforms

Image is a two-dimensional function .DWT of an image requires Φ (x, y) a two-dimensional scaling function and a three-dimensional wavelets $\Psi^H(x, y)$, $\Psi^V(x, y)$ and $\Psi^D(x, y)$ which measure the intensity variations for images along different directions [4][8][10]. Where $\Psi^H(x, y) = \Psi(x)\ \Phi(y)$ measure the intensity variations along horizontal directions $\Psi^V(x, y) = \Phi(x)\ \Psi(y)$ measure the intensity variations along vertical directions $\Psi^D(x, y) = \Psi(x)\ \Psi(y)$ measure the intensity variations along diagonal directions

The DWT of an M*N image can be found using the equation

$$W_{\Phi}(j_0, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y)\Phi_{j_0,m,n}(x, y) \qquad 2.1$$

$$W_{\psi}^{i}(j, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y)\ \psi_{j,m,n}^{i}(x, y) \qquad 2.2$$

where j_0 is the arbitrary starting scale. Equation 2.1 gives the approximation of f(x, y) at scale j_0 and equation 2.2 add horizontal, vertical and diagonal details for scale $j \geq j_0$ .we normally let $j_0 = 0$ and select $N = M = 2^j$ where j = 0, 1, 2, j-1 and m, n = 0, 1, 2, ….. 2^{j-1}. This is implemented by using a series of digital filters, down samplers at two scales and the block diagram is shown in figure 1. The IDWT of the transformed image is determined by the equation and the block diagram is shown in figure 2.

ISSN: 2278-0181
Vol. 1 Issue 10, December- 2012

$$f(x,y) = \frac{1}{\sqrt{MN}} \sum_{m} \sum_{n} W_{\Phi}(j0,m,n)\, \Phi_{j0,m,n}(x,y) + \frac{1}{\sqrt{MN}} \sum_{i=H,V,D} \sum_{j=j_0} \sum_{m} \sum_{n} W_{\psi}^{i}(j,m,n)\, \psi_{j,m,n}^{i}(x,y) \qquad 2.3$$

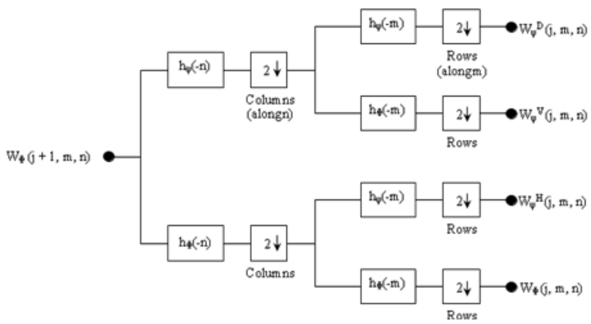


Figure 1. Decomposition Algorithm

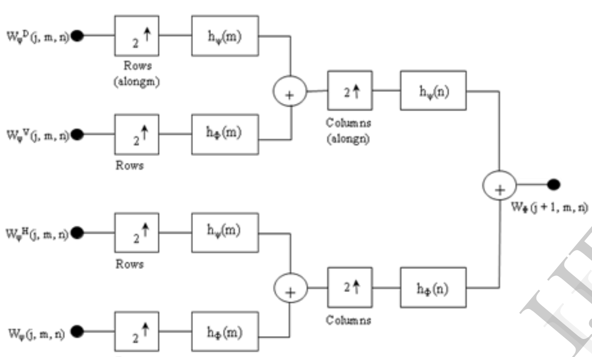


Figure 2. Reconstruction Algorithm

3. Haar wavelet

It is one of the simplest and oldest orthonormal wavelets which is a real function and is localized in time domain [8]. It is given by

$$\Psi(x) = \begin{cases} 1, & \text{for } 0 < x < 0.5 \\ -1, & \text{for } 0.5 < x < 1 \\ 0, & \text{otherwise} \end{cases}$$

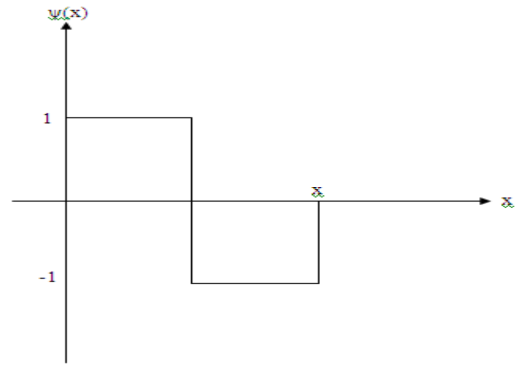


Figure 3. Haar wavelet function

4. Wavelet shrinkage denoising

The wavelet coefficient which is governed by either soft thresholding (or) hard thresholding is widely used in noise reduction by handling the wavelet coefficient. Threshold selection plays a crucial role in shrinkage methods which may adaptive or non adaptive.

Hard thresholding is also called as gating. If a coefficient value is below a preset value it is set to zero otherwise unchanged (or) replace by another value[4][8]. It is defined as

$$y = \begin{cases} x, & \text{for } |x| >= \sigma \\ 0, & \text{for } |x| < \sigma \end{cases}$$

where σ is the gate value.

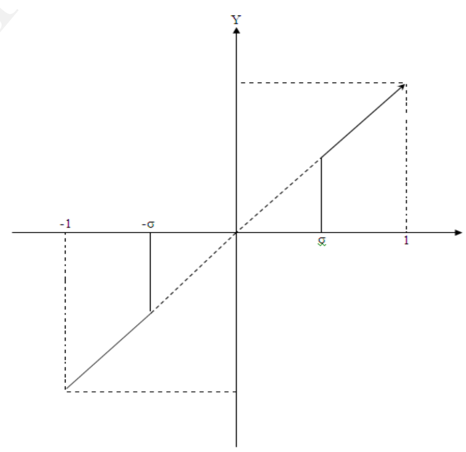


Figure 2. Hard thresholding

Soft thresholding is defined as

$$y = \begin{cases} \operatorname{sgn}(x)\, f(|x| - \sigma) & \text{for } |x| >= \sigma \\ 0, & \text{for } |x| < \sigma \end{cases}$$

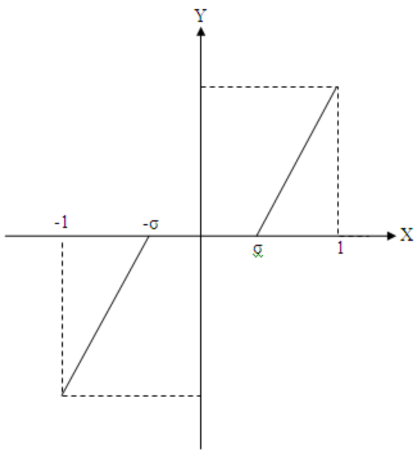


Figure 5. Soft thresholding

4.1 Universal Threshold

It is defined as

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

where N is the signal length and σ is the noise variance. It gives better result when the number of samples is large [6]. It is an optimal threshold.

4.2 Visushrink

It handles additive noise and it can be viewed as a hard threshold. It is defined as

$$\sigma^2 = \left|\frac{median\left|y_{i,j}\right|}{0.6745}\right|^2$$

where $y_{i,j}$ is the detail coefficients of the wavelet transform. But visushrink cannot remove speckle noise completely [6][7].

4.3 Proposed Algorithm

A new thresholding method is proposed to remove the speckle noise in natural image. The algorithm is framed by first considering the intensity values of the image and secondly by handling the variance, mean of the image to efficiently discard the noisy pixels in the image and preserve the fine details of the image. The procedure is as follows

Step1. Perform two scale decomposition using Haar basis on the speckle noise corrupted image.

Step2. Find the mid-pixel value (P_{Mid}) of the decomposed image by considering the (P_{Min}) minimum and (P_{Max}) maximum intensity value.

Step3. Threshold the decomposed image using P_{Mid} and compute the average intensity value by dividing it by the number of rows which is the threshold Th_1.

Step4. Find the second threshold value using

$$Th_2 = \frac{2*(\log(\sigma^2 - m^2))}{L-1}$$

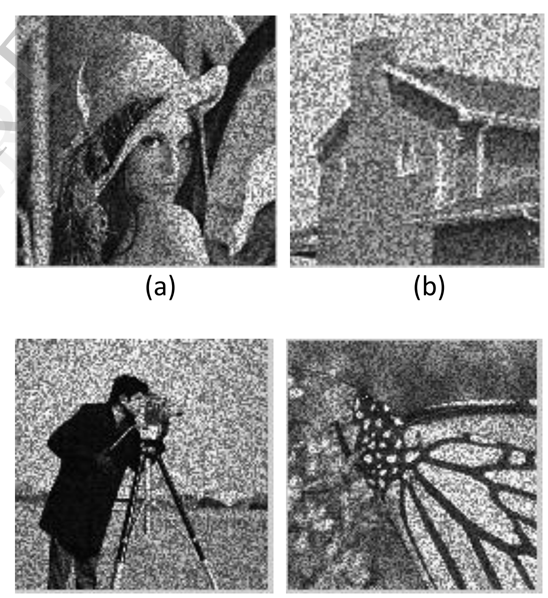
where σ^2 is the variance, m is the mean value of the image and L is the length of the image.

Step5. After finding the two thresholds compute the difference of each pixel with the median value of the decomposed image and find the wavelet coefficient.

Step6. The wavelet coefficient is compared with Th_1.if it is greater than (or) equal to Th_1 then the coefficient is replaced by square of the mean value, otherwise kept unchanged.
Following Th_1 the coefficient is compared with Th_2. If the coefficient is less than threshold it is set to zero, otherwise kept unchanged.

Step7. The above step is repeated for all the wavelet coefficients.

Step8. Finally the two scale inverse wavelet using Haar basis gives the restored image.



(a) (b)

(c) (d)

Figure 6. Noisy images *(a) lena (b) house (c) Cameraman (d) monarch*

(a) (b) (c) (d)

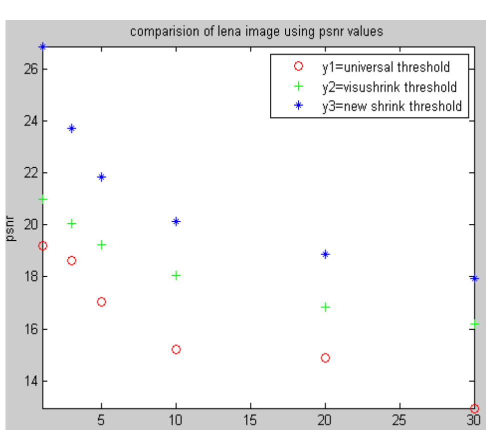
Figure 7. Denoised images using universal threshold *(a) lena (b) house (c) cameraman (d) monarch*

(a) (b) (c) (d)

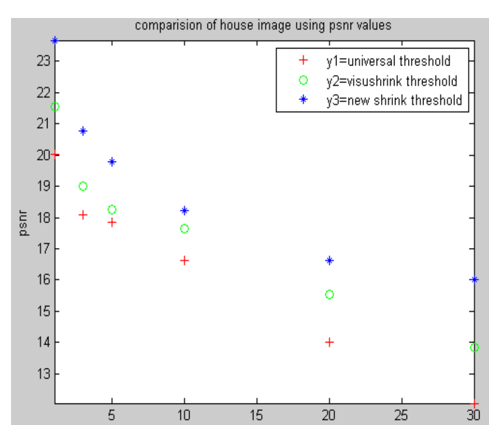
Figure 8. Denoised images using visushrink threshold *(a) lena (b) house (c) cameraman (d) monarch*

(a) (b) (c) (d)

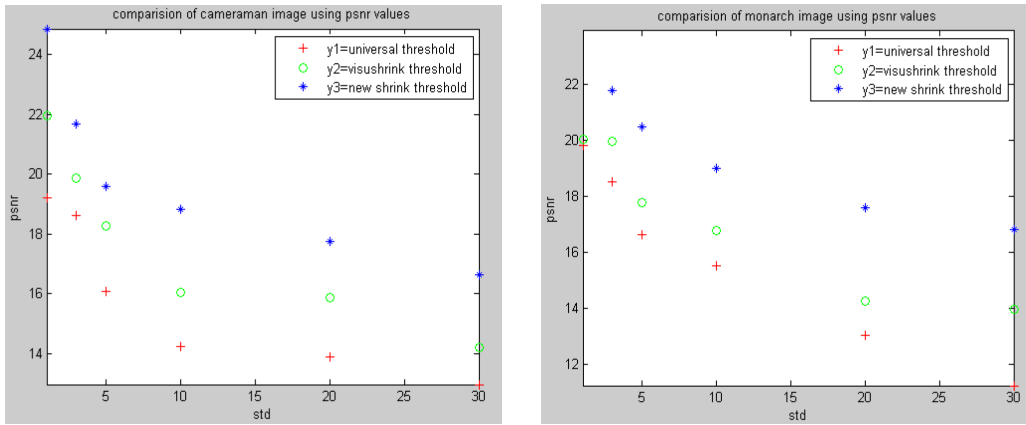
Figure 9. Denoised images using new threshold model *(a) lena (b) house (c) cameraman (d) monarch*



(a)



(b)



(c) *(d)*

Figure 10. *Comparison graph for different noise levels of universal, visushrink and new threshold (a) Lena (b) house (c) cameraman (d) monarch*

5. Conclusion

In this paper the problem of denoising the speckle noise in natural image is proposed. Experiments are carried out on some standard images like lena, cameraman, house and monarch for 6 different noise levels. The proposed technique is compared with the existing universal threshold and visushrink shows that the new thresholding technique gives high PSNR than existing methods.

6. References

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