Image Denoising Using Wavelet Transform

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***Abstract*—An image is often corrupted by noise in its acquisition and transmission. Removing noise from the original image is still a challenging problem for researchers. In this work new approach of threshold function developed for image denoising algorithms. It uses wavelet transform in connection with threshold functions for removing noise. Universal, Visu Shrink, Sure Shrink and Bayes Shrink, normal shrink are compared with our threshold function, it improves the SNR efficiently.**

Keywords-universashrink, baysshrink, sureshrink, normalshrink, vishushrink, etc.

I. Introduction

Noise reduction plays a fundamental role in image processing, and wavelet analysis has been demonstrated to be a powerful method for performing image noise reduction [1]. The procedure for noise reduction is applied on the wavelet coefficients achieved using the wavelet decomposition and representing the image at different scales. After noise reduction, the image is reconstructed using the inverse wavelet transform. Decomposition and reconstruction are accomplished using two banks of filters constrained by a perfect reconstruction condition. The threshold selection for this denoising technique is application dependent. Section II summarizes review of wavelet transform. Section III deals with the types of the threshold functions used. Sections IV explain Image denoising algorithm. Section V Consists the performance evaluation and results. Section VI describes the conclusions.

II. Review of Wavelet Transform

By wavelet transform [10] the decomposition of a signal with a family of real orthonormal bases $\psi_{m,n}(x)$ obtained through translation and dilation of a kernel function $\psi(x)$ known as the mother wavelet, i.e.

$$\psi_{m,n}(x)=2^{(-m/2)}\Psi(2^{-m}x-n) \quad \ldots\ldots(1)$$

Where m and n are integers. Due to the orthonormal property , the wavelet coefficients of a signal f(x) can be easily computed via

$$C_{m,n}= \int_{-\infty}^{+\infty} f(x)\, \psi_{m,n}(x)\, dx \quad \ldots\ldots (2)$$

And the synthesis formula

$$F(x)=\Sigma_{m,n}C_{m,n}\psi_{m,n}(x) \quad \ldots\ldots(3)$$

The transformed signal is a function of two variables, the translation and scale parameter. The $\Psi(t)$ is the transforming function and it is called the mother wavelet transform. The term mother wavelets mean a small wave. The smallness refers to the condition that this (window) function is of finite length (compactly supported). The term translation is related to the location of the window, as the window is shifted through the signal[12]. This term obviously corresponds to time information in the transformdomain. To construct the mother wavelet $\psi(x)$, first determine a scaling function $\phi(x)$, which satisfies the two scale difference equation

$$\phi(x) = \sqrt{2}\ \Sigma_k h(k)\, \phi(2x-k) \quad \ldots\ldots (4)$$

Then , the wavelet kernel $\psi(x)$ is related to the scaling function via

$$\psi(x) = \sqrt{2}\ \Sigma_k g(k)\, \phi(2x-k) \quad \ldots\ldots(5)$$

Where $g(k) = (-1)^k\ h(1-k)$

The coefficients is h(k) in have to meet several conditions for the set of basis wavelet function in to be unique, orthonormal, and have degree of regularity . The coefficient h(k) and g(k) play a very crucial role in a given discrete wavelet transform. To perform the wavelet transform does not require the explicit form of the $\phi(X)$ and $\psi(X)$ but only depends on h(k) and g(k) . Consider a J – level wavelet decomposition which can be written as

$$Fo(x)= \Sigma\, C_{o,k}\, \phi_{o,k}(x)=\Sigma_k^{k}\,(C_{j+1,k}\phi_{j+1,k}(x)+\Sigma_{j=0}^{J} d_{j+1,k}\, \psi_{j+1,k}(x) \quad \ldots\ldots(6)$$

where coefficients $C_{o,k}$ are the given and coefficients C_{j+1} and $d_{j+1,k}$ at scale j+1 are related to the coefficients $C_{j,k}$ at scale j via

$$C_{j+1,n} = \Sigma k C_{j,k}\, h(k-2n)$$

$$.d_{j+1,n}=\Sigma_k C_{j,k} g(k-2n) \quad \ldots\ldots(7)$$

Where $0 \le j \le J$ .Thus provides recursive algorithm for wavelet decomposition through h(k) and g(k) and the final outputs include a set of J-level wavelet coefficients $d_{j,n}$, $1 \le j \le J$ and the coefficients $C_{j,n}$ for low resolution component $\phi_{j,k}(x)$. By using a similar approach, we can derive recursive algorithm for function synthesis based on its wavelet coefficients $d_{j,n}$, $1\le j \le J$ and $C_{j,n}$

$$C_{j,k}=\Sigma_n C_{j+1,n}h(k-2n)+\Sigma_n d_{j+1,n}g(k-2n) \quad \ldots\ldots(8)$$

It is convenient to view the decomposition as passing a signal $C_{j,k}$ through a pair of filters H and G with impulse response h(n) and g(n) and down sampling the filtered signals by two, where h(n) and g(n) are defined as

$$.\ h(n) = h(-n)\ , g(n) = g(-n) \quad \ldots\ldots(9$$

The pair of filters H and G corresponds to the half band low pass and high pass filters, respectively, and is called the quadrature mirror filters in the signal processing it is shown in Figure 1. The reconstruction procedure is implemented by up sampling the subsignal C_{j+1} and d_{j+1} (inserting zero between the neighboring samples) and filtering with h(n) and g(n), respectively, and adding these two filtered signals together[13] [14]. Usually the signal decomposition scheme is performed recursively to the output of the low pass filter h. It leads to the conventional wavelet transform or the so called pyramid structured wavelet decomposition. Presenting the simplest form of wavelets, the Haar basis[6][7]. It covers one-dimensional wavelet transforms and basis functions.

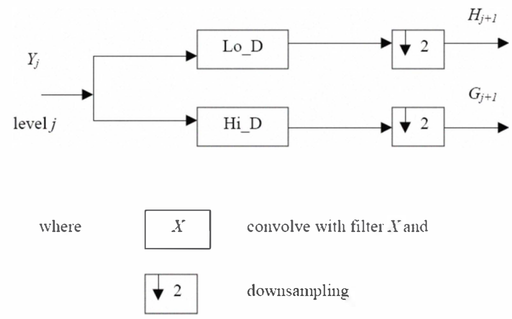

Figure 1. One level downsampling

As mentioned earlier, the wavelet equation produces different wavelet families like Daubechies, Haar, coiflets, etc. Wavelets are classified into a family by the number of vanishing moments *N*. Within each family of wavelets there are wavelet subclasses distinguished by the number of coefficients and by the level of iterations. The wavelet decomposition of an image is done as follows: In the first level of decomposition, the image is split into 4 subbands, namely the HH, HL, LH and LL subbands as shown in Figure 2. The HH subband gives the diagonal details of the image; the HL subband gives the horizontal features while the LH subband represents the vertical structures [4] [5]. The LL subband is the low resolution residual consisting of low frequency components and it is this subband which is further split at higher levels of decomposition [13].

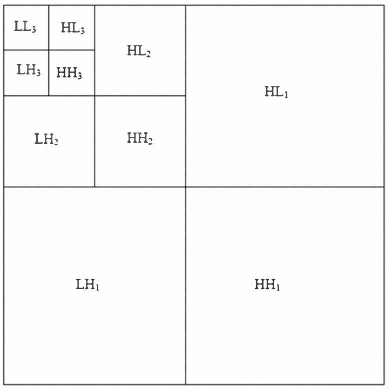

Figure 2. subbands of image after decomposition

The choice of a threshold is an important point of interest. It plays a major role in the removal of noise in images because denoising most frequently produces smoothed images, reducing the sharpness of the image. Care should be taken so as to preserve the edges of the denoised image..

III. Types of Threshold

Noise is present in an image either in an additive or multiplicative form. An additive noise follows the rule, $w(x, y) = s(x y) + n(x, y)$,

While the multiplicative noise satisfies $w(x, y)=s(x, y)\times n(x, y)$, Where $s(x,y)$ is the original signal, $n(x,y)$ denotes the noise introduced into the signal to produce the corrupted image $w(x,y)$, and (x,y) represents the pixel location[14]. *Gaussian Noise* is evenly distributed over the signal. This means that each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value. *Salt and Pepper Nois* is an impulse type of noise, which is also referred to as intensity spikes. This is caused generally due to errors in data transmission. The corrupted pixels are set alternatively to the minimum or to the maximum value, giving the image a "salt and pepper" like appearance. Unaffected pixels remain unchanged. *Speckle Noise* is a multiplicative noise. Th is type of noise occurs in almost all coherent imaging systems such as laser, acoustics and SAR (Synthetic Aperture Radar) imagery. The source of this noise is attributed to random interference between the coherent returns[1], [2], [3]. Fully developed speckle noise has the characteristic of multiplicative noise.

A. Universal Threshold

The universal threshold can be defined as ,

$$T = \sigma\sqrt{2\log(N)} \quad \ldots\ldots\ldots\ldots\ldots\ldots (10)$$

N being the signal length, σ being the noise variance is well known in wavelet literature as the *Universal threshold*. It is the optimal threshold in the asymptotic sense and minimizes the cost function of the difference between the function. However, it is useful for obtain a starting value when nothing is known of the signal condition. One can surmise that the universal threshold may give a better estimate for the soft threshold if the number of samples is large[2][26].

B. Visu Shrink

Visu Shrink was introduced by Donoho[5]. It uses a threshold value *t* that is proportional to the standard deviation of the noise. It follows the hard thresholding rule. An estimate of the noise level σ was defined based on the median absolute deviation given by

$$\hat{\sigma} = \frac{Median\left(\left\{\left|g_{j=1,k}\right| : k = 0,1,\ldots\ldots 2^{j-1}-1\right\}\right)}{0.6745} \quad \ldots\ldots (11)$$

Where $g_{j-1,\ k}$ corresponds to the detail coefficients in the wavelet transform. VisuShrink does not deal with minimizing the mean squared error. It can be viewed as general-purpose threshold selectors that exhibit near optimal minimal error properties and ensures with high probability that the estimates are as smooth as the true underlying functions. However, VisuShrink is known to yield recovered images that are overly smoothed. This is because VisuShrink removes too many coefficients. Another disadvantage is that it cannot remove speckle noise. It can only deal with an additive noise. VisuShrink follows the global thresholding scheme where there is a single value of threshold applied globally to all the wavelet coefficients[3].

C. *Sure Shrink*

A threshold chooser based on Stein's Unbiased Risk Estimator (SURE) was proposed by Donoho and Johnstone and is called as Sure Shrink. It is a combination of the universal threshold and the SURE threshold [5]. This method specifies a threshold value *tj* for each resolution level *j* in the wavelet transform which is referred to as level dependent thresholding. The goal of Sure Shrink is to minimize the mean squared error[16], defined as,

$$MSE = \frac{1}{n^2}\sum_{x,y=1}^{n}(Z(x,y)-S(x,y))^2 \ \ldots\ldots\ldots\ldots\ldots \ (12)$$

Where $z(x,y)$ is the estimate of the signal while $s(x,y)$ is the original signal without noise and n is the size of the signal. Sure Shrink suppresses noise by thresholding the empirical wavelet coefficients. The Sure Shrink threshold t^* is defined as

$$t^* = \min(t, \sigma\sqrt{2\log n}) \ \ldots\ldots\ldots\ldots\ldots\ldots \ (13)$$

Where t denotes the value that minimizes Stein's Unbiased Risk Estimator, σ is the noise variance computed from Equation, and n is the size of the image. Sure Shrink follows the soft thresholding rule. The thresholding employed here is adaptive, i.e., a threshold level is assigned to each dyadic resolution level by the principle of minimizing the Stein's Unbiased Risk Estimator for threshold estimates. It is smoothness adaptive, which means that if the unknown function contains abrupt changes or boundaries in the image, the reconstructed image also does.

D. *Bayes Shrink*

Bayes Shrink was proposed by Chang, Yu and Vetterli. The goal of this method is to minimize the Bayesian risk, and hence its name, Bayes Shrink [22]. It uses soft thresholding and is subband-dependent, which means that thresholding is done at each band of resolution in the wavelet decomposition. Like the Sure Shrink procedure, it is smoothness adaptive. The Bayes threshold, *tB*, is defined as

$$t_B = \sigma^2/\sigma_s \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ (14)$$

Where σ^2 is the noise variance and σ_s is the signal variance without noise. The noise variance σ^2 is estimated from the subband HH by the median estimator shown in equation ().

From the definition of additive noise we have $w(x, y)=s(x, y)+n(x, y)$.

Since the noise and the signal are independent of each other, it can be stated that

$$\sigma^2_w = \sigma^2_s + \sigma^2 \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ (15)$$

σ^2_w can be computed as shown below:

$$\sigma^2{}_w = \frac{1}{n^2}\sum_{x,y=1}^{n} w^2(x,y) \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ (16)$$

The variance of the signal, σ^2_s is computed as

$$\sigma_s = \sqrt{\max(\sigma^2{}_w - \sigma^2, 0)} \ \ldots\ldots\ldots\ldots \ (17)$$

With σ^2 and σ^2_s, the Bayes threshold is computed from Equation (14). Using this threshold, the wavelet coefficients are threshold at each band.

E. *Normal Shrink*

The threshold value which is adaptive to different subband characteristics

$$TN = \beta\sigma^2 / \sigma_y$$

Where the scale parameter β is computed once for each scale using the following equation.

$$\beta = \sqrt{\log\left(\frac{L_K}{J}\right)} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots \ (18)$$

Lk is the length of the subband at Kth scale

σ^2 is the noise variance, which is estimated from the subband HH using equation (11).

F. *Proposed Threshold*

This function is calculated by

$$newth = \sqrt{2m \times \log(M)}$$

Where, M is the total number of pixel of an image.

IV. Image Denoising Algorithm

The problem boils down to finding an optimal threshold such that the mean squared error between the signal and its estimate is minimized. The different methods for denoising we investigate differ only in the selection of the threshold. Soft thresholding is used for all the algorithms due to the following reasons: Soft thresholding has been shown to achieve near minimax rate over a large number of Besov spaces [3]. Moreover, it is also found to yield visually more pleasing images. Hard thresholding is found to introduce artifacts in the recovered images. We now study four thresholding techniques Universal, VisuShrink, Sure Shrink and Bayes Shrink and investigate their performance for denoising on Lena image. Fig 3. Shows that denoising technique in details such as

x: the original noise-free digital one or two-dimensional signal which has M samples.

w: an additive white Gaussian noise with zero mean and variance w, which is assumed to the same size M but

independent of the original signal x, y=x+w: the noisy version of the original noise-free signal.
Y=DWT (y): the DWT of the noisy signal y.
T(Y,λ): the thresholding transformation with threshold ¸.
X^: the thresholded wavelet coe±cients obtained after applying the thresholding operator x^: the denoised version of the noisy image y, which represents an approximation of the original image x.

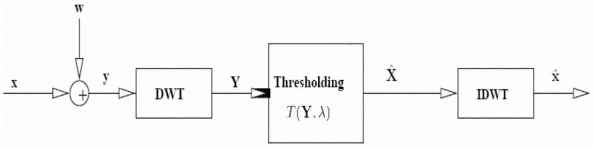

Figure 3: Denoising using DWT & IDWT

The goal behind using wavelets for denoising purposes is to smooth out some areas where noise is present but to leave other areas unaffected. The addition of noise to a signal will contribute noisy coefficients. Unlike noisy coefficients that are contributing to all coefficients, signal is contributed to only a few high amplitude coefficients. Therefore, since the signal is concentrated in a few coefficients, it is possible to threshold out the noise only leaving the signal. In order to pick a threshold by which to filter out noise requires complete knowledge of the signal and an estimate of the noise process. One global and non-linear method involves knowing the standard deviation of the noise and the number of wavelet coefficients or signal samples

A. Proposed algorithm:

We have considered the block of the approximation coefficient. Then calculate the threshold function using the Bays threshold, normal threshold, Sure Shrink, VisuShrink & universal threshold. In denoising each coefficient is *threshold* by comparing against a threshold; if the coefficient is smaller than the threshold it is set to zero, otherwise, it is kept. Then we will recover the denoised image.

V. RESULTS

We compared various denoising method on several test images widely used in image processing community. Here, we report the result only for the Lena image Result shown in tabular format. By applying the new threshold function our result is improved drastically. From the experimental and mathematical results it can be concluded that for Gaussian noise image Normal threshold & Sure Shrink gives better result. In case of Poisson noise Bays threshold, Normal threshold & Sure Shrink gives better quality result. For salt and pepper noise, Bays threshold & Normal threshold gives us better result. For speckle noise Bays threshold, Normal threshold & Sure Shrink gives better quality result. Result analysis for input image Lena size (512 x 512) is shown in table 1.

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TABLE I. RESULT ANALYSIS FOR LENA IMAGE

Name of the noise	Name of the Technique	Original ImageSNR In DB	Noisy Image SNR in DB	After denoising (Recovered image) SNR in DB	After denoising using Block only
Gaussian Image	Visushrink	13.2505	13.5400	14.2110	13.5583
	Universal threshold			9.2979	**13.4046**
	Sureshrink			16.8720	13.5442
	Normal Shrink			15.4684	13.5418
	Bays shrink			15.3220	13.5452
	NEW Approach				**15.0061**
Speckle	Visushrink	13.2505	12.6249	12.2023	**12.6241**
	Universal threshold			9.8297	**12.3477**
	Sureshrink			14.7922	12.6302
	Normal Shrink			15.0069	12.6260
	Bays shrink			14.9716	12.6735
	NEW Approach				**14.5171**
Salt & Pepper	Visushrink	13.2505	14.0302	11.8957	**13.3760**
	Universal threshold			9.6062	**15.6247**
	Sureshrink			17.2951	13.3792
	Normal Shrink			17.2498	13.3849
	Bays shrink			16.9775	13.3718
	NEW Approach				**15.5274**
Poisson	Visushrink	13.2505	13.7428	11.6988	13.7780
	Universal threshold			9.5227	**12.7115**
	Sureshrink			14.3082	13.7788
	Normal Shrink			14.5519	13.7481
	Bays shrink			14.6518	13.7785
	NEW Approach				**13.9969**

VI. CONCLUSION AND FUTURE SCOPE

In the case where an image is corrupted with Gaussian noise, the wavelet shrinkage denoising has proved to be nearly optimal. The output from Bayes Shrink method is much closer to the high quality image and there is no blurring in the output image unlike the other two methods. VisuShrink cannot denoise multiplicative noise unlike BayesShrink. Denoising salt and pepper noise using VisuShrink and Universal has proved to be inefficient.
Since selection of the right denoising procedure plays a major role, it is important to experiment and compare the methods. As future research, we would like to work further on the comparison of the denoising techniques. Besides, the

complexity of the algorithms can be measured according to the CPU computing time flops. This can produce a time complexity standard for each algorithm. These two points would be considered as an extension to the present work done.

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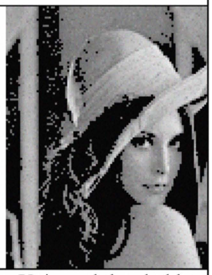
Original image Lena	**Noisy Image**			
	Poisson noise	Gaussian	Salt & Paper	Speckle

Result: By applying threshold function to the all **wavelet coefficient (approximation & Detail coefficients)**

Output for Gaussian noise image

				
Bays threshold	Normal threshold	Sure shrink	Visushrink	Universal threshold

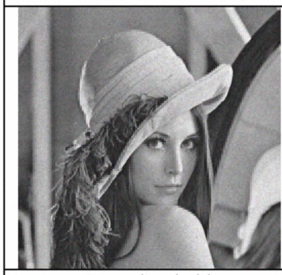
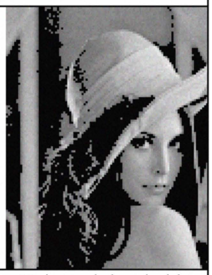
Output for Salt & Pepper noise image

				
Bays threshold	Normal threshold	Sure shrink	Visushrink	Universal threshold

Output for Speckle noise image

				
Bays threshold	Normal threshold	Sure shrink	Visushrink	Universal threshold

Output for Poisson noise image

				
Bays threshold	Normal threshold	Sure shrink	Visushrink	Universal threshold

Result: By applying threshold function to only **approximation coefficients** of wavelet transform

Output for Gaussian noise image

				
Bays threshold	Normal threshold	Sure shrink	Visushrink	Universal threshold

Output for Salt & Pepper noise image

Bays threshold	Normal threshold	Sure shrink	Visushrink	Universal threshold

Output for Speckle noise image

Bays threshold	Normal threshold	Sure shrink	Visushrink	Universal threshold

Output for Poisson noise image

Bays threshold	Normal threshold	Sure shrink	Visushrink	Universal threshold

Result By Applying the Proposed threshold Function for different noisy image

Salt & Pepper	Gaussian	Poisson	Speckle