Image Denoising Based on Adaptive Wavelet Multiscale Thresholding Method

Priyadharshini .S, Gayathri .K, Priyanka .S, Eswari .K

Abstract—This paper introduces a new technique called adaptive wavelet thresholding and wavelet packet transform to denoised the image based on generalized Gaussian distribution.It chooses an adaptive threshold value which is level and subband dependent based on analyzing the subband coefficients.Experimental results, on different test images under different noise intensity conditions, shows proposed algorithm, called OLI-Shrink, yields better peak signal noise ratio with superior visual image quality measured by universal image quality index compared to standard denoising methods. It also performs some of wavelet-based denoising techniques.wavelet transform enable us to represent image with high degree of scarcity.wavelet transform based denoising technique are of greater interest because of their fourier and other spatial domain methods.

Index Terms—Adaptive wavelet thresholding, OLI Shrink, wavelet packet transform (WPT), optimal wavelet basis (OWB),subband weighting function(SWF).

I. INTRODUCTION

In many applications, image denoising is generally used to produce a good estimate of the original image from noisy states. Image denoising technique is necessary to eliminate as much random additive noise as possible while retaining requires image features, such as edges and texture. wavelet denoising is used to remove the noise present in the image while preserving the image features regardless of its frequency content. wavelet thresholding (shrinking) algorithm was introduced by Donoho in 1995 as a powerful tool in denoising image degraded by additive white noise.

For several years, classical signal processing was concentrated mostly in the characteristics of signals and on the designing of the time-invariant and space-invariant operator that modify stationary signal properties. But the largest amount of information is concentrated on transients rather than in stationary signals.

In the literature, several techniques for selection of threshold values and new thresholding methods including fuzzy logic, neural networks, and wavelet packet (WP) base using Wiener filtering are reported. scientists exploit different types of techniques to improve denoising further.

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We implemented WP transform (WPT) along with optimal wavelet basis (OWB) for image decomposition. Then, for each wavelet subband, an adaptive threshold value is estimated based on analyzing the subband's statistical parameters.

Next, a new thresholding method, called OLI-Shrink, is proposed to shrink small coefficients leading to calculate a modified coefficients. The modification is done by using optimal linear interpolation between each coefficient and the mean value of the corresponding subband.

The proposed algorithm has both significantly low mean square error (MSE) and improved the Signal quality of the denoised image. Wavelet transform has wide acceptance as a valuable tool for common signal and image processing tasks because the wavelets are localized in both time and frequency domains.

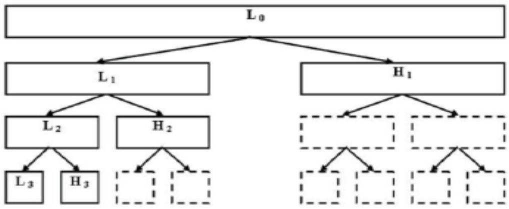

Fig. 1. WP decomposition.

II. WP AND OWB

In wavelet packet transform, the optimal basis of the input signal is selected by optimizing a function known as "cost function" in every subband. The cost functions will determine the cost value for each node and its children node in the obtained full binary tree. The algorithm starts with estimating the cost values from the deepest level nodes. If the sum of the cost values for two children nodes is lower than the cost value of their parent node, then the childrens are accepted, otherwise, they are eliminated.

The cost value computation process is recursively repeated upto the root of the tree. The result is a basis that has the low cost among all the possible basis in this tree, so-called best basis or optimal basis. In this paper, Shannon entropy cost function is selected and implemented.

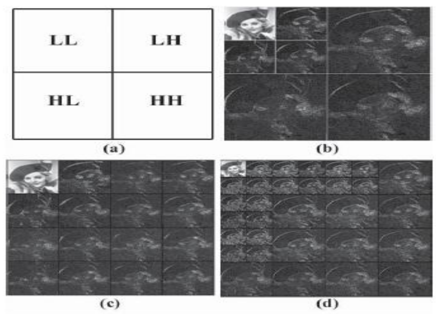

Fig. 2. Results of different wavelet decompositions. (a) Image decomposition scheme. (b) Traditional DWT. (c) WP decomposition. (d) Obtained OWB.

III. PROPOSED WAVELET SHRINKING ALGORITHM

In this paper, a new adaptive wavelet thresholding method is introduced to improve the image denoising efficiency. Besides, instead of using a traditional wavelet transform for test image an OWB is employed. The reason behind selecting the OWB packet is its dynamic decomposition nature in subbands. The threshold value is then selected based on analyzing the statistical parameters of each subband coefficient. The thresholding function is obtained using Bayesian maximum *a posteriori* (MAP) estimate. Then, the optimal linear interpolation between each subband coefficient and the mean value of the corresponding subband are used to estimate the dominant coefficients.

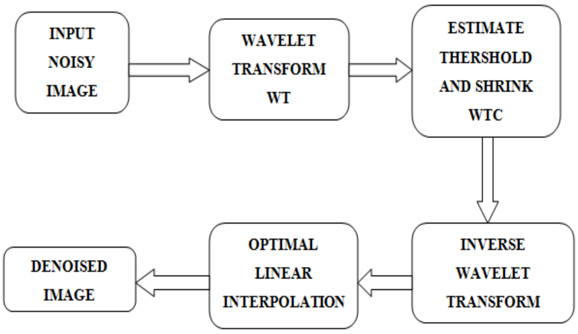

Fig3.block diagram of image denoising using wavelet transform

IV. SHRINKAGE ALGORITHM

The wavelet shrinkage approach can be summarized as follows:

1. Apply the wavelet transform to the signal.
2. Estimate a threshold value.

T = sqrt(2*log(N))

where N is the number of pixels in the image and T is the threshold value.

3. Remove (zero out) the coefficients that are smaller than the threshold.

   X^(X,T) = Sgn (X) max(0 , X-T)

4. Reconstruct the signal (apply the inverse wavelet transform).

A. Fast OWB Extraction

The proposed algorithm uses the bottom-up procedure to extract the optimal basis from the WP tree of an input image. Instead of the above highly computational complex algorithm, an alternative fast method for extracting OWB, which was introduced by Kaur *et* is employed.

This method is a top-down procedure for selecting the optimal basis. The algorithm starts at the root and generates the optimal basis.In this algorithm, we implemented Shannon entropy to produce the optimal wavelet basis.

B. Threshold Value Determination

Selecting an optimal threshold value is not an easy task. A small value of threshold may let noisy coefficients be admitted, and hence the resultant images remain noisy. A large threshold value sets a larger number of coefficients to zero, which leads to smoothing of the image and may cause blurring and artifacts and hence the resultant images may lose some signal values. Therefore, an optimum threshold value, which is adaptable to each subband, is desired to maximize the PSNR and minimize the MSE.

The image noise is assumed to be Random noise.In some image denoising applications, the value of the input noise variance is known or can be measured based on the information other than the image corrupted by noise. Since image information in low frequency subband is more than in the high frequency subband and since the probability of noise in the high-frequency component is greater, applying a greater threshold value to the high-frequency subbands reduces the effect of noise effectively.

The soft thresholding is more efficient tan hard thresholding and yields better visually pleasing images, but it does not use the optimal value for modification of large coefficients.

In order to overcome this problem, we introduce a new thresholding algorithm (OLI-Shrink) that uses optimal linear interpolation between each coefficient and corresponding subband. optimal linear interpolation between each coefficient and subband's mean is combined with wavelet thresholding method to yield our proposed thresholding function.

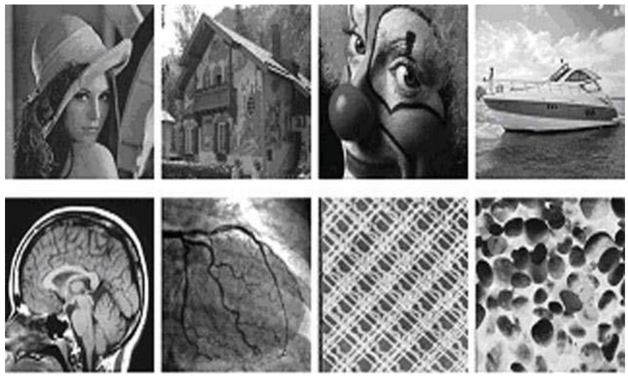

Fig.4. Natural, medical and textural test images

V. EXPERIMENTAL RESULTS

The performance of the proposed image denoising algorithm iscalculated using quantitative performance measures such as peak signal noise ratio (PSNR) and in terms of the visual quality of the images.

$$\text{PSNR}\ (X, \hat{X}) = 10\ \log_{10}\left(\frac{255^2}{\text{MSE}}\right) dB$$

where X is the original image and X^ is the denoised image and the MSE between the original and denoised images is given as,

$$\text{MSE} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(X(i,j) - \hat{X}(i.j))^2$$

we evaluated the effect of different parts of proposed method on image denoising performance. In these experiments, eight images contaminated by Gaussian white noise at different standard deviations: σ = 5, 10, 15, 20, 30, 40, and 50 are used. Daubechies wavelet with eight vanishing moments (Db8) is used to decompose the input image into four wavelet levels. The performance of the thresholding method is evaluated by comparing it with the soft and hard thresholding methods.

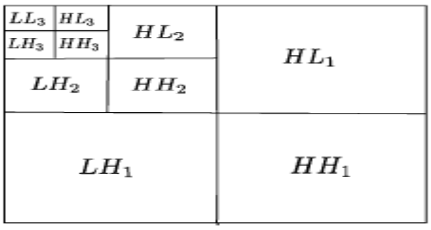

Fig.5.Schematic Representation of image decomposition using Db8

We conclude that the proposed image denoising algorithm yields the better PSNR value compared to the other methods for all noise intensity situations.Finally, Without any optimization of its MATLAB code, it will take around 8.5 sec to process one 512 × 512 image on a PC with a Pentium-IV 3.2-GHz CPU and a 2.0-GB RAM.

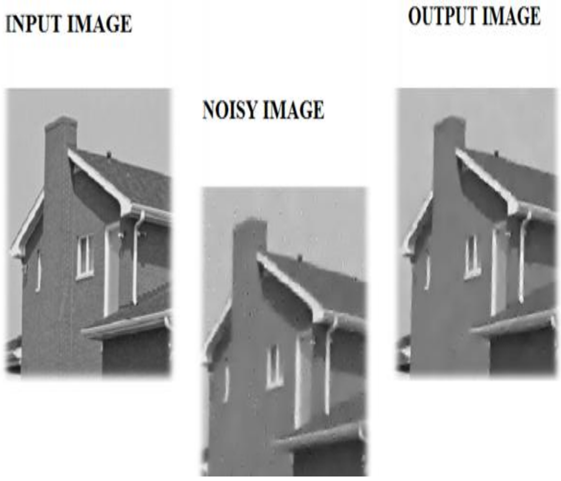

Fig.6.simulated output

VI.CONCLUSION

In this paper, we proposed an efficient image denoising algorithm for adaptive noise reduction which combines the optimal linear interpolation and adaptive thresholding techniques in the WPT domain. Experiments were conducted on different test images, which were corrupted by various random noise levels, to find the performance of the proposed algorithm, named OLI-Shrink, wavelet-based denoising methods. The results indicated that the proposed method outperforms all but one of the methods and is categorically more visually pleasant than all of the other methods. In addition, the computational cost of the proposed method is moderate. so it is suitable for many image processing applications, such as medical image analyzing systems, noisy texture analyzing systems, display systems, and digital multimedia broadcasting. It is further suggested that the proposed algorithm may be extended in future to color images and video framework, which may further improve video denoising.

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