Wavelet-Based Image Denoising with Locally Adaptive Window Maximum Likelihood

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***Abstract*— Denoising is the fundamental step in image preprocessing. It is necessary because image is often contaminated by noise during acquisition and transmission. Denoising process removes noise by retaining all other characteristics of image. In the proposed method Discrete Wavelet Transform (DWT) is used that has the ability to capture energy of the signal into few energy transform value. The threshold value is computed by estimating the noise and signal variance from the transformed image. Then thresholding the transformed image is done by using a Locally Adaptive Window Maximum Likelihood (LAWML) shrinkage function. Evaluation is carried out in terms of PSNR. Experimental results over a range of noise power levels indicate that the proposed method is better than other denoising methods.**

***Keywords*— Image denoising, locally adaptive window, PSNR, shrinkage function, wavelet transforms.**

I. Introduction

Digital images are often degraded by additive noise during acquisition and transmission that can be modeled as Gaussian. The main objective of image denoising is to remove noise by preserving all other characteristics of image. Wavelet based methods has obtained abundant interest in noise removal due to scarcity, energy compaction and multiresolution structure [12], [6]. One way to remove noise in wavelet domain is to kill the noisy coefficients by thresholding the wavelet coefficients. This algorithm was proposed by Donoho and Johnstone named wavelet shrinkage, gives obvious efficiency on signal denoising [3]. After Donoho method many works were proposed for finding the threshold [2-4]. The methods depend on the threshold value are VisuShrink [3], [5], SureShrink [2], [13] and BayesShrink [1]. VisuShrink [3] uses universal threshold to denoise an image. In SureShrik threshold is determined based on Stein's Unbiased Risk Estimator (SURE) [5] which minimizes the mean square error using universal threshold and sure threshold. The BayesShrink [1] is a data-driven adaptive image denoising method. Even though wavelet thresholding de-correlates the noisy signal, some inter-scale and intra-scale dependencies between wavelet coefficients exist. The denoising performance can be improved by considering the dependencies. Sendur and Selesnick [10], [11] proposed a denoising method in which the estimated wavelet coefficient depends on the parent coefficient gives better shrinkage if the parent coefficient is smaller. Mihcak et al. [8] model the image wavelet coefficients as a doubly stochastic process on local variance for each coefficient, using the observed noisy data in a local neighborhood. Then an approximate mean square error estimation procedure is used to restore the noisy coefficients. Image denoising using local mixture in sparse domain yields better PSNR and visual appearance [9]. In [7] hybrid neighborhood filter is used for denoising results in high PSNR and computational time is less. All the above denoising methods estimate the denoised image pixel based on the information of limited surrounding neighborhood. Hence these methods are known as local methods.

In the proposed method the threshold value is estimated by the noise variance and signal variance. The noise variance is computed using robust median estimator. The signal variance is found by describing a window size and processing each sub band separately in a loop by preparing parent matrix for each sub band. The basis of the algorithm is to use this threshold value along with Locally Adaptive Window shrinkage function based on Maximum Likelihood (LAWML). The experimental result shows that the proposed method is better than other existing technique in terms of PSNR.

The organization of the paper is as follows section 2 describes the basics of LAWML, section 3 discusses about the proposed method, section 4 describes about experimental results and finally section 5 deals with conclusion.

II. LOCALLY ADAPTIVE WINDOW (LAW)

A noisy image in wavelet domain is given by

$$y = w + n \tag{1}$$

Here y is the observed image, w is the unknown original image and n is the white Gaussian noise.

The objective is to recover the denoised image from the observationy. In [11] a denoising method based on the dependencies of local wavelet coefficients within each scale is proposed that estimate the value using an approximation maximum likelihood. The signal variance estimated by LAWML is given by

$$\hat{\sigma}_k^2 = \left(\frac{1}{|c(k)|}\sum_{y_m \in c(k)} y_m^2 - \sigma_n^2\right)_+ \tag{2}$$

Where $c(k)$ is the coefficients with in a local window and $(g)_f = \begin{cases} 0, & \text{if } g \leq 0 \\ g, & \text{otherwise} \end{cases}$.

The noisy wavelet coefficient is restored by using an approximate minimum mean square error estimator given by

$$\hat{w}_k = \frac{\hat{\sigma}_k^2}{\hat{\sigma}_k^2 + \sigma_n^2}\, y_k \tag{3}$$

III. IMPLEMENTATION METHODOLOGY

In the proposed method image is contaminated with white Gaussian noise. Pre-filter process is done by taking forward DWT which results in four sub bands. Here decomposition level is six and for each sub band the wavelet coefficient and corresponding parent matrix is found. Then the threshold value is determined by estimating the noise variance and signal variance. The noise variance is calculated using robust median estimator and signal variance by using the neighbor coefficient in a rectangular region with window size 7×7. Finally the wavelet coefficients are estimated by using the noisy coefficient, its parent and the estimated threshold value using LAWML shrinkage function. The experimental result shows that the proposed method is better than other existing techniques.

IV. RESULTS AND DISCUSSION

In this section the performance of the proposed method is evaluated using PSNR which is defined as

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{255^2}{\mathrm{MSE}}\right) \tag{4}$$

Where MSE is the mean square error given as

$$\mathrm{MSE} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \tag{5}$$

Here $I(i,j)$ is the original image, $K(i,j)$ is the denoised image and m, n are the number of rows and columns of the image.

The proposed approach is tested on 8-bit Lena image of size 512×512 which is contaminated with white Gaussian noise at four different variances. The result is compared with two different existing methods. From table 1 it is clear that the PSNR measure of the proposed method is higher than other denoising techniques.

Table I summarizes the results obtained for Lena image. Analyzing the result it is clear that the proposed method outperforms the existing methods approximately by +0.8dB of average gain for hybrid neighborhood Filter [7] at noise percentage 30.The noisy image for different noise power levels and its denoised image are shown in Fig. 1 and Fig. 2.

TABLE I

COMPARISON OF LENA IMAGE WITH PSNR VALUES OF DIFFERENT DENOISING METHODS

σ	**10**	**20**	**30**
Hybrid Neighborhood Filter [7]	33.66	29.95	27.91
Proposed method	34.35	30.78	28.71

Fig 1. Noisy images of Lena for noise levels σ = [10, 20, 30]

Fig 2. Denoised images of Lena for noise levels σ = [10, 20, 30]

V. Conclusion

The proposed method investigates the performance of locally adaptive window based on maximum likelihood in wavelet domain for image denoising. The proposed method is compared with other denoising methods in order to illustrate the effectiveness of the proposed technique. The comparison suggests that the proposed method is better than other state-of-art methods in terms of PSNR.

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