

# Adaptive Wavelet Thresholding & Joint Bilateral Filtering for Image Denoising

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**Abstract**—This paper proposes an efficient algorithm for removing noise from corrupted images by incorporating a wavelet based thresholding with a spatial based joint bilateral filter. Although wavelet-based methods are efficient in image denoising, they are prone to producing low-frequency noise and edge ringing which relate to the structure of the underlying wavelet. On the other hand, most spatial-based algorithms output much higher quality denoising image with less artifacts. However, they are usually too computationally demanding. In order to reduce the computational cost, an efficient joint bilateral filter by using the wavelet denoising result rather than directly processing the noisy image in the spatial domain is developed. The joint bilateral filtering is applied to the approximation (low-frequency) subband of wavelet decomposed image using a wavelet filter bank and wavelet thresholding method is applied to the detailed subbands. The proposed method for image denoising is demonstrated on a number of standard images and the performances are evaluated in terms of peak signal to noise ratio.

**Index terms** - Image Denoising, Bilateral Filter, Joint Bilateral Filter, Spatial domain, Wavelet Domain.

## I. INTRODUCTION

Due to poor image acquisition or by transferring the image data through noisy communication channels, images are often corrupted by noise, which can be modeled as Gaussian in most of the cases. The main aim of an image denoising algorithm is thereby to reduce the noise level, while preserve the image features.

In the past few years, various methods for denoising have been introduced. There are two basic approaches to image denoising, one is spatial filtering method and other one is transform domain filtering method. Spatial filters employ a low pass filtering on a group of pixels with the assumption that the noise occupies the higher region of frequency spectrum.

The wavelet shrinkage method is a nonlinear image denoising method to eliminate noise by shrinking the empirical wavelet coefficients in the wavelet domain. In recent years there has been a fair amount of researches on wavelet thresholding and threshold selection. The motivation is that the wavelet transform is good at energy compaction. The small coefficient are more likely due to noise and the large coefficients due to important signal features. The small coefficients can be thresholded without affecting the significant features of the image.

In wavelet domain, we can have different denoising methods by considering different shrinkage functions, noise estimates and shrinkage rules. One of the most well-known shrinkage function is soft thresholding analyzed by Donoho [1]. The

shrinkage rule determines the threshold. Various threshold selection methods have been proposed, such as, VisuShrink [2], SureShrink [3], Baye's Shrink [4] and NormalShrink [5]. VisuShrink is a thresholding by applying the Universal threshold [6], which is a function of the noise variance and the number of samples. The threshold value in the SureShrink approach is optimal one in terms of the Stein's unbiased risk estimator. The Baye's Shrink approach determines the threshold value by applying Bayesian rule, through modeling the distribution of the wavelet coefficients as Gaussian. The threshold value in NormalShrink is computed by  $\beta\sigma^2/\sigma_y$  where  $\sigma$  and  $\sigma_y$  are the standard deviation of the noise and the subband data of noisy image respectively.  $\beta$  is the scale parameter, which depends upon the subband size and number of decompositions. These shrinkage methods have been further improved with the help of interscale and intrascale correlations of the wavelet coefficients [7], [8], [9] and [10].

Bilateral filtering is a spatial domain based denoising method proposed in [11]. It is a non iterative scheme for edge preserving smoothing that is noniterative and simple. Bilateral filtering smooths images while preserving edges, by means of a nonlinear combination of nearby pixel values.

In Multiresolution Bilateral Filtering for Image Denoising [12], the bilateral filter is combined with wavelet thresholding to provide an image denoising framework, which helps in removing noise in real noisy images. But in this proposed work, the Joint Bilateral Filter [13] is combined with wavelet thresholding to get an improved peak-signal-to-noise ratio (PSNR). The experimental results prove that the proposed method eliminates the noise significantly while preserving the image details as compared to other spatial domain methods adopted.

## II. FILTERING IN WAVELET DOMAIN

### A. Wavelet Thresholding

Let  $\mathbf{f}$  be the  $M \times M$  matrix of the original image to be recovered. During the transmission  $\mathbf{f}$  is corrupted by independent and identically distributed zero mean, white gaussian noise  $n_{ij}$  with standard deviation  $\sigma$  and at the receiver end, the noisy observations  $g_{ij} = f_{ij} + \sigma n_{ij}$  is obtained. The goal is to estimate the signal  $\mathbf{f}$  from noisy observations  $g_{ij}$  such that Mean Squared error (MSE) is minimum. Let  $W$  and  $W^{-1}$  denote the two dimensional orthogonal discrete wavelet transform (DWT) matrix and its inverse respectively. Then  $Y = Wg$  represents the matrix of wavelet coefficients of  $g$  having four subbands (LL, LH, HL and HH). Let  $J$  be the

total number of decompositions. The size of the subband at scale  $k$  is  $N/2^k \times N/2^k$ . The subband  $LL_J$  is the low-resolution residue. The wavelet thresholding denoising method processes each coefficient of  $Y$  from the detail subbands with a soft threshold function to obtain  $\hat{X}$ . The denoised estimate is inverse transformed to  $\hat{f} = W^{-1}\hat{X}$ .

### B. Parameter Estimation for NormalShrink

Though there are many methods to estimate threshold, the NormalShrink method is used here since it gives the best PSNR among the wavelet thresholding methods. This section describes the method for computing the various parameter used to calculate the threshold value.

The subband adaptive threshold is

$$T_N = \frac{\beta \hat{\sigma}^2}{\hat{\sigma}_y} \quad (1)$$

Where, the scale parameter  $\beta$  is computed once for each scale using the following equation:

$$\beta = \sqrt{\log \frac{L_k}{J}} \quad (2)$$

$L_k$  is the length of the subband at  $k^{th}$  scale.  $\hat{\sigma}^2$  is the noise variance, which is estimated from the subband HH1:

$$\hat{\sigma}^2 = \left[ \frac{\text{median}(|Y_{ij}|)}{0.6745} \right]^2 \quad (3)$$

and  $\hat{\sigma}_y$  is the standard deviation of the subband under consideration.

The NormalShrink thresholding technique performs soft thresholding with adaptive, data driven, sub band and level dependent threshold  $T_N$ .

## III. FILTERING IN SPATIAL DOMAIN

### A. Bilateral Filtering

The bilateral filter [11] is a image smoothening filter. It takes a weighted averaging of the pixels in a local neighborhood; the weight depends on both the spatial distance and the intensity distance. It is suitable for strong smoothening in computational photography. By this way, the edges are kept in perfect while noise is eliminated. It is conceptually simple. It applies spatial weighted averaging without smoothing edges. The bilateral filter is a robust filter because of its range weight, pixels with different intensities. It averages local small details and ignores outliers.

Mathematically, at a particular pixel location  $v$ , the joint bilateral filter output is calculated as follows,

$$G'(v) = \frac{\sum_{p \in N(v)} \exp \left( -\frac{\|v-p\|^2}{2\sigma_c^2} \right) \exp \left( -\frac{|F(v)-F(p)|}{2\sigma_s^2} \right) G(p)}{\sum_{p \in N(v)} \exp \left( -\frac{\|v-p\|^2}{2\sigma_c^2} \right) \exp \left( -\frac{|F(v)-F(p)|}{2\sigma_s^2} \right)} \quad (4)$$

Here  $\sigma_c$  and  $\sigma_s$ , are parameters which controls the fall-off of the weights in spatial and intensity domains.  $N(v)$  is a spatial neighborhood of  $v$ .

The main drawback in bilateral filter is its incapacity in eliminating salt-and-pepper noise. The second drawback of the bilateral filter is that it produces staircase effect and it is also single resolution in nature.

### B. Joint Bilateral Filter

The major problem of the bilateral filter in image denoising is that the computation of the edge stopping function. It could not be estimated accurately based on the noisy image. In JBF, the basic bilateral filter is modified to compute the edge stopping function using the original image. In the joint bilateral filter, the parameters,  $\sigma_s$  and  $\sigma_c$  vary with respect to the reference image quality and the noise level. If noise level is so low that the reference image is very close to the

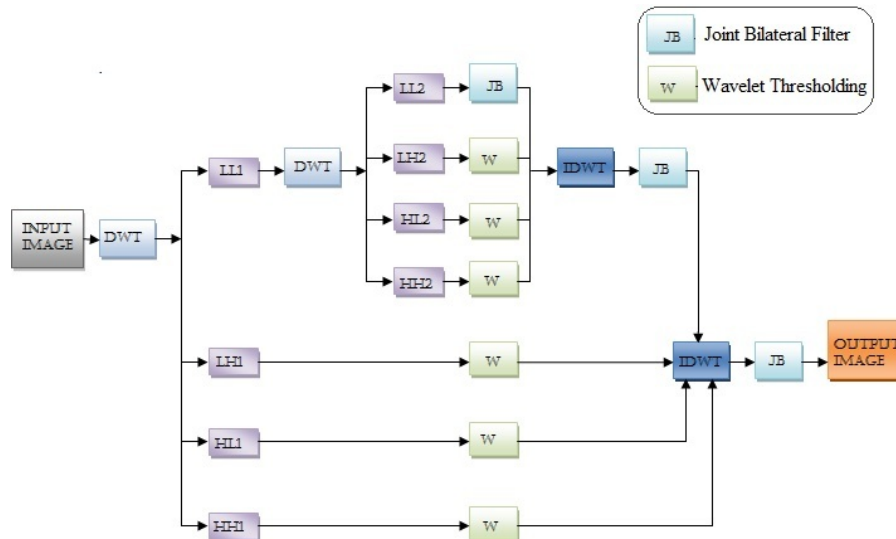


Fig. 1. Illustration of the proposed method

original image, then this could be a good choice. The main difference between bilateral filter and joint bilateral filter is the use of original image as reference image, in order to calculate the edge-stopping function. This provides a better result than bilateral filter.

Mathematically, at a particular pixel location  $v$ , the joint bilateral filter output is calculated as follows,

$$G'(v) = \frac{\sum_{p \in N(v)} \exp \left( -\frac{\|v-p\|^2}{2\sigma_c^2} \right) \exp \left( -\frac{|F(v)-F(p)|}{2\sigma_s^2} \right) G(p)}{\sum_{p \in N(v)} \exp \left( -\frac{\|v-p\|^2}{2\sigma_c^2} \right) \exp \left( -\frac{|G(v)-G(p)|}{2\sigma_s^2} \right)} \quad (5)$$

Here  $G$  represents the original image.

#### IV. PROPOSED METHOD

The input image subjected to 2 level DWT decomposition and it results in  $LL_2$  (approximation),  $LH_2$ ,  $HL_2$ ,  $HH_2$ ,  $LH_1$ ,  $HL_1$  and  $HH_1$  (detail) subbands. Then all detail sub bands are wavelet thresholded while JBF is applied on  $LL_2$ . The inverse wavelet transformed images is again subjected to joint bilateral filtering to get the output image. The block diagram of the proposed method is shown in figure 1.

The performance of the proposed image denoising algorithm and the reconstructed image quality are measured using Mean Squared Error (MSE) and Peak Signal to Noise Ratio (PSNR), given in equations 6 and 7 respectively.

$$MSE = \frac{1}{MN} \sum_{m=1}^M \sum_{n=1}^N (x(m,n) - \hat{x}(m,n))^2 \quad (6)$$

$$PSNR = 10 \log \frac{255^2}{MSE} \quad (7)$$

where  $x(m,n)$  denotes the sample of original image and  $\hat{x}(m,n)$  denotes the sample of distorted image. M and N are number of pixels in row and column directions respectively.

#### V. EXPERIMENTAL RESULTS AND DISCUSSIONS

The experiments are conducted on several natural gray scale test images like Lena, Barbara, Goldhill of size  $512 \times 512$  at different noise levels  $\sigma = 10, 20, 30$  and  $40$ . The wavelet transform employs Daubechies least asymmetric compactly supported wavelet with eight vanishing moments. To assess the performance of the proposed work, it is compared with NormalShrink, Multiresolution Bilateral Filtering for Image Denoising and Wiener.

The PSNR from various methods are compared in Table I. The proposed method outperforms NormalShrink and MRBF most of the time in terms of PSNR as well as in terms of visual quality. Moreover it is faster than MRBF. Comparisons are also made with the best possible linear filtering technique i.e. *Wiener filter* (from the MATLAB image processing toolbox, using  $3 \times 3$  local window). Figure 2 shows the original image, noisy image and resulting images of *Wiener filter*, MRBF NormalShrink and the proposed method for Lena at  $\sigma = 30$ .

#### VI. CONCLUSION

An image denoising framework, which integrates joint bilateral filtering and wavelet thresholding is presented in this paper. The vital factor that determines performance of the proposed method is the application of JBF on multiresolution subbands. It aids the elimination of the coarse-grain noise present in the images. The wavelet thresholding is a definite advantage to the proposed method as it efficiently eliminates the noise components in detail subbands.

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TABLE I  
PSNR RESULT FOR VARIOUS TEST IMAGES AND  $\sigma$  VALUES

	Noisy image	Normal	Proposed Method	MRBF	Wiener
<b>Lena</b>					
$\sigma = 10$	28.13	33.54	34.42	33.61	33.57
$\sigma = 20$	22.12	30.35	32.41	30.70	28.98
$\sigma = 30$	18.62	28.53	30.07	29.12	25.62
$\sigma = 40$	16.14	26.89	29.10	27.81	23.94
<b>Barbara</b>					
$\sigma = 10$	28.13	31.37	32.11	31.50	29.82
$\sigma = 20$	22.12	27.33	28.98	27.42	26.79
$\sigma = 30$	18.62	25.23	26.93	25.51	24.29
$\sigma = 40$	16.14	23.54	25.82	24.33	23.11
<b>Goldhill</b>					
$\sigma = 10$	28.13	31.71	33.13	32	31.81
$\sigma = 20$	22.12	28.66	31.80	28.91	28.26
$\sigma = 30$	18.62	27.09	29.11	27.54	25.35
$\sigma = 40$	16.14	26.11	28.73	26.52	24.05



Fig. 2. Comparing performances of various methods on lena with  $\sigma = 20$  (a) Original Image (b) Noisy image (c) Wiener Filter (d) MRBF (e) NormalShrink (f) Proposed Method

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