Scientific Journal of Impact Factor (SJIF): 4.72
e-ISSN (O): 2348-4470
p-ISSN (P): 2348-6406

International Journal of Advance Engineering and Research Development

Volume 4, Issue 10, October -2017

Weighted Hybrid Wavelet Wiener Filter for Gaussian Noise Removal

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Abstract — *A novel technique capable of removing Gaussian noise with less computational complexity has been presented. This paper proposes a hybrid filter which employs Wavelet Transforms, a very powerful multiresolution tool, employing modified Bayes thresholding, in conjunction with the Wiener Filter. The Wiener filter tries to build an optimal estimate of the original image by enforcing a minimum mean-square error constraint between estimate and original image. In the first step, Discrete Wavelet transform is applied to the given image, using modified Bayes thresholding for better performance. This is followed by application of Wiener Filter to the output obtained in the previous stage. The proposed algorithm is tested on a number of benchmark images and is found to produce better results in terms of the qualitative and quantitative measures of the image for both low and high values of noise variance in comparison to many existing techniques. The proposed technique removes Gaussian noise and the edges are better preserved with less computational complexity and this aspect makes it easy to implement in hardware.*

Keywords- *Gaussian noise, Denoising, Wiener filter, Wavelets, Bayes-Shrink, Noise variation, PSNR*

I. INTRODUCTION

Noise is any undesired signal that contaminates an image and is the consequent of errors in the image acquisition process that result in pixel values not displaying the true picture. During acquisition, transmission and retrieval, images are vulnerable to get contaminated with a wide variety of noises, the prominent being the impulse noise, additive noise and the multiplicative noise. The main objective of image processing is to extract the true information from the images corrupted by such noises. Such techniques for removal of noise is known as noise filtering or denoising. For images contaminated by additive noise, a particular value from a certain distribution viz. Gaussian Probability Distribution is added to each image pixel. Such a noise is referred to as additive white Gaussian noise (AWGN).[1]-[3],[5]-[9]

A wide variety of linear and non-linear techniques have been proposed in the literature. This includes the Median filter[4], Arithmetic filter[4], Gaussian Filter[4], Wiener Filter[8],[17]-[19] and the Wavelet transform approach.[1]-[5] Conventional linear filters, such as arithmetic mean filter and Gaussian filter remove noise effectively but blur edges. The Wiener filter is the mean square error-optimal stationary linear filter for images degraded by additive noise and blurring. However a common drawback of the practical use of this method is the fact that they usually require some 'a priori' knowledge about the spectra of noise and the original signal. This information is necessary for optimal choice of parameter values and/or threshold selections. Unfortunately, such information is often not available in real time applications. Also Wiener filter experiences uniform filtering throughout the image, with no allowance for changes between low and high frequency regions, resulting in unacceptable blurring of fine detail across edges and inadequate filtering of noise in relatively flat areas. Since the goal of the filtering action is to cancel noise while preserving the integrity of edge and detail information, nonlinear approaches generally provide more satisfactory results than linear techniques.

A number of techniques using wavelet-based thresholding have been proposed recently by researchers. Wavelet transform[10]-[19], because of its signal representation with a high degree of sparseness and its excellent localization property, has rapidly become an indispensable image processing tool for a variety of applications, including denoising. A well known wavelet thresholding algorithm, named WaveShrink, was introduced by Donoho [14] in 1995 as a powerful tool for denoising signals degraded by additive white noise. Wave-shrink is based on the fact that for many of real-life signals, a limited number of wavelet coefficients in the lower subbands are sufficient to reconstruct the original signal. Usually, the numerical values of these coefficients are relatively large as compared to noise coefficients. Therefore, by eliminating (shrinking) coefficients that are smaller than a specific value, called threshold, the noise can be nearly eliminated, while preserving the coefficients necessary to keep important attributes of the original image such as edges. Thus, choosing threshold values is extremely important. In the literature, various techniques for adaptive selection of threshold values, and new thresholding methods including fuzzy logic[20], neural networks, and wavelet packet[21] based using Wiener filter are reported.

In this paper, a hybrid Wavelet-Wiener filter has been applied for reducing noise in digital images corrupted by Gaussian noise. The properties of both Wiener Filter and Wavelet transforms are exploited to bring out optimum performance.

The rest of the paper is arranged as follows. The proposed methodology is described in section II while the simulation results are presented in section III. The paper ends with a conclusion in section IV.

II. PROPOSED METHODOLOGY

This is a hybrid method employing the Wavelet and the Wiener filters. The Wavelet filter employs the Modified Bayes Thresholding technique as discussed below:

The modified BayesShrink, uses soft thresholding and is subband dependent, which means that thresholding is done at each band of resolution in the wavelet decomposition. The modified Bayes threshold (T_B) is smoothness adaptive and is given by:

$$T_B = \beta \frac{\sigma_n^2}{\sigma_s^2} \tag{1}$$

where σ_n^2 is the noise variance and σ_s^2 is the signal variance without noise. In the conventional Bayes threshold expression, $\beta = 1$. Here value of β is adaptive to different subband characteristics and is given in eq.(2) as

$$\beta = log \frac{L}{k} \tag{2}$$

where L is the number of wavelet decomposition level and k is the level at which subband is available.

The noise variance needs to be estimated first. In some situations, it may be possible to measure σ_n^2 based on information other than the corrupted image. If such is not the case, it is estimated from the subband HH_1 (fig. 1) by the robust mean estimator shown in eq.(3) below:

$$\sigma_n = \frac{Median(|Y_{ij}|)}{0.6745}, \quad Y_{ij} \in \text{ subband } HH_1 \tag{3}$$

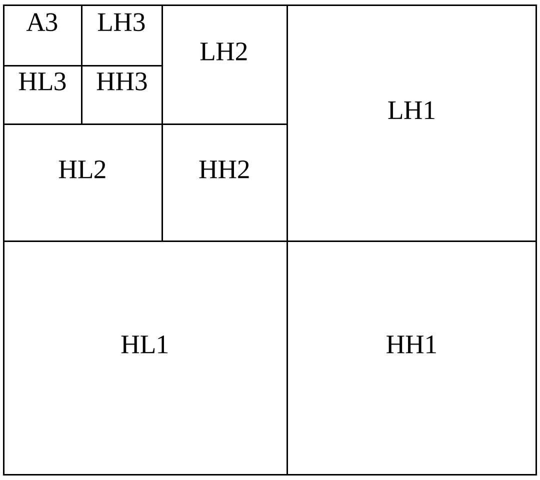

Fig. 1 Three levels of Wavelet decomposition

From the definition of additive noise,

$$X(i,j) = f(i, j) + n(i, j) \tag{4}$$

where $X(i,j)$ is the (noise) corrupted image, f(i, j) is the original signal and n(i, j) is the noise. Since the noise and signal are independent of each other, it can be stated that

$$\sigma_x^2 = \sigma_f^2 + \sigma_n^2 \tag{5}$$

Now σ^2_X can be computed as follows:

$$\sigma_x^2 = \frac{1}{n^2} \sum_{i,j=1}^{n} X^2(i,j) \tag{6}$$

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

$$\sigma_f^2 = \max(\sigma_X^2 - \sigma_n^2, 0) \tag{7}$$

In the trivial case, the value of σ_f^2 may be zero, making the value of threshold T_B to be infinite. In this case, all the coefficients are set to zero. With σ^2_f and σ_n^2, the Bayes threshold is computed using eq. (1). Using this expression of threshold, the wavelet coefficients are thresholded at each subband.

The procedure for reducing Gaussian noise using the hybrid technique is divided into three stages:

Stage 1 a)Decomposition of the corrupted image with db8 wavelet at level 4 so as to get detail and approximate sub-band.

b) Application of the modified Bayes threshold (as calculated by using eq. 1) to each of the detail subbands.

c) Application of the inverse wavelet transform to the output of stage 1(a) to obtain the denoised output, d_1.

d) Calculation of PSNR, h_1, of the denoised image.

Stage 2: Application of the Wiener filter to the original image to obtain the denoised image, d_2. Also obtain the PSNR, h_2, of the denoised image, d_2.

Stage 3: Calculation of the weighted average of the outputs of stage 1 and 2 using eq. 8 to obtain the final denoised image, d_3.

$$d_3 = [h_1/(h_1+h_2)] * d_1 + [h_2/(h_1+h_2)] * d_2) \tag{8}$$

III. EXPERIMENTAL RESULTS

Table 1 enlists the restoration result in PSNR (dB) of the proposed technique for 512 x 512 grayscale image 'Lena' corrupted by Gaussian noise of various noise levels. Fig. 2 and 3 show the restoration results of the various filters graphically and quantitatively.

TABLE 1
Comparison of Restoration Results of Proposed technique in terms of PSNR(dB) for image 'Lena'

Noise (σ)→ / Filtering technique↓	5	10	15	20	25	30	35	40	45	50
INPUT PSNR	34.13	28.13	24.61	22.12	20.20	18.70	17.41	16.36	15.42	14.60
AWMDF (3x3)	34.88	32.58	30.44	28.58	27.01	25.67	24.52	23.49	22.53	21.65
AWMF (3x3)	34.03	32.80	31.33	29.85	28.52	27.25	26.22	25.23	24.39	23.59
AVERAGE FILTER	35.9	31.3	28.1	25.5	23.64	22.5	21.43	20.2	19.73	18.4
VISUSHRINK [14]	34.3	28.2	24.6	22.1	20.67	18.7	17.34	16.4	15.73	14.6
SURESHRINK [22]	25.1	25.1	25.1	25.1	25.1	25.0	24.9	24.8	24.7	24.6
Proposed technique (WHWWF)	38.31	34.61	32.33	30.76	29.53	28.49	27.58	26.94	26.22	25.63

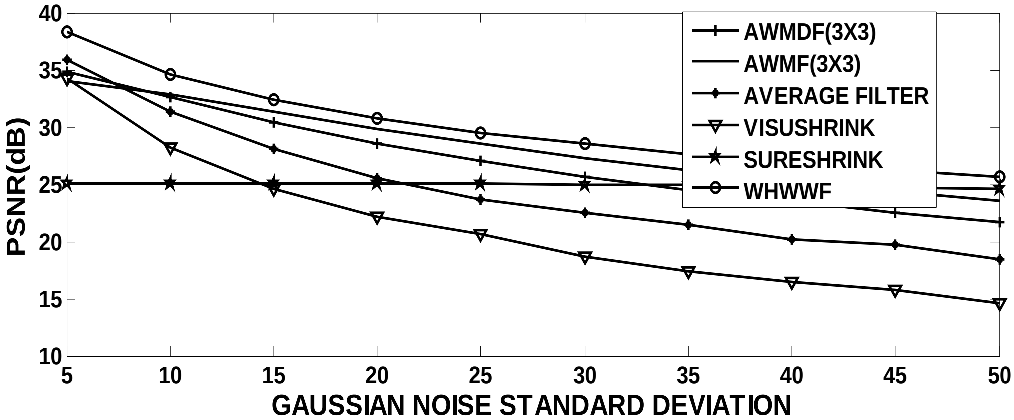

Fig. 2. Restoration Results for 'Lena' Image

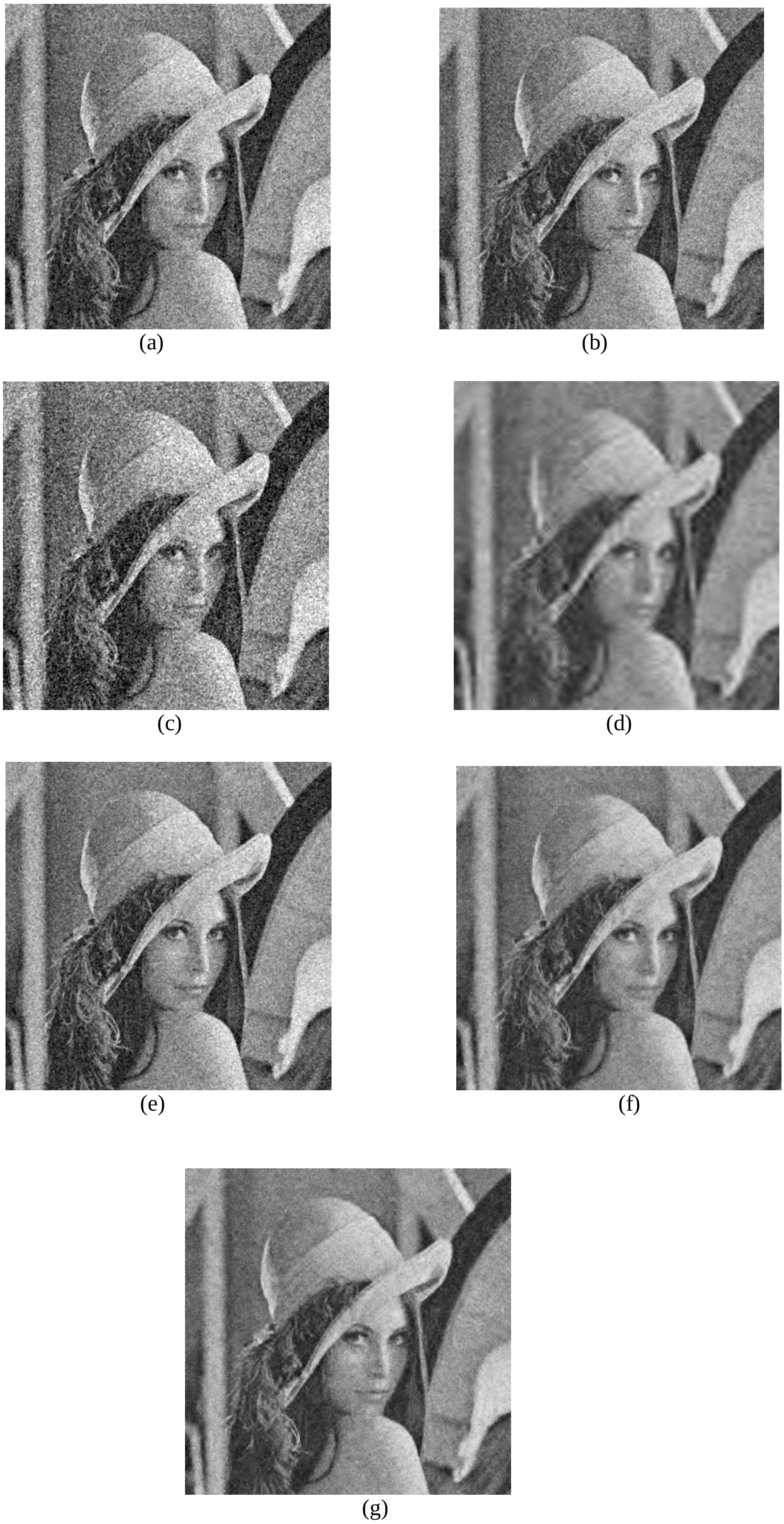

Fig. 3 Restoration Results for σ=50 for Various Methods (a) AWMDF(3X3) (b) AWMF(3X3) (c) Wiener Filter (d) Average Filter (e) VisuShrink (f) SureShrink (g) Proposed technique

Table 1 lists the restoration result in PSNR (dB) of the hybrid median method for 512x512 grayscale image 'Lena' corrupted by Gaussian noise of various noise levels. The graphical and qualitative results have been presented in Fig. 1 and 2 respectively.

The simulation results demonstrate that the Hybrid Wavelet Wiener Filter performs better than the Adaptive Window Median Filter (AWMDF), Adaptive Window Mean Filter (AWMF), Wiener, Average, VisuShrink and SureShrink at all noise levels.

IV. CONCLUSION

This paper proposes a hybrid filter technique that exploits the properties of both the Wavelets and the Wiener filter. The weighted average of the outputs of both the filters is used to obtain the final denoised image. The simulations results obtained both quantitatively and qualitatively are quite satisfactory and outperform those obtained by other standard filters at all values of noise variation from 5 to 50.

The future work may focus on further improving the PSNR values and reducing the processing time.

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