Performance Analysis of Adaptive Image Denoising Techniques for Different Levels of Wavelet Decomposition using Orthogonal and Compactly Supported Wavelet Families

Ram Paul, Singara Singh Kasana, Rajesh Kumar Gupta

Abstract— **This paper presents performance analysis of image denoising techniques using different orthogonal and compactly supported wavelets functions of various vanishing moments. The wavelet-based methods such as universal thresholding, level-adaptive and subband-adaptive thresholding are compared with the state-of-the-art Wiener filtering. The wavelet coefficients are modeled by the generalized Gaussian distribution random variables within the subbands. A minimal threshold is calculated from the noise standard deviation of the diagonal subband of the first decomposition level. Then the soft thresholding scheme is applied. The procedure of noise reduction is applied with Daubechies, Symlets and Coiflets wavelet functions of different vanishing moment upto forth decomposition levels. Then the efficiency and performance of these image denoising techniques are compared based on their Peak Signal to Noise Ratios and visual perception. The wavelet domain thresholding is evaluated and examines some improvements for different image complexities contaminated by Gaussian noise of various densities.**

Index Terms— **Subband-adaptive Thresholding, Level-adaptive Thresholding, Wiener Filtering, Image Denoising and PSNR**

I. INTRODUCTION

A natural image encounters the additive white Gaussian noise (AWGN) during image acquisition and its transmission due to faulty equipments [1]. Image denoising is the noise reduction procedure which is used to recover the image contaminated from AWGN while retaining the image sharpness and smoothness as much as possible. The objective of an image denoising technique is to reduce the noise while preserving the original image features and other fine details [1-6]. An efficient image denoising technique is still a challenge to the researchers due to the different complexities of the images [7-9].

An image filter can be used to reduce the different type of noises from an image to visualize it noise free and real. An image denoising techniques through filtering are categorized into linear filtering and non-linear filtering [2] in frequency domain and in transform domain. These both type of filtering can be achieved in frequency domain and transform domain [1]. Frequency domain techniques generate the undesired structures in the image such as blurs, artefacts and Gibb's phenomenon [3, 6]. So they are replaced by transform domain techniques which denoise the image with preserving its features and avoid the generation of undesired elements which degrade the image quality.

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In the literature, image processing has developed powerful wavelet based methods for the multiscale representation and analysis of images [6-12]. Discrete wavelet transform (DWT) is capable of localize the information in the time-frequency plane and differ from the frequency based discrete transform techniques [6]. The independent identically distributed (i.i.d.) random variables with generalized Gaussian distribution (GGD) models the wavelet coefficients within the subbands [18]. In wavelet based denoising, DWT on the noisy image is applied to find the wavelet coefficient subbands [10]. Let W denotes the 2-D DWT and W^{-1} denotes its inverse respectively and is given as:

$$X = Wx \qquad and \qquad x = W^{-1}X \tag{1}$$

In wavelet based denoising, DWT on the noisy image is applied to find the wavelet coefficient subbands. DWT based linear denoising techniques may be achieved by applying Wiener filtering scheme [7, 12]. The objective and subjective results of the linear filters are not satisfactory. These filters blur the sharp edges of an image and destroy other finer details. The non-linear filtering is used to avoid these problems which are popular in the images denoising in wavelet domain [22]. In these techniques, the noise standard deviation is calculated from the diagonal detail subband coefficients HH_1 of first decomposition level as given below:

$$\hat{\sigma}_{noise} = \frac{median(|HH_1|)}{0.6745} \tag{2}$$

Then the noise variance is estimated for each subband and level using this calculated standard deviation of the noise and optimal threshold value is calculated. This computed threshold is used through soft thresholding to the noisy wavelet coefficients of detail subbands for desired decomposition levels to reduce the noise while preserve the image features. The experimental results confirm that denoised images are preserving more detail information and with less blurring [20].

The work in this paper is organized as follows. In Section I, basic about image denoising and the application of DWT in the image denoising are explained. Section II provides brief review of the wavelet-based image denoising technique with block diagram. Section III provides brief review of the

Wiener filtering and the wavelet coefficients thresholding schemes used and their structures. Section IV explains the performance parameters like mean square error (MSE) and Peak Signal to Noise Ratios (PSNR). The experimental results analysis of the image with three samples of noise variance (low, medium and high) for each technique is reviewed in Section V and it also provides the comparison of PSNR values of denoised image using different wavelet types and versions for each method in the Table I. In Section VI, all the conclusions from the work are given and Section VII is closed with future scope.

II. DWT IN IMAGE DENOISING

The image denoising reduces the noise while preserving the fine details of an image. DWTs are popular from the work of Donoho and Johnstone [2]. They proposed a simple nonlinear estimator by thresholding the wavelet coefficients that were nearly minimax in a large family of functional spaces. This approach is the basically used for developing the various methodologies in wavelet domain.

The following three steps are required for DWT based image denoising scheme:

- Computation of the DWT of the noisy image after finalizing the followings:
  - Choice of a wavelet types (e.g. Daubechies, symlets, coiflets etc) and
  - Number of decomposition levels.
- Wavelet coefficient thresholding by:
  - Estimation of standard deviation of noise from the first level diagonal subband.
  - Shrinkage rule i.e. threshold calculation using the estimated variance.
  - Shrinkage function i.e. apply the calculated threshold to the detail coefficients. This can be accomplished by *hard* or *soft* thresholding.

Apply the inverse DWT for the thresholded coefficients.

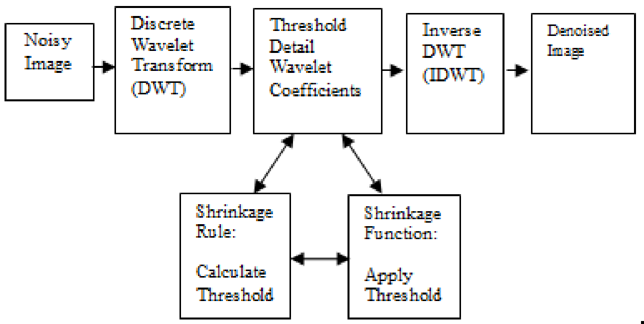


Fig. 1. Block diagram of Wavelet-based Image Denoising Method

A. *Step I: DWT of Noisy Image*

The localization property of wavelets in space and scale makes them suitable for adaptive methods [4, 6]. The DWT decomposes the noisy images into sub-image of different spatial domain and independent frequency domain. DWT separate image signal and noise signal in the wavelet domain effectively using the scarcity property.

DWT maps AWGN of the image into the white noise in the transform domain [6, 10]. Before computation of the DWT of the noisy image, one must finalize the type of the selected wavelet and level of decomposition. There is no universal wavelet basis which suites all types of the image complex structures [5]. The wavelet function may not necessarily be best adapted to an underlying image complexity. When an image includes more complex structures with fine details, it becomes necessary to adaptively select an appropriate *best basis* which provides the best image estimate upon thresholding the noisy coefficients [5]. The efficiency of a basis to handle the complex structures of the image is according to the symmetry and regularity of the wavelet [16]. These properties are well fulfilled by orthogonal and compactly supported wavelets like Daubechies, Symlets and Coiflets families. A search of best basis in the wavelet families is analysed in this paper.

In DWT, a noisy image can be decomposed into a sequence of four frequency subbands namely, LL_1, LH_1, HL_1 and HH_1 as shown in Figure 2 (a). The decomposed image shows a coarse approximation image in the lowest resolution low pass band (LL_1), and three detail images in higher bands (LH_1, HL_1 and HH_1) [15. 17]. The next level of wavelet transform is applied to the low frequency subband image LL_1 only and it can be further decomposed into four subbands namely LL_2, LH_2, HL_2, and HH_2 as shown in Figure 2 (b). The process of decomposition continues until the desired number of levels determined by the application is reached [2].

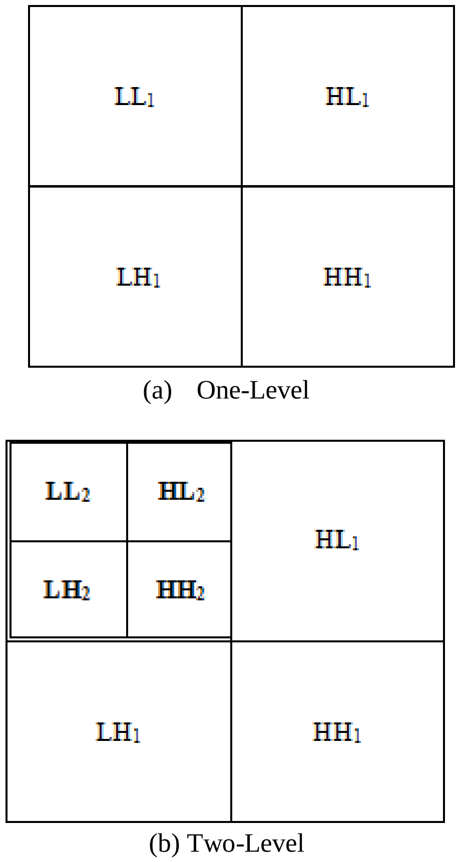


Fig. 2: 2D-DWT decomposition

This process is continued upto fourth decomposition level [17]. After this decomposition level, the wavelet coefficients become smoother. As the subband HL_2 is smoother than HL_1, so the threshold value of HL_2 should be smaller than that of HL_1. The magnitude of the wavelet coefficient varies depending on the decomposition level. Only severer noise remains after forth decomposition level.

B. Step II: DWT Coefficients Thresholding

After the wavelet decomposition is performed on the noisy image, it is needed to do thresholding. The wavelet coefficients thresholding has two parameters: shrinkage rule and shrinkage function. The shrinkage rule is how to calculate the threshold and shrinkage function is how to apply the calculated threshold. Researchers published different schemes for the threshold estimation and its application.

i). Shrinkage Rule i.e. Threshold Selection

The selection of a suitable threshold value is the challenging issue of a wavelet-based image denoising methodology [13]. The noisy coefficients are retained by selecting small threshold value and the fine details of images are smoothened by large threshold. The threshold value may be adaptive and non-adaptive approach across the wavelet scales and locations. The non-adaptive approach reveals a universal threshold proposed by Donoho and Johnstone [2] and an adaptive approach can give a level or subband adaptive threshold. This threshold value is estimated by using the noise standard deviation, as given in equation (2) above.

The spatial configuration of wavelet coefficients can classify the noise-signal differentiation for higher noise [15, 21]. The threshold must be estimated adaptively based on scale and space of wavelet coefficients to preserve the important features of the image. An adaptive threshold is computed by fixing the optimum noise standard deviation depending on the decomposition level and subbands. This threshold estimation scheme is called Bayesian estimator [14, 25] and used in this paper.

The unique threshold for all the wavelet coefficients is called universal threshold proposed by Donoho and Johnstone [2]. This threshold estimation criterion is called VisuShrink. The same threshold is applied to all levels of decomposition [6, 18]. The universal threshold is not capable to differentiate the smooth (flat) and non-smooth (feature-based) region of the image and is applicable only when noise level is low.

Under the high noise circumstance, the spatial configuration of wavelet coefficients can play an important role in noise-signal classifications [15, 19]. The threshold must be estimated adaptively based on scale and space of wavelet coefficients which is different for different level or subband. In this way, important features of the image may be preserved. An adaptive thresholding is also used by fixing the optimum thresholding value depending on the decomposition level. This threshold estimation scheme is called Bayesian estimator.

ii). Shrinkage Function i.e. Threshold Application

In the wavelet transform domain, the noise is uniformly spread throughout the coefficients, while most of the image information is concentrated in few significant coefficients [15]. Therefore, one straightforward way of distinguishing information from noise in the wavelet domain is to threshold the wavelet coefficients. The application of threshold to the wavelet transformed coefficients is known as thresholding [1, 16]. Two types of thresholding scheme used literature are: hard thresholding (3) and, soft thresholding (4).

The hard thresholding is a keep or kill procedure. It removes the small wavelet coefficients while others are left untouched. But this method causes artifacts in the images as a result of unsuccessful attempts of removing moderately large noise coefficients. To overcome the demerits of hard thresholding, *soft thresholding* based on DWT is used. In this scheme, the wavelet coefficients smaller than the threshold are removed while larger coefficients are shrunk by the absolute value of the threshold itself.

$$T_{hard}(w)=\begin{cases} w, & if\,|w|>\lambda \\ 0, & if\,|w|\le\lambda \end{cases} \tag{3}$$

$$T_{soft}(w)=\begin{cases} sign(w)(|w|-\lambda), & if\,|w|>\lambda \\ 0, & if\,|w|\le\lambda \end{cases} \tag{4}$$

The application of hard thresholding over smoothen the images at discontinuity, due to which artifacts are reconstructed in denoised image. The soft thresholding scheme is used in this paper.

C. Step III: Inverse DWT of Thresholded Coefficients

After trimming down the small wavelet coefficients, i.e. after removing the noisy wavelet coefficients from all the detailed subband coefficients, image reconstruction is performed using the same wavelet function type and version as used at the time of decomposition of the image. The image reconstruction is the exact reverse process of wavelet decomposition [24] by finding the inverse DWT (IDWT). The additive low pass and high pass synthesis filters are used to sample the approximation and detail coefficients through the same number of decomposition levels as used in DWT.

III. ADAPTIVE IMAGE DENOISING METHODS

This section covers the details regarding the Wiener filtering, universal thresholding, subband-adaptive and level-adaptive techniques of image denoising along with their theory. All these techniques have different methods of computing the threshold value and are explained as follows.

A. Weiner Filtering

The Wiener filter reduced the AWGN [8] from a noisy image based on local statistics of each pixel. It performs little smoothing for large noise variance. When the noise variance is small, this filter performs more smoothing and reduces the sharpness of the image.

This filter produces better results for image denoising in the literature. Wiener filter is characterized by the following criteria:

Assumption: the given images and AWGN have known spectral characteristics which are stationary linear random processes.

Requirement: the filter must be causal *i.e.* physically realizable.

Performance criteria: The main performance parameter is the minimum mean-square error (MMSE).

Steps in Weiner Filtering:

i. A local window n *x* n of the noisy pixel is used to remove AWGN from the image.

ii. These equations are used to estimates local mean and local standard deviation.

$$\mu = \frac{1}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} f(i, j) \tag{5}$$

$$\sigma_{noise}^2 = \frac{1}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} f^2(i, j) - \mu^2 \tag{6}$$

iii. Finally apply Wiener filter for each pixel inside local window $n \times n$ to obtain denoised pixel.

iv. After this, new denoised pixel *D(i, j)* is found by shifting local window one step from left to right:

$$D(i, j) = \mu + \frac{\sigma^2 - \sigma_{noise}^2}{\sigma^2} \left(f(i, j) - \mu \right) \tag{7}$$

note: i, j = 3, 5, 7

B. Universal Thresholding Technique

In wavelet domain, the highest frequency subband HH_1 can contain a significant amount of noise, so this diagonal subband is used to estimate the threshold value by using noise standard deviation $\hat{\sigma}_{noise}$ as given equation (2) above. The universal threshold is calculated as follows:

$$\lambda_v = \hat{\sigma}_{noise} \sqrt{2 \log L} \tag{8}$$

where $L = M \times N$ is the image size. The processed image may be overly smoothened due to the larger threshold value so that sufficient image features are not preserved and the image gets blurred. So an adaptive thresholding is required for image features preservation.

C. Level-adaptive Thresholding Technique

Bayesian estimator uses a Bayesian mathematical framework in which wavelet coefficients in each detail subbands follow the GGD to minimize the Bayesian risk [10]. The level-dependent threshold is calculated using Bayesian estimator. The Bayesian threshold, T_B, is defined as:

$$T_B = \frac{\hat{\sigma}_{noise}^2}{\hat{\sigma}_{signal}} = \frac{\hat{\sigma}_{noise}^2}{\sqrt{\max\left(\hat{\sigma}_G^2 - \hat{\sigma}_{noise}^2, 0\right)}} \tag{9}$$

where $\hat{\sigma}_{noise}^2$ is the noise variance and $\hat{\sigma}_{signal}^2$ is the signal variance without noise.

$\hat{\sigma}_G^2 = \frac{1}{N_s} \sum_{x,y=1}^{N_s} G_{xy}^2$ where G_{xy} are the HH_1 wavelet coefficients.

The noise variance $\hat{\sigma}_{noise}^2$ is estimated from the subband HH_1 by the median estimator as,

$$\hat{\sigma}_{noise} = \frac{median(|HH_1|)}{0.6745} \tag{10}$$

The variance of the signal, $\hat{\sigma}_{signal}^2$ is computed as follows:

$$\hat{\sigma}_{signal}^2 = \sqrt{\left[\max\left(\hat{\sigma}_w^2 - \hat{\sigma}_{signal}^2\right)\right]} \tag{11}$$

with $\hat{\sigma}_w^2$ and $\hat{\sigma}_{signal}^2$ the Bayes threshold is computed.

The wavelet coefficients are thresholded using this threshold at each subband of a decomposition level. This is repeated for each decomposition level further.

D. Subband-adaptive Thresholding Technique

As the decomposition levels increased, the wavelet coefficients of the subband usually become smoother [17]. The higher subband HH_3 is smoother than the corresponding lower subband in the previous level (HH_2), so the threshold value of HH_3 should be lower to remove fewer coefficients than the one for HH_2.

A subband-adaptive threshold is calculated to characterize local features of the image. A separate threshold is calculated for each subband using equation (2) from different levels based on Bayesian estimator. A subband-dependent thresholding scheme is used to threshold the small wavelet coefficients (noisy) within that subband while preserving edges adaptively. The implementation steps are given as:

1. The images are loaded into the workspace by using MATLAB function.
2. This image is made corrupted with Gaussian noise using the MATLAB function.
3. The image obtained is subjected to a DWT using Daubechies, Symlets and Coiflets wavelet families. This function generates wavelet coefficients for the corrupted image.
4. There are four subbands namely, LL_1, LH_1, HL_1 and HH_1, where LL_1, corresponds to the approximation coefficients, while LH_1, HL_1 and HH_1 are the detail coefficients over which thresholding is done.
5. The standard deviation of the noise is calculated from the diagonal subband (HH_1) of the first decomposition level
6. The noise variance for each subband is computed to calculate the threshold value using Bayes estimator.
7. Soft thresholding of the wavelet coefficients is brought using the MATLAB function.
8. Inverse DWT using MATLAB function is done on the modified wavelet coefficients to get the denoised image.

IV. PERFORMANCE PARAMETERS

The above wavelet-based denoising algorithms namely universal thresholding, level-adaptive thresholding and subband-adaptive thresholding are applied on the image of size 256*x*256 at different Gaussian noise levels: (Standard Deviation) 10, 15, 20, 25, 30, 35, 40. Different orthogonal and compactly supported wavelets family functions are used namely db5, db8 of Daubechies, sym5, sym8 of Symlets and coif5 of Coiflets as the wavelet type and up to four decomposition levels are analysed for the noisy image.

The performance of these image denoising methods is evaluated by comparing their PSNR value for different noise densities [7, 17, 18] for each image. PSNR is given as the ratio of maximum power of original image and the power of the image's noise. It is commonly used by the researchers to measure the quality of reconstructed images objectively that have been denoised. The lower quality denoised images have lower PSNR values and a higher quality denoised images have higher PSNR values. PSNR values are expressed in decibels (dB) as the images can have a wide dynamic range [8]. It is calculated using the MSE for two $M \times N$ images $I(i, j)$ *and* $\hat{I}(i, j)$, where one of the images is considered a noisy approximation of the other. The *PSNR* is defined by:

$$PSNR = 10\log_{10} \frac{MAX^2}{MSE} dB \qquad (12)$$

where, MAX is equal to 255 when the pixels are represented using 8 bits per sample and MSE is given by:

$$MSE = \frac{1}{MxN} \sum_{i=1}^{I} \sum_{j=1}^{J} [I(i, j) - \hat{I}(i, j)]^2 \qquad (13)$$

V. Experimental Analysis of Denoised ImageS

Here four images of different complexities and format are considered namely *lena.bmp, parrot.png, cameraman.jpg* and *peppers.png*. The results are shown for low, medium and high noise densities for *lena.bmp* and *peppers.png* images with their PSNR values with considered orthogonal and compactly supported wavelets of different vanishing moments.

A. *Objective Evaluation*

All the techniques implemented are compared by finding the MSE and then PSNR in dB using wavelet types ‘db5’, ‘db8’, ‘sym5’, and ‘coif5’ as they are more suitable in image denoising. Following table I illustrates the comparison with Wiener filtering all considered wavelet domain thresholding, namely universal thresholding, subband-adaptive thresholding and level- adaptive thresholding on the basis of PSNR values for the images of different structure. Further, output PSNR have been compared and analyzed for these thresholding schemes at different noise standard deviation 10, 15, 20, 25, 35 and 40 respectively (low, medium and high), as shown ahead in Table 1. The used image denoising methods are better than those having lower PSNR values.

Table I: PSNR values for all techniques for ***lena*** image

Noise Standard Deviation, σ_n	Wiener Filter	Wavelet Type	Universal Thresholding	Level-adaptive Thresholding	Subband-adaptive Thresholding
10	30.6467	db5	31.6819	31.8672	33.4576
		db8	31.3055	31.7309	33.4603
		sym5	31.6078	29.1504	32.6858
		coif5	31.8612	30.6297	33.2818
15	29.5048	db5	29.3286	28.9038	30.9537
		db8	29.1524	29.6566	30.8734
		sym5	29.3153	28.3576	30.9003
		coif5	29.396	28.586	31.1713
20	28.3404	db5	27.933	27.7291	29.1669
		db8	27.7541	27.8073	29.251
		sym5	27.6329	26.5586	29.0956
		coif5	27.8345	27.7136	29.1346
25	27.3029	db5	26.733	25.3275	28.0613
		db8	26.6542	26.7604	28.2245
		sym5	26.4596	24.746	27.6593
		coif5	26.8965	25.6071	27.8043
30	26.4747	db5	25.9271	24.9305	27.1334
		db8	25.8977	24.4917	27.3878
		sym5	25.401	24.7347	26.33
		coif5	25.0171	25.9379	26.9262
35	25.5617	db5	24.165	24.1566	26.4753
		db8	24.1041	24.1847	26.5185
		sym5	24.6731	24.0348	25.4485
		coif5	25.6992	25.2512	26.2055
40	24.8093	db5	24.5921	23.9787	26.5347
		db8	24.6107	24.361	25.9402
		sym5	24.0658	23.7513	24.7864
		coif5	24.6748	24.7048	25.5246

B. Subjective Evaluation

The results of the universal and adaptive thresholding are shown for low, medium and high noise densities for all the images with their PSNR values. The denoised images show the comparison among the different noise standard deviation of subband-adaptive thresholding on the basis of PSNR values and visual perception. The subband- adaptive thresholding technique restores the most of the image details at the high noise standard deviation and avoids the artifacts in the image of different intensities.

i). Subjective results for *lena* image using *db8*:

a). Level-adaptive Thresholding:

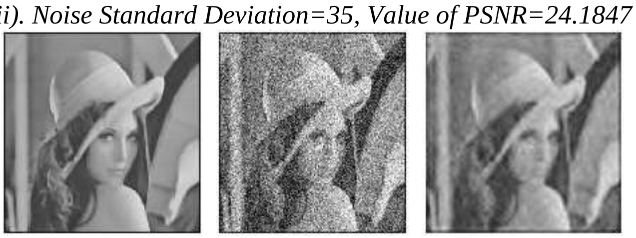
i) Noise Standard Deviation=15, Value of PSNR=31.7309

Original image Noisy image Denoised image

ii) Noise Standard Deviation=25, Value of PSNR=26.7604

Original image Noisy image Denoised image

iii). Noise Standard Deviation=35, Value of PSNR=24.1847



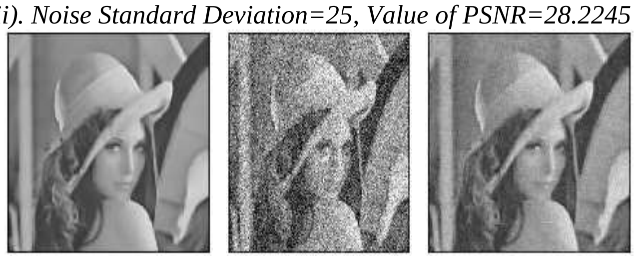
Original image Noisy image Denoised image

b). Suuband-adaptive Thresholding:

i) Noise Standard Deviation=15, Value of PSNR=33.4603

Original image Noisy image Denoised image

ii). Noise Standard Deviation=25, Value of PSNR=28.2245



Original image Noisy image Denoised image

iii). Noise Standard Deviation=35, Value of PSNR=25.4485

Original image Noisy image Denoised image

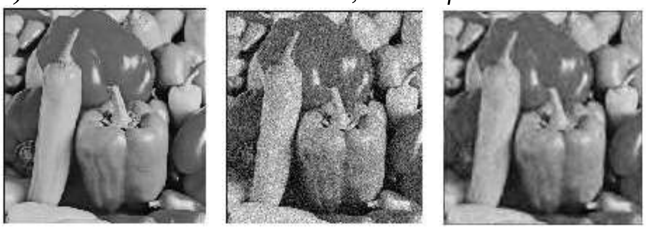
ii). Subjective results for *peppers* image using *Coiflet5:*

a). Level-adaptive Thresholding:

i) Noise Standard Deviation=15, Value of PSNR=27.9031

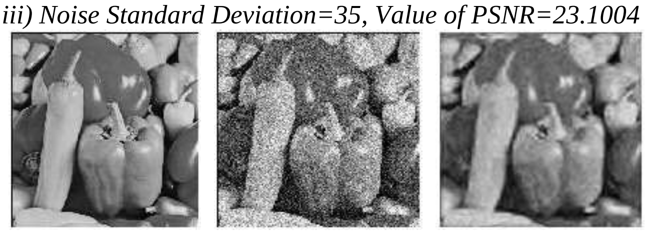
Original image Noisy image Denoised image

ii) Noise Standard Deviation=25, Value of PSNR=24.2028



Original image Noisy image Denoised image

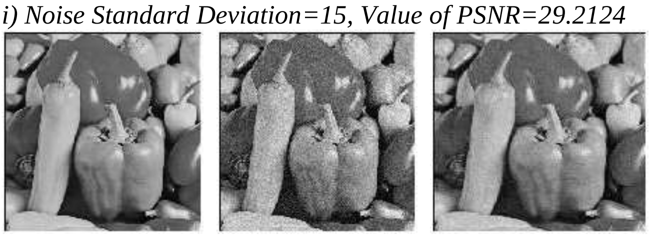
iii) Noise Standard Deviation=35, Value of PSNR=23.1004



Original image Noisy image Denoised image

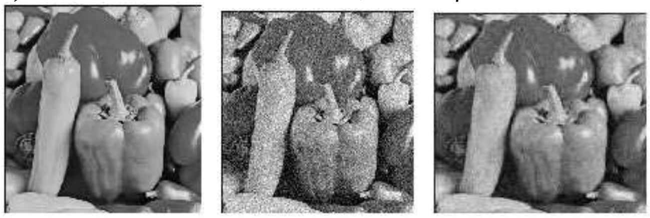
b). Suuband-adaptive Thresholding:

i) Noise Standard Deviation=15, Value of PSNR=29.2124

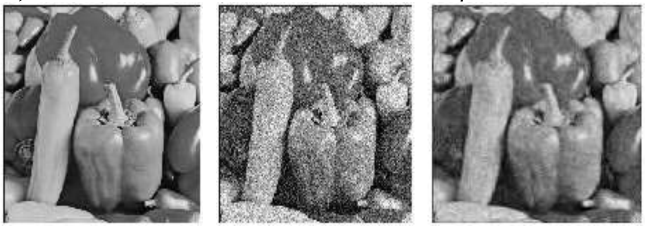


Original image Noisy image Denoised image

ii). Noise Standard Deviation=25, Value of PSNR=26.5942



Original image Noisy image Denoised image *iii). Noise Standard Deviation=35, Value of PSNR=24.6748*



Original image *Noisy image* *Denoised image*

V. CONCLUSIONS

In this paper, various wavelet-based methods are evaluated for recovering an image from noise contamination effectively. They are based on the DWT of the image and the GGD modeling of the subband coefficients. The results of the adaptive image denoising algorithms namely level-adaptive thresholding and subband-adaptive thresholding are demonstrated with Wiener filtering and universal thrresholding. The noise standard deviation of low, medium and high are considered for different densities for the image. The noise variance is estimated by Bayesian estimator method. To analyze the noise reduction and edge preserving capability of the all the methods, different performance indices like MSE and PSNR have been used. The visual perception of the denoised images is also considered.

In this work, it was demonstrated that adaptive thresholds greatly improves the denoising performance over universal thresholds. The Wiener filtering is used here for comparison which is the best linear filtering possible. The image quality of subband-adaptive is superior to all of others denoising methods.

After implementing all these denoising techniques, a comparative analysis is performed on all the techniques with different orthogonal and compactly supported wavelet type and came to the following conclusions

i). The resulting image is very smooth and has a non-pleasant visual appearance in universal thresholding scheme. It is the worst technique in preserving the image features and sharpness. This can also be verified by looking at the denoised images or the PSNR comparative *Tables I* above. The PSNR values for this method are quite high for low noise densities and come down significantly for images with more noise. The denoised images are blurred and have artifacts.

ii). Level-adaptive thresholding method provides reasonable and consistent image denoising even though the PSNR values are not that high. The denoised images look quite sharp and low loss of important information takes place compared with universal thresholding. But it performs over smoothing higher decomposition levels.

iii). Subband-adaptive thresholding method provides better denoised images than the level-adaptive thresholding, though the difference is more pronounced at lower noise levels. Similarly, the denoised images are sharp and no loss of information takes place. Also, the over smoothing of the image is avoided by this method. It is more suitable for all types of images.

iv). As inferred from the PSNR *Table I*, Subband-adaptive thresholding gives us the better results and these are confirmed by looking at the output denoised images. Level-adaptive thresholding though is better than the Wiener algorithm and universal thresholding. The only possible setback faced in Subband-adaptive thresholding can be the time required to obtain the threshold from each subband which is not as high.

The Gaussian noise is reduced at the cost of smoothing of the image textures and other fine details as shown in denoised images subjectively. The PSNR values given in *Table I* for all the methods have been extensively analyzed. The experimental results demonstrate the significance of the image denoising for visual perception of the images.

The results show that Daubechies wavelet with eight vanishing moments (db8) provides marginally better performance than other wavelet versions for each type of natural images and each noise densities in all the methods. However the choice of a minimal adaptive threshold requires further attention by the researchers.

VI. FUTURE SCOPE

The best adaptive method is suggested among all the considered methods based on the objective and subjective experimental results analysis. Therefore, future work can be done based on local adaptivity which can improve the experimental results objectively and subjectively. Also the spatially adaptive non-linear filters can be included in the study. Although the setting in this paper was in the decimated wavelet domain, the same idea can be extended to undecimated wavelet domain. This would likely improve the denoising performance.

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