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Improved denoising using Local Adaptive Real Oriented Dual-Tree Wavelet

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Abstract – **Image Denoising is a subject of digital image processing, used to eliminate the noise in image that is corrupted in the process of acquisition, transmission, reception and storage. Denoising filters out noise from distorted image , while retaining the edges and other detailed features as fine as possible. AWGN is the most common noise which corrupts images in our daily life. In this research work, Local Adaptive Real Oriented Dual-Tree Wavelet Method and improved Denoising method are used to find out the denoised image. An improved denoising approach is based on Local Adaptive Wavelet Image Denoising in both spatial and transform domain. In this paper, we have estimated and compared performances of improved denoising method and the local adaptive real oriented dual-tree wavelet image denoising method. Performance evaluation of these methods are compared using peak signal to noise ratio (PSNR) and mean squared error (MSE) between the original image and noisy image and PSNR between the original image and denoised image. Result shows an improvement of 18.15% (avg.) in PSNR and MSE is decreased by 45.84% (avg.).**

Keywords – **Denoising, DTWT, MSE, PSNR.**

I. Introduction

Image denoising is a course of action in digital image processing aimed at the removal of noise. The most compelling reason to diminish noise is that extraneous features will otherwise cause successive errors in recognition. Another inspiration is that noise removal lessens the size of the image and this conversely decreases the time required for progressive handling and storage. The reason in the configuration of a filter to diminish noise is that it evacuates; however much of the noise as could reasonably be expected while keeping up the more significant part of the image qualities [1],[2].

It is assumed in image denoising methods that the characteristics of the corrupting the noises and the system are assumed to be known ahead of time. Through linear function, the image s(x, y) is blurred, and noise n(x, y) is superimposed or added to form the corrupted image w(x, y). This is convolved to generate the noise-free image z(x, y) [3],[4].

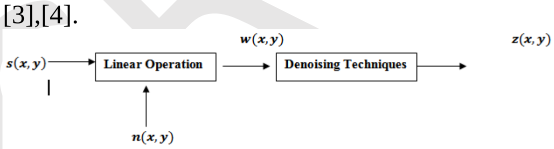

Figure 1: Denoising concept [2]

As shown in Figure 1 the "Linear operation" is the result of the addition or multiplication of the noise n(x, y) to the signal s(x, y). After attaining the corrupted image w(x, y), it is exposed to the denoising method to get the denoised image z(x, y) [5].

Denoising method based on Fourier transform method is localized in the frequency domain, and the wavelet transform scheme is confined in both frequency, and spatial domain but both the methods are not data adaptive, however, if the filtering approach is data adaptive it comes out with promising results [6]. Independent Component Analysis is one of the data adaptive methods. Data adaptiveness plays an essential role in image denoising process because denoising of images is also dependent on the image (type) which is to be denoised [7].

The main objective of this paper is to find out the denoised image with the help of improved denoising method and the Local Adaptive Real Oriented Dual-Tree Wavelet Method.

The rest of the paper is organised as follows.

Section II presented the proposed methodology. In Section A , Local Adaptive Wiener filter is briefly described. Section B describes Local Adaptive Wavelet Wiener Filter(Both Domain) which is used in proposed methodology. In Section C, Dual Tree

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Wavelet transform is discussed. Out of three threshoding technique, Soft thresholding technique is used in this paper described in Section D. In Section III, Simulation and results obtained are shown and tabulated respectively.The results are expressed in terms of PSNR and MSE. Finally We conclude this paper with % of improvement in image and with some possible future work in Section IV.

II. Proposed Methodology

Removal of noise is an essential task in image processing. The basic model for denoising of the image is demonstrated in Figure 2. In the execution of these techniques, first, the noisy image is decomposed by dual-tree wavelet transform. After this, by utilizing thresholding shrink decomposed images and apply adaptive Wiener filter to decomposed images. At last denoised image is acquired by utilizing converse binary tree wavelet transform as depicted in Figure 2.

In the proposed method an image has been carried out firstly based on adaptive Wiener filtering in the wavelet domain and then based on an adaptive Wiener filter in the spatial domain. In the implementation of this method, first, a denoised image is obtained with the thresholding in the wavelet domain. Then an adaptive Wiener filtering in the spatial domain is applied to the reconstructed image to improve the accuracy. Here, the spatial wiener filtering is one of the classical linear filterings in the spatial domain, while the wavelet domain wiener filtering is a new signal estimation method. To form an improved denoising method, we can combine the methods of the image denoising in the spatial domain and the one in the wavelet domain [8].

In this method, to denoise the image, the following steps follows:

- First, select an image, check, is it gray image or color image? If color image then firstly convert this image into a gray image. Then use it as an input image.
- The next step will be to apply the Dual-Tree Wavelet Transform (DTWT) to decompose the noisy image into six subbands. After this adopt wiener filter for each band.
- Then reconstructs the image by Inverse Dual-Tree Wavelet Transform (IDTWT) transform, and gets the denoised image.
- Wiener filter also adopts to get the denoised image by spatial domain adaptive Wiener filtering and also we get the denoised image by Wavelet [9].
- To process the result of improved denoising method again apply a Wiener filter to it.
- Finally, calculate PSNR between the original image and noisy image and PSNR between the denoised image and original image, to make sure a match between wavelet domain adaptive Wiener filtering and spatial domain adaptive Wiener filtering.

The main benefit of using this method is that it reduces ripples like artifacts around image edges. Hence the denoised image has a better visual effect.

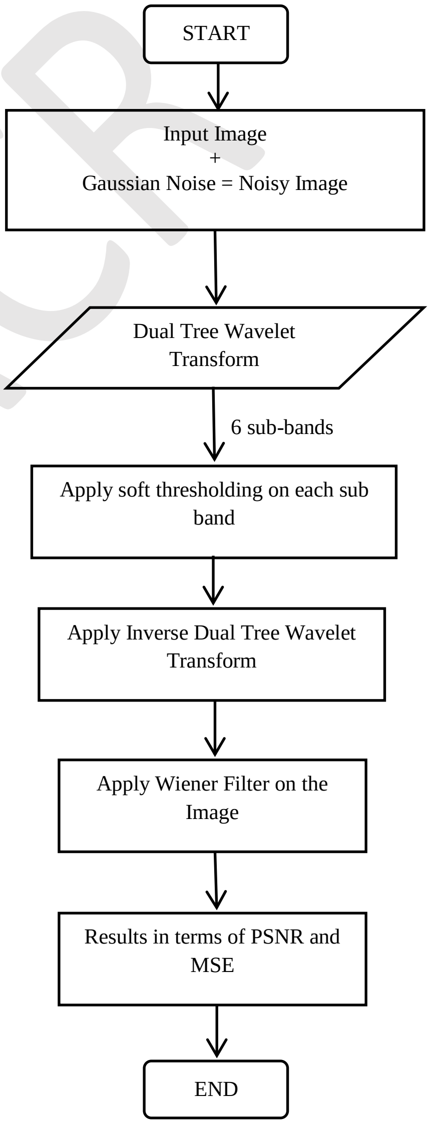

Figure 2: Flow diagram for proposed work

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A. Local Adaptive Wiener Filtering

In 1994 Norbert Wiener proposed the method of optimal filter called a Wiener filter which can give satisfactory results for image denoising [10]. Due to its simplicity and effectiveness, we use the adaptive Wiener filter in improved denoising method and the local adaptive wavelet image denoising method.

Consider an image is corrupted with additive Gaussian white noise. The noisy image can be modeled as:

$$y(i,j) = x(i,j) + n(i,j) \quad (1)$$

Where $y(i,j)$ is the noisy image, $x(i,j)$ is the original image and $n(i,j)$ is additive gaussian white noise. The goal of image denoising is to suppress noise from noisy imaa ge with minimum mean square error. Here, the wiener filter minimizes the mean square error between the estimated image $\hat{x}(i,j)$ and the original image $x(i,j)$. This error measure can be expressed as [11]:

$$e^2 = E\left[\left(x(i,j) - \hat{x}(i,j)\right)^2\right] \quad (2)$$

Wiener filters the image using pixel-wise adaptive Wiener filtering, using neighborhoods of size M-by-N to estimate the local image mean and standard deviation. Here it assumes that the noise is stationary with zero mean and variance σ_n^2 and uncorrelated with the original image $x(i,j)$. Based on these assumptions wiener filter estimates local mean and variance around each pixel using (3) and (4) as below [12]:

$$\mu = \frac{1}{NM}\sum_{i,j\in k} y(i,j) \quad (3)$$

$$\sigma^2 = \frac{1}{NM}\sum_{i,j\in k} y^2(i,j) - \mu^2 \quad (4)$$

Where μ is local mean and σ^2 is local variance. Then wiener filter creates a pixel wise filtering using these estimates and the estimated image is given in (5) as below:

$$\hat{x}(i,j) = \mu + \frac{\sigma^2 - \sigma_n^2}{\sigma^2}\left(y(i,j) - \mu\right) \quad (5)$$

Where σ_n^2 is noise variance, if noise variance is not given, wiener filter uses avthe erage of all local estimated variances.

B. Local Adaptive Wavelet Wiener Filter

Local adaptive Wiener filter in wavelet domain can be used to improve the signal to noise ratio of image [13]. We can improve the PSNR result of improved denoising method using local adaptive filters in this method. Local adaptive filters can be obtained from several 1-D windows which could be constructed on the direction character of sub-image in the Wiener filter. In this research work, to improve the signal to noise ratio of an image by local adaptive wavelet image denoising method following steps follows:

- First, we apply the Dual-Tree Wavelet Transform (DTWT), i.e., to decompose the noisy image into six subbands.
- The next step will be to construct local adaptive filters using several 1-D windows on the direction information contained in each sub-image.
- After this apply wiener filter for each sub-image and apply both local adaptive filters and thresholding to remaining sub-images.
- Then reconstructs the image by Inverse Dual-Tree Wavelet Transform and we got the denoised image.
- Finally, to calculate PSNR between the original image and noisy image and PSNR between the denoised image and original image.

C. Dual-Tree Wavelet Transform (DTWT)

Suppose an image x (Given by $x_{ij}, i = 1,2 \ldots and\ j = 1,2 \ldots$) is a vector of $m \times n$ pixels corrupted due to any noise. Let n_{ij} is the noise added by system than tthe the he resultant image for experimentation will be given by:

$$y_{ij} = x_{ij} + n_{ij} \quad (6)$$

The denoising methods attempt to locate information of x from image y in constraints of minimum means square error (MSE). The wavelet coefficients of equation (6) can be illustrated using two-dimensional wavelet (W) [14].

$$X = Wx, Y = Wy, Z = Wz \quad (7)$$

The wavelet distribution of input image has high-frequency Detailed Coefficients (DC) and low-frequency Approximate Coefficients (AC). The DC in case of the image is a combined term of 3 points, i.e., horizontal details, vertical details, and diagonal details. Figure 3 represents the illustrative block diagram of a wavelet transform format.

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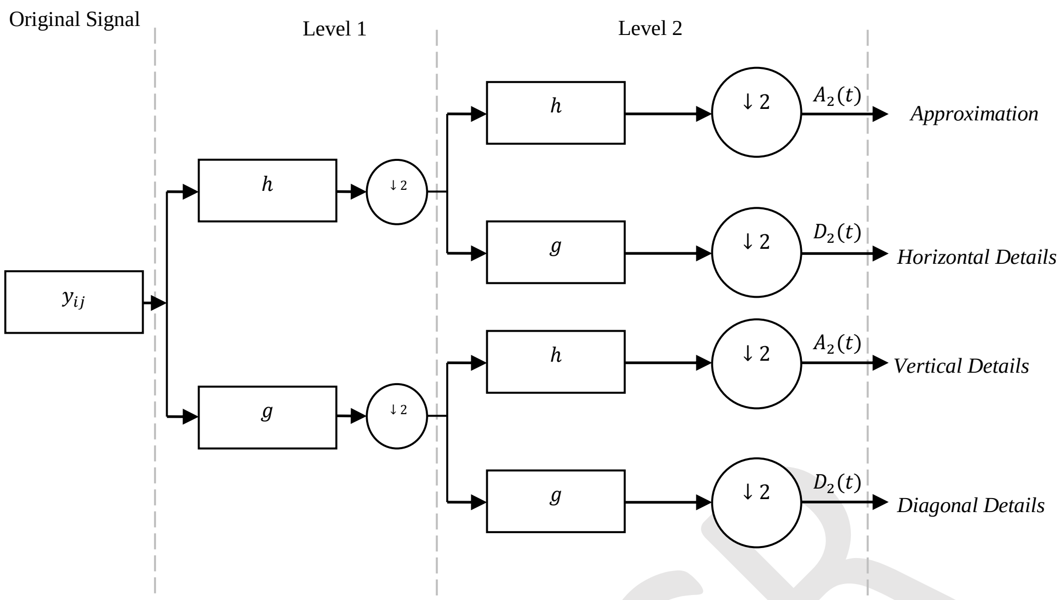

Figure 3: Block Representation of 2-Level DWT Process

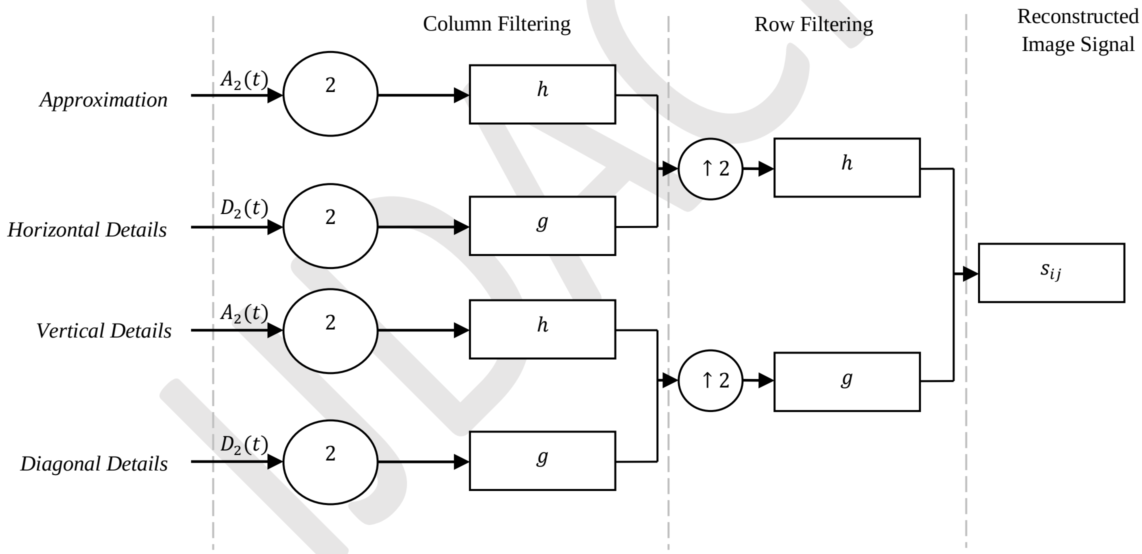

Figure 4: Reconstruction of Image from Wavelets

The image of equation (6) can be written in their wavelet transforms as;

$$Y = X + N \tag{8}$$

This Y as the input of wavelet (Figure 3) first segments the rows in the first level. In the second level of wavelets, columns are filtered out. The subsampling of image results in four outputs.

D. Soft Thresholding

Thresholding in analytic form is expressed as:

$$y = sign(x)(|x| - T) \tag{9}$$

The level of thresholds are subjected to thresholding criteria based on minimizing average squared error,

$$\arg\min\left[\frac{1}{N}\sum_i\left(\hat{Y}_i - X_i\right)^2\right] \tag{10}$$

Here, $\hat{Y}_i$ *and* X_i represents the detailed threshold coefficients of noisy athe nd original image respectively.

The images after thresholding are reconstructed to original forms using the inverse wavelet transform W^{-1}.

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The output of Figure 4 should be x_{ij} identically, but since the information of noise is not available in defining the number of wavelets, s_{ij} is considered as the filtered output (with some traces of noise). The PSNR and MSE of experimental inputs in results section support this conclusion. However, the outputs of wavelet transform are clean enough to generate the noise pattern in image.the the L et K represents the noise pattern for any specific noise:

$$s_{ij} = x_{ij} + k_{ij} \qquad (11)$$

Here, the noise k_{ij} is considered instead of n_{ij} as soft threshold filtering in wavelethe t transform filtered the input image x_{ij}, thus $n_{ij} \gg k_{ij}$. Being k_{ij} very small, and to classify the noise, this term is neglected from equation (11). Also, s_{ij} can be considered as the original x_{ij} ($s_{ij} \sim x_{ij}$), hence subtracting equation (11) from equation (6); noise pattern can be obtained:

$$y_{ij} - x_{ij} = n_{ij} \qquad (12)$$

III. Simulation And Results

The performance of proposed algorithms has been studied using MATLAB simulation.

Figure 5: Original Image-1

Figure 6: Noisy Image for image-1

Figure 7: Local Adaptive Wiener Filtering for image-1

Figure 8: Applying Discrete wavelet transform for image-1

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Figure 9: Image output from Improved Denoising Method for image-1

Figure 10: Image output from Local Adaptive Wavelet Denoising Method for image-1

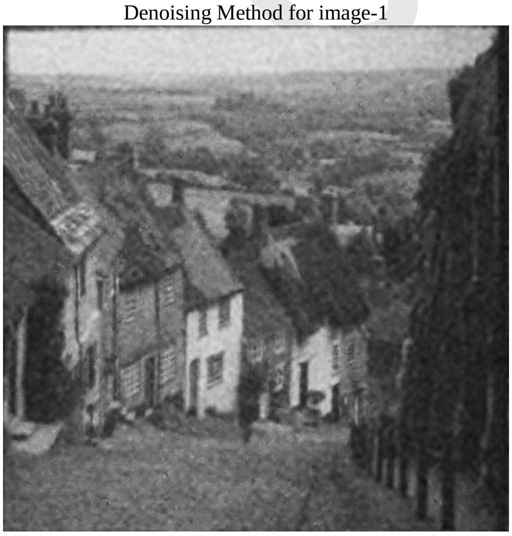

Figure 11: Image output from the proposed method for image-1

Table 1: Result Analysis for image-1

Method	PSNR (dB)	MSE
Local Adaptive Wiener Filtering (Spatial Domain)	22.803	341
Discrete Wavelet Transform	19.748	689.16
Improved Denoising Method	26.95	131.25
The Local Adaptive Wavelet Denoising Method (Both Domain)	26.958	131.01
Local Adaptive Real Oriented Dual-Tree Wavelet Method	27.045	129.82

IV. CONCLUSION

This paper explained several well-known algorithms like Adaptive Wiener filtering, DWT and DTWT for image denoising The performance of the local adaptive wavelet image denoising method is better compared to the improved denoising method in terms of PSNR between the denoised image and the original image as shown in Table 1. Image denoising using Local Adaptive Wavelet Denoising Method and Local Adaptive Real Oriented Dual-Tree Wavelet Method has shown a much significant improvement in salt and Gaussian noise. On analyzing the results, an improvement of 18.15% (avg.) is seen in PSNR, whereas MSE has decreased by 45.84% (avg.) in the case of the proposed method.

Algorithm's performance explained in this paper was comparatively assessed in the research directions which have a scope of further investigation. This research work can be extended to color image. As future research, we would like to work further on the comparison of the denoising techniques.

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