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IMAGE DENOISING USING STATIONARY WAVELET TRANSFORM

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***Abstract* – In this paper, the work done is mainly focused on removal of noise from digital images, that is denoising of images. In digital image processing, decreasing the noise from an image is an important method to analyze and enhance the main facts in an image. Still removal of noise is a challenging task for many of the researchers as the fine edge details are not being preserved in the restored image. But the fine edge details are to be preserved for better analysis of an image. So therefore, to overcome this drawback is our objective. In this, initially the noise is considered to be gaussian. The noisy image undergoes decomposition using Stationary Wavelet Transform (SWT) and is decomposed into different frequency bands. The detail coefficients of the image undergoes thresholding. Inverse Stationary Wavelet Transform (ISWT) is applied. The processed image is now passed through a sharpening filter.**

***Keywords*- Denoising, Stationary Wavelet Transform, Thresholding, sharpening filter**

I . INTRODUCTION

Digital images play a vital role in real life applications like astronomy, medical field, satellite TV, magnetic resonance imaging (MRI). Boldly, instruments having low capability that is low performance during capturing the image that is during the acquisition of image and low channel conditions during transmission, the fine details of information of the image tend to degrade. Image denoising is necessary and should be done anterior before the image data is processed or analyzed. Image denoising is the process in which an original image is estimated from the noisy image without distorting the useful information of fine details of the image such as discontinuities and edges. So, the principal aim of digital image denoising is removal of the noise while preserving features such as edges in an image. The aim is to estimate the uncorrupted image from noisy image.

Original image can be restored from noisy image using numerous methods. But preferring the best method is also important. Because of the trade-off between noise removal and fine-data preservation, denoising techniques tends to be a major problem. Distortions in the edges of an image is a common problem in conventional denoising techniques. So, the main objective of this work is to reduce the Gaussian noise in the images and to retain fine details including edges in the restored image.

II. RELATED WORK

Spatial filtering is the best method which can be used when additive noise alone is present. It is again classified into categories i.e., linear and non-linear filters. Linear filters are again classified as mean filter and wiener filter. In mean filter, the image is smoothed out because it reduces the intensity variations between the adjacent pixels. It applies mask over each pixel in an image. Wiener filter filters out noise in an image by taking statistical approach. By using this filter desired frequency response can be acquired. For performing the filtering operation, one should have prior knowledge of the spectral properties of the original image. The main drawback of linear filters are they blurs the sharp edges, and fine details such as curves and lines in an image. Nonlinear filter includes median filter. The median of window is calculated by sliding the window through each pixel and center of each window is replaced with the median value. This method removes noise but cannot distinguish fine details from noise.

Wavelet Based Thresholding uses wavelet transform for denoising of the images. The removal of noise is done by replacing less relevant coefficients to zero. It is very effective as well as a simple technique and mainly depends upon the thresholding parameter and the efficiency of denoising depends upon the choice of threshold. For image compression bi-orthogonal wavelet transform has been used, and the results obtained were optimal as compared to other applications such as deconvolution, filtering etc. The loss of translation-invariance property in the discrete wavelet transform leads to a large number of artefacts in an image that is reconstructed from modified wavelet coefficients. Translation invariance can be achieved by removing the down samplers and up samplers in the DWT (Discrete Wavelet Transform). So, researches are carried out in stationary wavelet transform, even though there is a great amount of redundancy. So, Stationary Wavelet Transform (SWT) is used in order to overcome the deprived translation-invariance of the DWT.

A context-based diffusion in stationary wavelet domain is proposed by Ajay K. Mandava. In this method, strong edges are kept as it is while the smooth regions are diffused out. Thus, this method adapts to local context. The transform energies at scale one and two of two levels SWT control the diffusion. Junmei Zhong et. al. a new algorithm which takes the advantage of the edge preserving property of anisotropic diffusion model. Dyadic Wavelet Transform is used to construct a linear scale space for noisy image. Minimum Mean-Squared Error (MMSE) based filtering is performed on the finest scale followed by anisotropic diffusion. However, the computational complexity of this technique is very high.

III. PROPOSED SYSTEM

The figure 1 shows the block diagram of the proposed system. The noise is considered to be gaussian. The noisy image undergoes decomposition using Stationary Wavelet Transform (SWT) and is decomposed into different frequency bands. The detail coefficients of the image undergoes thresholding. Inverse Stationary Wavelet Transform (ISWT) is applied. The processed image is now passed through a sharpening filter.

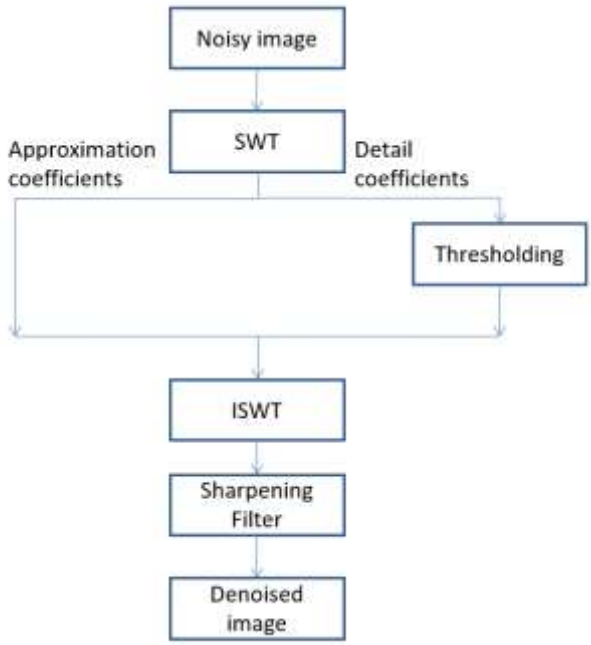

Figure 1: Block diagram of proposed system

The first is that initially gaussian noise is added to the original image. The additive noise is obtained as follows.

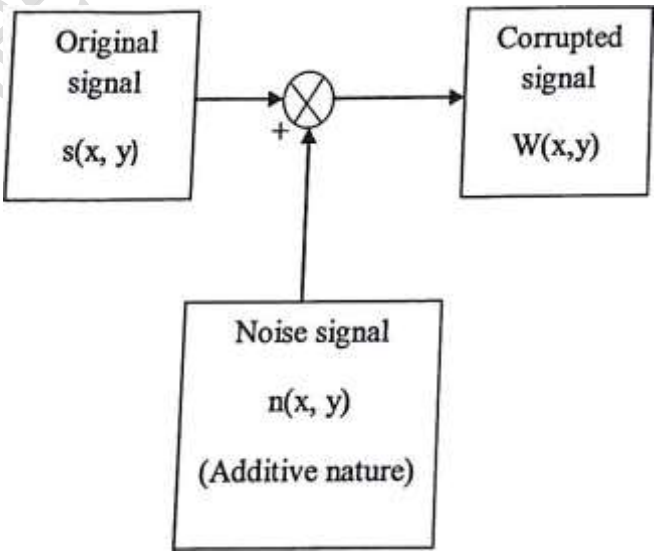

Figure 2: Additive noise model

As shown in the above figure:

s (x, y) is the original image intensity,

n(x,y) denotes the noise introduced ,
W(x,y) is the noise added image,
So,

$$W(x,y)=s(x,y)+n(x,y) \quad (1)$$

3.1 Stationary Wavelet Transform (SWT)

Many new algorithms have been proposed in the area of image enhancement in the wavelet domain till recently. DWT is one of the wavelet transforms used in image processing. DWT decomposes an image into different sub band images, which gives approximation of the image, vertical details, horizontal details and diagonal details. The SWT is another transform which has been used in several image processing applications.

The basic idea of SWT is to fill the gap caused by decimation in the standard wavelet transform. This results in over determined representation of the original data, having much statistical potential. The SWT is an inherently redundant scheme as the output of each level of SWT contains the same number of samples as the input. So, for a decomposition of N levels, there is a redundancy of N in the wavelet coefficient. SWT is similar to the DWT except that the filters are up-sampled instead of sub-sampling the signal at each level of decomposition. Each level's filters are up- sampled versions of the previous ones. The one-dimensional SWT decomposition is stated here to have a clear understanding of two-dimensional signals, i.e., images. The decomposition and filters are shown in figure3.

In Figure 3, the two-dimensional SWT decomposition along with filters are shown. Hj and Lj represent high pass and low pass filters at scale j, resulting from interleaved zero padding of filters Hj-1 and Lj-1 (j >1). LL0 is the original image and the output of scale j, LLj, would be the input of scale j+1. LLj+1 denotes the low frequency (LF) estimation after the stationary wavelet decomposition, while LHj+1, HLj+1 and HHj+1 denote the high frequency (HF) detailed information along the vertical, horizontal and diagonal directions, respectively.

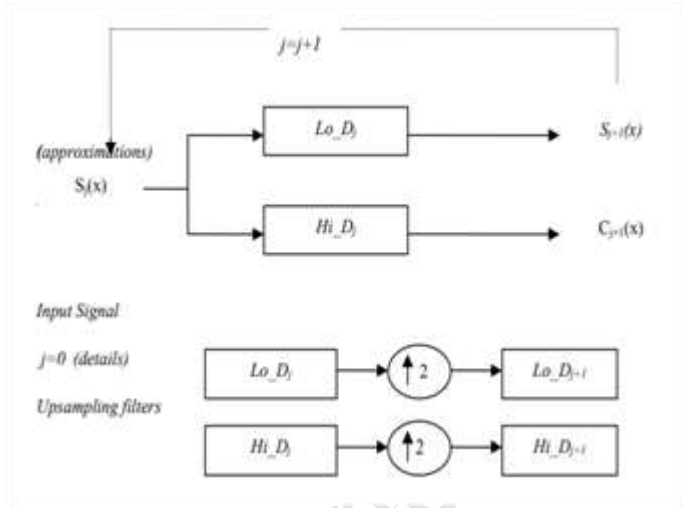

Figure 3: SWT decomposition and filters

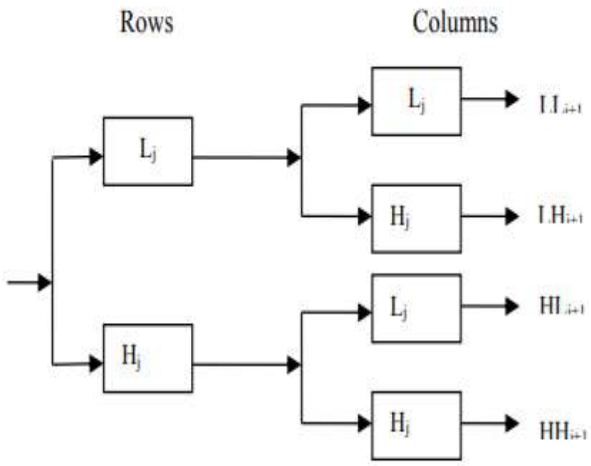

Figure 4: Two level SWT decomposition

In the above figure, LL is the approximation coefficient and LH, HL and HH are the detail coefficients.

3.2 Thresholding

The gaussian noise with zero mean and some variance σ^2 is added to the original image. And the wavelet coefficient of the noisy image is given by

$$w_{i,j} = s_{i.j} + n_{i,j} \qquad (2)$$

Where, $w_{i,j}$ is the noise wavelet coefficient, $s_{i.j}$ is the true coefficient, $n_{i,j}$ is the gaussian noise.

The locally adaptive linear minimum mean square error estimation (LALMSE) scheme is given as:

$$\hat{s_{i,j}} = k_{i,j}.w_{i,j} \qquad (3)$$

Where $k_{i,j}$, is the weighting factor and is given by:

$$k_{i,j} = \frac{\sigma^2_{s(i,j)}}{\sigma^2_{s(i,j)} + \sigma^2} \qquad (4)$$

Where, $\sigma^2_{s(i,j)}$ is the estimated variance of noiseless coefficient and σ^2 is the variance of the noise added.

3.2.1 Algorithm

1. Initially perform four level Stationary Wavelet Transform.

2. For each sub band (LH, HL, HH) estimate the noise free coefficients by applying thresholding.

3. Reconstruct the denoised image from the processed and LL sub bands by applying Inverse Stationary Wavelet Transform.

3.3 Sharpening filter

Actually, human perception is very sensitive to the edges. These edges contain high frequency components. So if we degrade or attenuate the high frequency components in the image it leads to degradation of visual quality of an image. Therefore, for highlighting fine edge details in an image, an image enhancement technique called sharpening filter is used.

The sharpening process works by first creating a slightly blurred version of the original image, the unsharp mask. This is subtracted away from the original to detect the presence of edges. Contrast is then selectively increased along these edges using this mask — leaving behind a sharper final image.

Consider a weighted high pass filter mask shown below, which is applied to a grayscale image,

$$W = \frac{1}{3}\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix} \qquad (5)$$

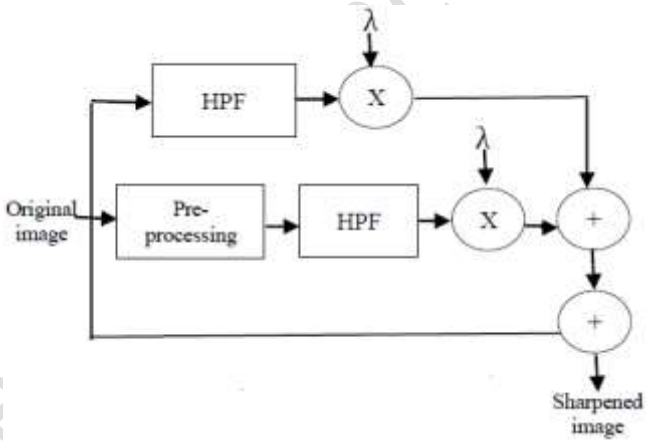

Figure 5: Image sharpening filter

IV. METRICS USED FOR COMPARISION

The performance of the proposed method is evaluated using Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index (SSIM).

PSNR: The PSNR block computes the peak signal-to-noise ratio, in decibels, between two images. This ratio is used as a quality measurement between the original and a compressed image. The higher the PSNR, the better the quality of the compressed, or reconstructed image.

To compute the PSNR, the block first calculates the mean-squared error using the following equation:

$$MSE = \frac{\sum_{M,N} [I_1(m,n) - I_2(m,n)]^2}{M * N}$$

$$PSNR = 10 \log_{10}\left(\frac{R^2}{MSE}\right)$$

(6)

SSIM: The Structural Similarity (SSIM) index is a method for measuring the similarity between two images.

The SSIM between two windows of common size x and y is given by:

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} +}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2}$$

Where, μ_x is the average of x
μ_y, is the average of y

c_1=$(k_1 L)^2$, c_2=$(k_2 L)^2$ where k_1=0.01, k_2=0.03 by default.

L is the dynamic range.

V. EXPERIMENT PROCEDURE

1. Gaussian noise with zero mean and standard deviation σ is added to the original image.

2. The noisy image is now decomposed into approximate sub band and detail sub bands using SWT.

3. The detail sub bands i.e., LH, HL and HH undergoes thresholding as described in section 3.2.

4. Apply ISWT to the processed sub bands and approximation sub band (LL) to get the reconstructed image.

5. To enhance edges and fine details, the reconstructed image is passed through a sharpening filter with optimum tuning parameter, as described in section 3.3.

6. For each value of, PSNR and SSIM are calculated and tabulated for four different images (Pepper, Cameraman, Lena,).

VI. RESULTS

Four natural images (Pepper, Cameraman, Lena) are given as input to the denoising algorithm to evaluate the performance. The experiment is implemented on MATLAB.

Figure 6 - 8 shows the original image, noisy image, denoised image after ISWT and denoised image after sharpening for Pepper, Cameraman, Lena and Barbara images respectively.

(a) (b) (c) (d)

Figure 6: Pepper: (a) Original image (b) Noisy image (σ = 40) (c) Denoised image after ISWT (d) Reconstructed image

Figure 7: Cameraman: (a) Original image (b) Noisy image (σ = 40) (c) Denoised image after ISWT (d) Reconstructed image

Figure 8: Lena: (a) Original image (b) Noisy image (σ = 40) (c) Denoised image after ISWT (d) Reconstructed image

The performance is compared between the previous method (DWT) and proposed method. The proposed denoising scheme is tested for the natural images affected with noise for five different standard deviations 10, 20, 30, 40, 50. The following tables represents the comparison between PSNR, SSIM for different standard deviation values.

The table 1 shows the comparison of PSNR (dB) for different images at different noise levels.

The table 2 shows the comparison of SSIM (dB) for different images at different noise levels.

Noise standard deviation	PSNR (dB)					
	Cameraman		**Lena**		**Peppers**	
	Previous method	Proposed method	Previous method	Proposed method	Previous method	Proposed method
10	29.201509	29.205413	28.303995	28.327913	30.304223	30.792256
20	29.122267	29.185454	28.213551	28.304564	30.782760	30.799332
30	28.106593	28.982724	28.791306	28.807656	29.389160	30.620382
40	25.269216	28.346522	25.777043	27.192728	26.853797	29.645539
50	22.21373	25.352005	22.596724	24.917359	23.764924	26.718327

Table 1: Comparison of PSNR (dB) for different images at different noise levels.

Noise standard deviation	**SSIM**					
	Cameraman		**Lena**		**Peppers**	
	Previous method	Proposed Method	Previous method	Proposed method	Previous method	Proposed Method
10	0.852475	0.896056	0.835879	0.836263	0.919554	0.934081
20	0.830298	0.891236	0.812351	0.825307	0.912121	0.912971
30	0.874469	0.880394	0.814589	0.858615	0.869819	0.907775
40	0.802872	0.832963	0.759685	0.790496	0.785943	0.879661
50	0.704466	0.763507	0.616353	0.723667	0.661407	0.814128

Table 2: Comparison of SSIM for different images at different noise levels.

VII. CONCLUSION AND FUTURE SCOPE

Hence, an efficient algorithm is proposed for noise removal and fine edge preservation. The experimental result shows that the proposed method provides slightly higher PSNR and SSIM compared to previous methods in denoising an image corrupted with Gaussian noise. To enhance edges and fine details, sharpening filter is used which increased the PSNR and SSIM values.

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