Performance Analysis of Image Denoising System for different levels of Wavelet decomposition

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Abstract - In diverse fields from planetary science to molecular spectroscopy and medical imaging to satellite imaging, scientists are faced with the problem of recovering original images from incomplete, indirect and noisy images. The conventional Fast Fourier Transform (FFT) based image denoising method is essentially a low pass filtering technique in which edge is not as sharp in the reconstruction as it was in the original. The drawback of the FFT is the fact that the edge information is spread across frequencies because of the FFT basis functions, not being localized in time or space and hence low pass-filtering results in the smearing of the edges. But the localized nature of the wavelet transform both in time and space results in denoising with edge preservation. In this paper, the performance of an Image Denoising System using Discrete Wavelet Transform (DWT) is experimentally analyzed for four levels of DWT decomposition, for Speckle noise added two facial and two CT images.

I. INTRODUCTION

Digital images play an important role both in day to-day applications, such as, satellite television, magnetic resonance imaging, computer tomography as well as in areas of research and technology such as geographical information systems and astronomy. In the diverse fields, mentioned above, scientists are faced with the problem of recovering original images from incomplete, indirect and noisy images. Generally, data sets collected by image sensors are contaminated by noise. Imperfect instruments, problems with the data acquisition process, and interfering natural phenomena can all degrade the data of interest. There are many different cases of distortions. One of the most prevalent cases is distortion due to additive white Gaussian noise which can be caused by poor image acquisition or by transferring the image data in noisy communication channels. Other types of noises include impulse and speckle noises. Furthermore, noise can be introduced by transmission errors and compression.

Thus, denoising is often a necessary and the first step to be taken before the image data is analyzed. It is necessary to apply an efficient denoising technique to compensate for such data corruption. Image denoising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images. Denoising of electronically distorted images is an old but also still a relevant industrial problem. In the past two decades, many methods for de-noising have been developed and reported in the literature [1] - [7].

There are two basic approaches to image denoising, spatial filtering methods and transform domain filtering methods. Spatial filters employ a low pass filtering on groups of pixels with the assumption that the noise occupies the higher region of frequency spectrum. Spatial Low-pass filters will not only smooth away noise but also blur edges in signals and images while the high-pass filters can make edges even sharper and improve the spatial resolution but will also amplify the noisy background [8].

Fourier transform domain filters used in signal and image processing involve a trade-off between the signal-to-noise ratio (SNR) and the spatial resolution of the signal/image processed. The conventional Fast Fourier Transform (FFT) based image denoising method is essentially a low pass filtering technique in which edge is not as sharp in the reconstruction as it was in the original. The edge information is spread across frequencies because of the FFT basis functions, which are not being localized in time or space. Hence low pass-filtering results in the smearing of the edges. But, the localized nature of the wavelet transforms both in time and space results in denoising with edge preservation.

Wavelet Analysis, a new form of signal analysis is far more efficient than Fourier analysis wherever a signal is dominated by transient behavior or discontinuities. Several investigations have been made into additive noise suppression in signals and images using wavelet transforms. Much of the early work on wavelet noise removal based on thresholding the Discrete Wavelet Transform (DWT) coefficients of an image and then reconstructing it, was done by Donoho and Johnstone [9]. It has been found that wavelet based denoising is effective in that although noise is suppressed, edge features are retained without much damage [10].

This paper is organized as follows. Section II describes Wavelet Domain filtering. Section III describes Wavelet Based Denoising System. Exhaustive Experimental Results and Discussions are given in Section IV and finally Concluding Remarks are given in Section V.

II. WAVELET DOMAIN FILTERING

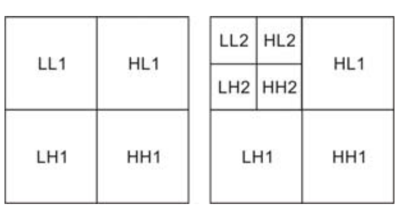
Working in the wavelet domain is advantageous because the DWT tends to concentrate the energy of the desired signal in a small number of co-efficients, hence, the DWT of the noisy image consists of a small number of coefficients with high Signal Noise Ratio (SNR) and a large number of coefficients with low SNR. After discarding the coefficients with low SNR (i.e., noisy coefficients) the image is reconstructed using inverse DWT. As a result, noise is removed or filtered from the observations.

A similar procedure could be carried out using any orthogonal signal representation, including the Fourier Transform. However, Fourier domain filtering is a spatially global operation that cannot adjust to local spatial variation and hence leads to excessive smoothing of edge information. On the other hand, the localized support of wavelet basis function enables DWT based filtering procedures to adapt to spatial variations [11].

A Discrete Wavelet Transform

Wavelets are functions generated from one single function Ψ by dilations and translations. The basic idea of the wavelet transform is to represent any arbitrary function as a superposition of wavelets. Any such superposition decomposes the given function into different scale levels where each level is further decomposed with a resolution adapted to that level [12].

The DWT is identical to a hierarchical sub band system where the sub bands are logarithmically spaced in frequency and represent octave-band decomposition. By applying DWT, the image is actually divided i.e., decomposed into four sub bands and critically sub sampled as shown in Fig.1 (a). These four sub bands arise from separable applications of vertical and horizontal filters. The sub bands labeled LH1, HL1 and HH1 represent the finest scale wavelet coefficients, i.e., detail images while the sub band LL1 corresponds to coarse level coefficients, i.e., approximation image. To obtain the next coarse level of wavelet coefficients, the sub band LL1 alone is further decomposed and critically sampled. This results in two-level wavelet decomposition as shown in Fig. 1(b).



(a) One-Level (b) Two-Level

Fig. 1. Image decomposition

III. WAVELET BASED DENOISING SYSTEM

The basic block diagram of wavelet based image denoising system is shown in Fig. 2. Wavelet Based Denoising method relies on the fact that noise commonly manifests itself as fine-grained structure in the image and DWT provides a scale based decomposition. Thus, most of the noise tends to be represented by wavelet co-efficients at the finer scales. Discarding these coefficients would result in a natural filtering of the noise on the basis of scale. Because the coefficients at such scales also tend to be the primary carriers of edge information, this method threshold the DWT coefficients to zero if their values are below a threshold. These coefficients are mostly those corresponding to noise. The edge relating coefficients on the otherhand, are usually above the threshold. The Inverse DWT of the thresholded coefficients is the denoised image.

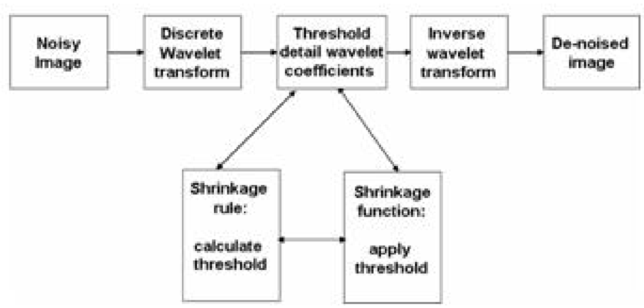


Fig. 2. Block diagram of wavelet based Image Denoising System

A Thresholding

Wavelet thresholding [13] - [15] is a signal estimation technique that exploits the capabilities of wavelet transform for signal denoising. It removes noise by killing coefficients that are insignificant relative to some threshold, and turns out to be simple and effective, depends heavily on the choice of a thresholding parameter and the choice of this threshold determines, to a great extent the efficacy of denoising.

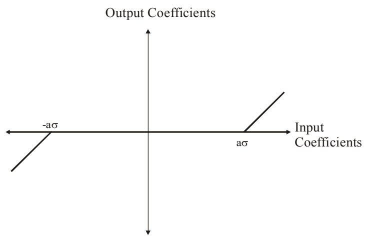
Threshold Selection: As one may observe, threshold selection is an important question when denoising. A small threshold may yield a result close to the input, but the result may still be noisy. A large threshold on the other hand, produces a signal with a large number of zero coefficients. This leads to a smooth signal. Paying too much attention to smoothness, however, destroys details and in image processing may cause blur and artifacts.

Thresholding Method: Some of thresholding methods are: (i) Hard thresholding, (ii) Soft thresholding, (iii) Semi-soft Thresholding and (iv) Quantile thresholding. In our implementation, soft thresholding method is used to analyze the performance of denoising system for different levels of DWT decomposition, since soft thresholding results in better denoising performance than other denoising methods [16].

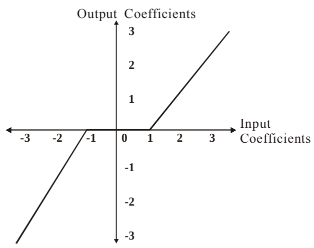
Soft thresholding leads to less severe distortion of the object of the interest than other thresholding methods. Several approaches have been suggested for setting the threshold for each band of the wavelet decomposition. A common approach is to compute the sample variance (σ^2) of the coefficients in each band and set the threshold to some multiple of standard deviation (σ) for that band [17]. Thus, to implement a soft threshold of the DWT coefficients for a particular wavelet band, the coefficients of that band should be thresholded as shown in Fig. 3(a). The soft thresholding is generally represented by,

$$\begin{aligned} d_{ik}^{soft} &= sign(d_{ik})\ \ (|d_{ik}| - \lambda) \quad if \quad d_{ik} > \lambda \\ &= 0 \qquad\qquad\qquad\qquad\quad if \quad d_{ik} \le \lambda \end{aligned} \tag{1}$$

The soft threshold characteristic with λ = 1 is shown in Fig. 3(b).



(a)



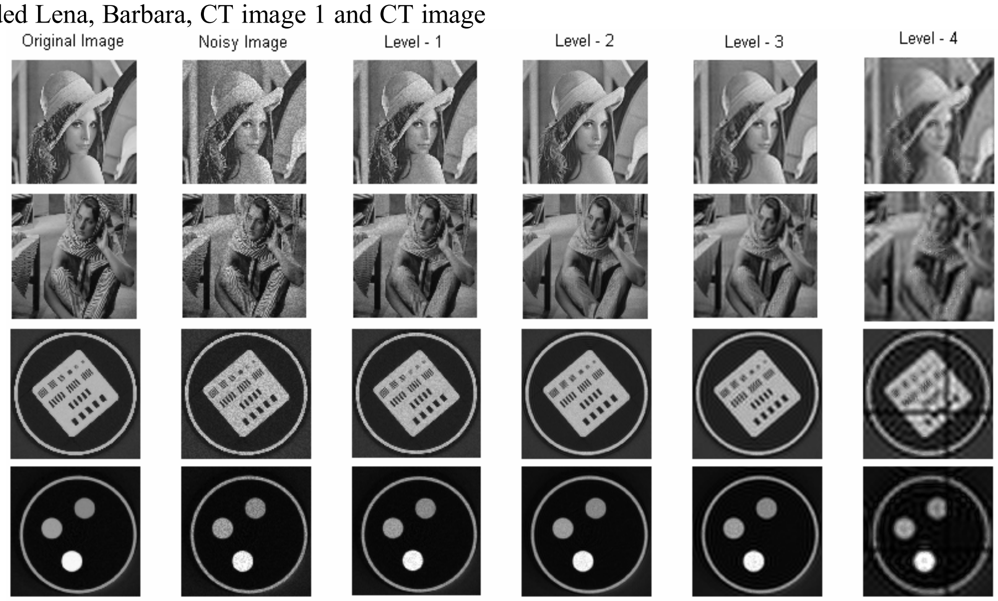
(b)

Fig. 3. Soft threshold Characteristics (a) with λ = aσ and (b) with λ = 1

IV. Experimental Results and Discussion

The performance of the developed Denoising System is analyzed for different levels of DWT decomposition for Speckle noise added Lena, Barbara, CT image 1 and CT image 2 using Discrete Meyer filter, since this filter result in better denoising performance [16]. The experimental results obtained for four levels of DWT decomposition are given in Table 1, where SNR represents the Signal to Noise Ratio between original and noisy images and SNRi represents the Signal to Noise Ratio between original and denoised images using i^{th} level of DWT decomposition. The corresponding Pictorial results are given in Fig. 4.

From the Table 1, it is observed that the highest Signal to Noise Ratio is obtained for first level of DWT decomposition (SNR1) for most of the Speckle noise added Barbara and CT image 1. Further, it is observed that for Lena and CT image 2, corrupted with lesser noise density two level of DWT decomposition is sufficient while for images corrupted with higher noise density second level of DWT decomposition is required. Moreover, it is interested to note that the SNR obtained for higher level of DWT decomposition is lesser than SNR1 or SNR2 and for fourth level of DWT decomposition, severe blurring occurs as evident in the pictorial results, irrespective of images.



(a) (b) (c) (d) (e) (f)

Fig. 4. Pictorial results of Wavelet based denoising - Speckle noise removal for different levels of DWT decomposition (a) Original images (b) Noisy images [σ = 25] (c) First Level (d) Second Level (e) Third Level and (f) Forth Level denoised images

TABLE I

IMAGE DENOISING RESULTS FOR SPECKLE NOISE ADDED IMAGES FOR DIFFERENT LEVELS OF DWT DECOMPOSITION

Standard Deviation (σ)	Lena					Barbara				
	SNR	SNR1	SNR2	SNR3	SNR4	SNR	SNR1	SNR2	SNR3	SNR4
5	39.798599	35.636352	30.453654	26.483321	23.208786	41.725888	26.737924	25.065089	23.852482	21.972172
10	33.792030	34.420402	30.291685	26.443065	23.195047	35.714881	26.614248	25.027767	23.830861	21.961450
15	30.263481	32.975339	30.044675	26.384946	23.169453	32.183475	26.420959	24.970949	23.802672	21.943829
20	27.767167	31.545867	29.765801	26.313438	23.141076	29.696203	26.163186	24.887931	23.762676	21.922071
25	25.828117	30.237359	29.423864	26.232902	23.109722	27.736175	25.855907	24.812394	23.718639	21.902919
30	24.230245	29.022926	29.070256	26.140641	23.075196	26.194996	25.511487	24.697555	23.661135	21.860229
35	22.902668	27.947719	28.668795	26.035795	23.043919	24.842277	25.152311	24.567289	23.602080	21.833414
40	21.733222	26.940023	28.274990	25.918603	22.994916	23.667549	24.736304	24.431707	23.540337	21.793180
45	20.725708	26.022376	27.876219	25.820030	22.951790	22.650961	24.355806	24.298883	23.473045	21.763473
50	19.830534	25.253168	27.452848	25.707328	22.906403	21.737585	23.965638	24.152785	23.398048	21.742024

Standard Deviation (σ)	CT image 1					CT image 2				
	SNR	SNR1	SNR2	SNR3	SNR4	SNR	SNR1	SNR2	SNR3	SNR4
5	42.274611	36.563553	29.828218	25.327439	18.651747	46.782263	46.287736	39.411833	32.063843	23.006477
10	36.271654	35.645144	29.740209	25.304195	18.646295	40.708420	43.425171	39.010159	32.010895	22.998757
15	32.717702	34.462535	29.586818	25.272743	18.639660	37.282174	40.933286	38.445738	31.907903	22.986101
20	30.273925	33.176605	29.388588	25.218701	18.635071	34.701480	38.854567	37.737792	31.769245	22.970987
25	28.291871	31.939403	29.170474	25.157104	18.616166	32.817538	37.032264	36.832237	31.606462	22.949647
30	26.738530	31.939403	28.882826	25.095036	18.611257	31.232816	35.640777	36.120703	31.412197	22.925865
35	25.364701	29.818739	28.583563	25.039302	18.591237	29.901438	34.278276	35.216196	31.196592	22.894324
40	24.242275	28.834759	28.323986	24.918356	18.574201	28.723847	33.188573	34.468379	30.910283	22.853293
45	23.212283	27.977934	27.958683	24.831139	18.554163	27.700036	32.164247	33.861873	30.699045	22.821129
50	22.270627	27.156685	27.628639	24.721633	18.543027	26.802623	31.400620	33.122829	30.360030	22.810773

V. CONCLUSION

From the exhaustive experiments, conducted with the developed image denoising software (i) for different noise parameters and (ii) for different levels of DWT decomposition using soft thresholding technique, the following conclusions are derived: (i) The highest PSNR (dB) is obtained for first level of DWT decomposition (SNR1) for most of the Speckle noise added images, (ii) Further, it is observed that the SNR obtained for higher level of DWT decomposition is lesser than SNR1 or SNR2 and for the fourth level of DWT decomposition, severe blurring occurs, irrespective of images and noise parameters and (iii) Moreover, it is interested to note that for images corrupted with lesser noise densities, single level of DWT decomposition is sufficient; while for images corrupted with higher noise densities, second level of DWT decomposition is required, irrespective of images.

ACKNOWLEDGEMENT

This project is funded by Defense Research Development Laboratory (DRDL), Hyderabad. The authors are expressing their sincere thanks to the Management and Principal, Mepco Schlenk Engineering College, Sivakasi for their constant encouragement and support.

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