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Image Denoising using Various Wavelet Transforms: A Survey

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Abstract

Objectives: Image processing basically comprises of techniques employed to either enhance or restore an image. Noise may creep into the image anywhere from acquisition to transmission phase.Denoising of images can be done in spatial or frequency domain.In this paper we have compared the work done by different researchers in the domain of image restoration using wavelets. **Methods/Statistical Analysis**: wavelet transform has proven to be an efficient and effective method to remove noise. Researchers have explored various types of wavelets and their variations and combinations for image denoising and restoration.Performance is measured in terms of PSNR, MSE and visual quality. Many of the current techniques assume the noise model to be Gaussian. **Findings**:On studying work of various researchers we got to know that as level of decomposition increases performance of denoising technique improves, third and fourth level of decomposition has good results. Wavelet transform performs better than normal average filtering, gaussian filtering and wiener filters. Intra scale and interscale correlations of non orthogonal wavelet coefficients need to utilized by developing good statistical models.And thresholding process needs to be optimized that is value of threshold has to be computed with strong statistical models. **Application/Improvements**: As we know image processing finds application in all most all spheres of life like medical science, remote sensing, military, space exploration etc.,

Keywords: Decomposition, Image Denoising, Restoration, Threshold, Wavelets

1. Introduction

Noise can be seen in all kinds of digitally acquired images and its magnitude can range from almost imperceptible specks on a digital photograph taken in bright light, to almost entirely noisy radioastronomical and optical images. Very small amount of information can be extracted from these noisy images even by applying sophisticated image processing techniques.

The main sources of noise in digital images during image acquisition (digitization) and transmission.

- Imaging sensors can be affected by ambient conditions
- Effects of sensor size, fill factor and sensor heat
- Interference can be added to an image during transmission
- Anything related to the environment and camera characteristics

Transmission through erroneous channels generally results in the received image being corrupted mostly with shot noise. Image restoration is a process in which a corrupted or noisy image is considered for removal of noise from it in order to recover the original image. A variety of denoising methods can be applied which are classified broadly into two main criterion: a) spatial domain methods and transform domain methods. In transform domain methods wavelet transform is the most widely used technique for denoising. It gives spatial information about the frequency components present in the signal. Wavelet transform[1-6] decomposes the original image into sub bands containing low and high frequency components. For a discrete input signal it gives the approximation and detailed coefficients. It is basically the time frequency analysis representation of a discrete signal. It also gives the information about spectral content of the signal at particular location. On carrying out wavelet decomposition

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of a signal, signal is broken down into low pass and high pass sections which independently carry information about original signal. Wavelets are also used for image compression[7-9]. Figure 1 and 2 show the Discrete Wavelet Transform decomposition and reconstruction steps of an image signal for level of 2; and Figure 3 and 4 show results of decomposition of wavelet transform for Lena image.

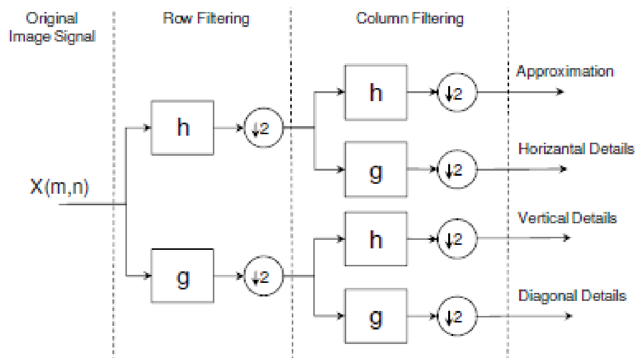

Figure 1. DWT decomposition.

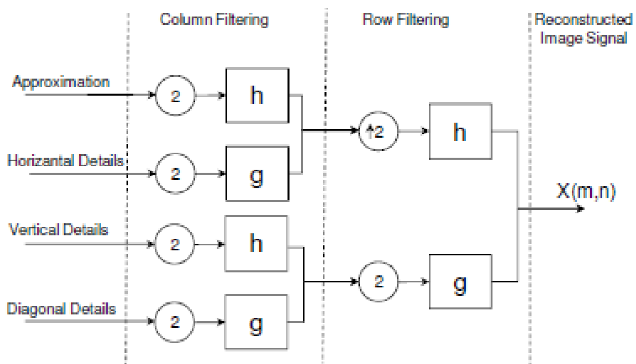

Figure 2. DWT reconstruction.

Figure 3. First level of decomposition.

Figure 4. Second level of decomposition.

2. Overview

Many researchers have worked over wavelet transform for denoising corrupted images and for compressing images too. Some have varied the wavelet bases, modified the thresholding process and have combined other filtering techniques and compared the performance of their proposed methods with other popular techniques. [10]have compared haar and DB3 wavelets to remove speckle noise from Ultrasound, MRI, X ray and CT scan images; [11]has compared Haar, Daubachies, symllet, coiflet wavelets with different thresholding techniques for removing additive white Gaussian noise ; [12]have determined the threshold and neighbouring window size for subband using its length for visuShrink, Modineighshrink and Neighshrink in wavelet transform for removing additive white Gaussian noise; [13]have compared Different filtering techniques with wavelet transform for denoising Gaussian, Salt and Pepper and speckle noise from Lena image; [14]have modified the basic thresholding process , applied circular kernel, Mean max approximation and Nearest Neighbor techniques for removing Gaussian, Poisson, Salt and Pepper and speckle noise from an image; [15]have used Weighted variance for computing threshold in wavelet domain for denoising speckle noise in Lena image;[16]have used Sub band decomposition of logarithmically transformed images described by alpha stable distributions then bayesian estimator uses it for calculating threshold for removing speckle noise in ultrasound images; [17]have designed an adaptive threshold estimation method based on the Generalized Guassian distribution (GGD) modeling of subband coefficients (NormalShrink) for removing Gaussian noise from Lena, Goldhill and Barbara images;[18] Varied wavelet bases and carried out Wavelet transformation from second to fourth level decomposition and applied thresholding techniques: Visushrink, Neighshrink and Modineighshrink for removing Gaussian noise from Lena image; [19]have used Stein's unbiased risk estimate and interscale orthonormal wavelet thresholding algorithm for removing Gaussian from Pepper, barbara, crowd, Goldhill, Boat, Bridge, Al images; [20]have used the Laplacian pyramid and the windowed Fourier transform for removing AWGN from 3D images; [21]have applied multi-wavelet transformation for removing AWGN from Mammographic Images; [22]also combined median filtering with wavelet transform for removing Salt and Pepper, Speckle and Gaussian noise from Lena Image; [23]have used Contourlet transform to remove AWGN from MRI images of brain and spine; [24] proposed a new method for obtaining threshold for image denoising via wavelet soft-thresholding which depends on data (Bayes Shrink) and has also tried to compress the image using MDLQ during denoising. [25]extended least square approach proposed by Salesnick has to 2D images for removing noise, used the wavelet coefficients instead of second order filter coefficients. [26]Proposed an image denoising technique based on least square weighted regularization. Detailed comparision of all these papers have been done in Table 1.

3. Discussion and Conclusion

The following conclusions were derived after rigorous understanding of different techniques:

- DB3 is found to be more efficient than Haar wavelet.
- Performance measured in terms of PSNR, MSE and visual quality.
- Many of the current techniques assume the noise model to be Gaussian.
- An ideal denoising procedure requires a priori knowledge of the noise, whereas a practical procedure may not have the required information regarding the variance of the noise or the noise model.
- Thresholding process is the one which decides the performance of the algorithm.
- Sparsity, multiresolution and multiscale nature of wavlet transform makes it more useful.
- Non orthogonal transform do have better perfomance but high overhead as compared to orthogonal ones.
- Intra scale and interscale correlations of non orthogonal wavelet coefficients need to utilized by developing good statistical models.
- As level of decomposition increases performance improves third and fourth level of decomposition has good results.

Table 1. List and comparison of Image denoising techniques using different wavelets in various forms

S.No.	Paper	Technique Employed	Images considered	Types of Noises	Methodology	Results	Remarks
1	In [10]	Contourlet transform	MRI images of brain and spine	AWGN	Contourlet transform coefficient estimation and thresholding	PSNR plotted against noise variance	Purposed technique gives better results than wavelet transform both visually and in terms of PSNR
2	In [11]	haar and DB3 filtering	Ultrasound, MRI, X ray and CT scan	Speckle Noise	thresholding	PSNR plotted against noise variance	DB3 is found to be more efficient than Haar wavelet both visually and in terms of PSNR
3	In [12]	Varied the wavelet bases: Haar, Daubachies, symllet, coiflet wavelets And used different thresholding techniques	General Image	AWGN	They have used Discrete stationary wavelet transform and applied linear thresholding techniques	Before and after thresholding results shown in terms of PSNR and MSE for various techniques	MSE for Haar global wavelet transform is least among all PSNR for Haar sure sink level 1 is maximum.

4	In [13]	Determined the threshold and neighbouring window size for subband using its length for visuShrink, Modineighshrink and Neighshrink in wavelet transform	Lena, Barbara and Goldhill	AWGN	Shrink the wavelet coefficients, obtained shrinkage factor and then depending on image quality used weiner filter or modified the shrinkage factor	Compared their method with visuShrink, Modineighshrink and Neighshrink by taking varying window sizes and noise level. Wavelet transform (4 level)	Purposed algorithm performed better for all window size and noise levels and also preserves the edges
5	In [14]	Different filtering techniques compared with wavelet transform based denoising	Lena	Gaussian, Salt & Pepper and speckle	Basic filtering techniques and wavelet transform done to de noise the image	Compared results of Averaging filter, Gaussian filter, wiener filter and Wavelet transform	Wavelet transform performs better than Averaging filter, Gaussian filter, wiener filter.
6	In [15]	New threshold, circular kernel, Mean max approximation and Nearest Neighbor	Lena	Gaussian, Poisson, Salt & Pepper and speckle	New threshold computed Based on number of pixels, kernel applied on wavelet coefficients, Mean max threshold obtained, nearest neighbour techniques employed	Wavelet transform performs better than Averaging	New threshold gives comparable or better results than existing ones while other functions give better performance in spatial domain
7	In [16]	Threshold value computed by using Weighted variance in wavelet domain denoising	Ultrasound images	Speckle	Threshold is calculated using weighted variance from sub band HH1 by robust median estimator	PSNR plotted against noise variance	Proposed algorithm is more efficient than Frost, Kaun, Visu, Bayest both visually and in terms of PSNR.
8	In [17]	Sub band decomposition of logarithmic ally transformed images described by alpha stable distributions then bayesian estimator uses it for calculating threshold	Ultrasound images	Speckle	Wavelet transform employed on logarithm of the image and Bayesian estimation is based on alpha stable distributions	Signal to MSE evaluated for different methods	Proposed algorithm is more efficient than Homomorphic weiner filtering and median filtering
9	In [18]	designed an adaptive threshold estimation method based on the Generalized Guassian distribution (GGD) modeling of subband coefficients (NormalShrink)	Lena, Goldhill & Barbara	Gaussian	Estimate noise variance & scale parameter and compute threshold using it, then go for soft thresholding	Compared results of Oracle Shrink,Sure Shrink,Normal Shrink,Bayes Shrink, Oracle Thresh and Wiener	NormalShrink performs better than OracleShrink SureShrink& BayesShrink and Wiener filtering in removing noise. It is 4% faster than BayesShrink too.

10	In[19]	discrete wavelet transform	Lena	Gaussian	Varied wavelet bases, Wavelet transformation second to fourth level decomposition and thresholding techniques: Visushrink, Neighshrink and Modineighshrink	Compared results in terms of PSNR for different wavelet bases, window sizes and thresholding techniques	Among all discrete wavelet bases, coiflet performs well in image de-noising. modified Neighshrink gives better result than Neighshrink, Weiner filter and Visushrink
11	In [20]	Stein's unbiased risk estimate, interscale orthonormal wavelet thresholding algorithm	Pepper, barbara, crowd, Goldhill, Boat, Bridge, Al, House	Gaussian	-Minimize MSE -Soft threshold -built a linearly parameterized denoising function -point wise denoising derivatives of Gaussians (DOG) taken -Building the Interscale Prediction -Integrating Inter scale predictor with denoising function	-Plotted PSNR vs T^2/σ^2 -Compared oracle soft thresholding(pointwise) -	-proposed algorithm has fewer number of artifacts -computation time is very less 0.4 s for 256* 256 images and 1.6 s for 512* 512 images - except for barbara image it outperforms all other algorithms in terms of PSNR obtained
12.	In [21]	Fourier-Wavelet Basis: the Laplacian pyramid and the windowed Fourier transform	3D Image	AWGN	forward FWT, adaptive thresholding, and inverse FWT	SNR values for Miss America video sequence and human knee MR image volume after denoising were compared	Fourier-Wavelet Basis algorithm performs better than Translation invariant for wiener filter (TIW) in terms of PSNR.
13.	In [22]	multi-wavelet transformation applied and threshold calculated for each sub band	Mammographic Images	AWGN	-Prepossessing to improve local contrast and discriminations of subtle details -multi wavelet transform applied -coefficients associated with noise modeled using lapalcian random variables	PSNR obtained of denoised image for multi wavelet and previous methods compared	three level decomposition and fourth level decomposition gave optimum results but blurring is there and neighborhood window of 3X3 and 5X5 are good choices for mammographic images
14.	In [23]	Used median filtering technique with wavelet transform	Lena	Salt & Pepper, Speckle and Gaussian	Tried to combine median filtering and discrete Wavelet Transform denoising corrupted images	PSNR plotted against noise variance	DWT combined with median filter of size 5X5 is best for removing Speckle and Gaussian noise. For low density noise median filter of size 3X3 is best For high density noise median filter of size 5X5 is best.

15.	In [24]	Purposed a new thresholding method for image denoising via wavelet soft-thresholding which depends on data (Bayes Shrink) and has also tried to compress the image during denoising	Lena, Gold hill, barbara and baboon	Gaussian	-bayesian threshold computed assuming generalized Gaussian distribution - σ_x andβ calculated which will give data driven estimate of threshold -MDLQ based compression done	MSE for OracleShrink, SureShrink, BayesShrink, BayesShrinkWITH MDLQ-COMPRESSION, OracleThresh, and wiener filtering denoised images compared	Bayes Shrink outperforms Donoho and Johnstone's SureShrink
16.	In [25]	least square approach proposed by Salesnick has been extended to 2D images for removing noise, the wavelet coefficients are used instead of second order filter coefficients	Lena, Cameraman, Barbara, Peppers and House	Gaussian, Salt and Pepper and Speckle	-Noisy image is taken -second order sparse based and least square based techniques employed to denoise image -results compared in terms of PSNR	PSNR for Haar, Daubechies, Symlet, Coiflet, Biorthogonal and Reverse biorthogonal compared with existing sparse band matrix	Proposed technique using least square based image denoising gives equivalent results to existing second order sparse matrix based technique.
17.	In [26]	Proposed an image denoising technique based on least square weighted regularization	Colored aerial and satellite images	Gaussian	-noisy image decomposed to RGB components -column wise least square regularization done -least square regularization done on transposed image	PSNR and computation time compared with Legendre-Fenchel, wavelet thresholding and total variation methods for different values of lambda and noise density.	Proposed method is simple and computationally very fast and outperforms existing methods based on time factor yet PSNR obtained is comparable.

- Wavelet transform performs better than normal average filtering, gaussian filtering and wiener filers.
- Using median filter with wavelet transform improves the result.
- Bayes Shrink outperforms Donoho and Johnstone's SureShrink.
- NormalShrink performs better than OracleShrink SureShrink, BayesShrink and Wiener filtering in removing noise.
- Among all discrete wavelet bases, coiflet performs well in image de-noising.
- Modified Neighshrink gives better result than Neighshrink, Weiner filter and Visushrink.
- Point wise denoising derivatives of Gaussians reduces artifacts to good extent.
- FWB algorithm performed better than TIW.
- least square approach gives equivalent results to existing second order sparse matrix based technique.
- least square weighted regularization is computationally very fast.

The survey done in this paper on the wavelet based noise removal techniques for images presents a vast scope for readers to understand the usefulness of these techniques. The elaborate and formal conclusions have been drawn.

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