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A Review on Image Denoising Techniques Using Wavelet Transform Methods

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Abstract- **The research area of image processing grew from electrical engineering as an addition of the signal processing branch. The enormous amount of data necessary for images is a main reason for the growth of many areas within the research field of computer imaging such as image processing and compression. The pre dealing being worked upon is the de noising of images. In order to get this in requisites of the concerned research work, wavelet transforms is applied. Wavelet transform and Un-decimated Discrete wavelet transform. DWT can also be added. This can be done in order to discover more possible combinations that may lead to the finest denoising technique. In this review paper we have tried to review the maximum aspects regarding to image denoising.**

Keywords- **Image Denoising, Image Filtering, Wavelet Transform and Wavelet Thresholding.**

I. INTRODUCTION

Image processing is a field that continues to grow, with new applications being developed at an ever increasing rapidity. It is an attractive and exciting area to be involved in today with application areas ranging from the entertainment industry to the space program. One of the most interesting aspects of this information revolution is the ability to send and receive complex data that transcends ordinary written text.

Image processing is a field that continues to grow, with new applications being developed at an ever increasing pace. It is a fascinating and exciting area to be involved in today with application areas ranging from the entertainment industry to the space program. One of the most interesting aspects of this information revolution is the ability to send and receive complex data that transcends ordinary written text. Image information, transmitted in the form of digital images, has become a main method of communication for the 21 century. Image processing is one form of signal processing for which the input is an image, these photographs or frames of video and the output of image processing can be either an image or a set of characteristics or parameters related to the image processing. The majority of image processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it.

There are applications in image processing that require the analysis to be localized in the spatial domain. The traditional way of doing this is through what is called Windowed Fourier Transform. Central thought of windowing is reflected in Short Time Fourier Transform (STFT). The STFT conveys the localized frequency component present in the signal during the short window of time.

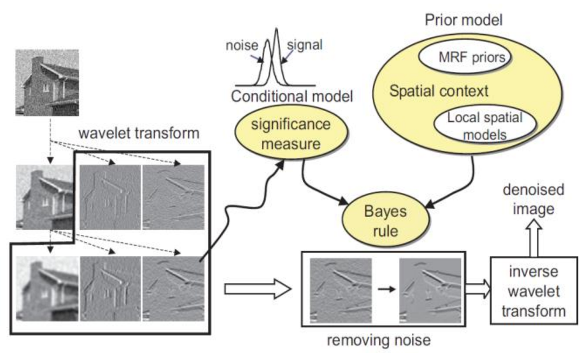

Fig 1.1: A Bayesian wavelet domain denoising framework.

The same perception can be extended to a two-dimensional spatial image where the localized frequency components may be determined from the windowed transform. This is the basis of the conceptual understanding of wavelet transforms. Therefore, wavelet transforms have been kept as the main consideration. It is very well known that while receiving the input image some abberations get introduced along with it and hence a noisy image is what is left with for next processing. The image de-noising as expected corrupted by noise is a classical problem in the field of signal or image processing system. Additive random noise may easily be removed using simple threshold methods.

De-noising of natural images corrupted by noise using wavelet techniques is very effective because of its ability to capture the energy of a signal in few energy transform values. The wavelet de-noising technique thresholds the wavelet coefficients arising from the wavelet transform. Wavelet transform helps a large number of small coefficients and a small number of large coefficients.

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General de-noising methods that employ the wavelet transform consist of given steps.

- Calculate wavelet transform of the given noisy signal.
- Modify noisy wavelet coefficients according to the rule.
- Compute inverse transform by using the modified coefficients.

The concept of wavelet was hidden in the works of mathematicians even more than a century ago. The term wavelet was originally used in the field of seismology to describe the disturbances that emanate and proceed outward from a sharp seismic impulse [22]. Wavelet means a "small wave". The smallness refers to the condition that the window function is of finite length (compactly supported) [23].

A wave is an oscillating function of time or space and is periodic. The wavelets are localized waves. They have their own energy concentrated in time and are suited to analysis of transient signals. As Fourier Transform uses waves to study signals, Wavelet Transform uses wavelets of finite energy [22].

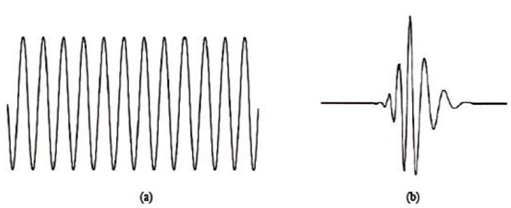

Fig 1.2 Difference between Wave and Wavelet (a) wave (b) wavelet.

In wavelet analysis the signal to be analyzed is multiplied with a wavelet function and then the transform is computed for each segment generated. Wavelet Transform, at high frequencies, gives good time resolution response and poor frequency resolution, as at low frequencies, Wavelet Transform gives good frequency resolution and poor time resolution.

II. DENOISING BY WAVELET THRESHOLDING

Wavelet thresholding is a popular approach for denoising due to its simplicity. In its nearly basic form, this technique operates in the orthogonal wavelet domain, wherever each coefficient is thresholded by comparing against a threshold; if the coefficient is smaller than the threshold it is set to zero, otherwise, it is reserved or modified. One of the primary reports about this approach was by Weaver et al. The systematic theory was developed mainly by Donoho and Johnstone [Donoho92a]-[Donoho95b].

They have shown that various wavelet thresholding schemes for denoising have near optimal properties in the mini-max sense and perform well in simulation studies of one dimensional curve estimation. An extensive review of wavelet thresholding in image processing is in [Jansen01b].

Wavelet Domain Image Denoising

In denoising there is always a trade-off between noise suppression and preserving actual image discontinuities. To remove noise without excessive smoothing of important details, a denoising algorithm needs to be spatially adaptive. The wavelet representation, due to its sparsity, edge detection and multire solution properties, naturally facilitates such spatially adaptive noise filtering. A common procedure is: (1) Compute the DWT or non-decimated wavelet transform; (2) Remove noise from the wavelet coefficients and (3) Reconstruct the denoised image. The scaling coefficients are usually kept unchanged, unless in certain cases of signal dependent noise.

Noise model and Notation

The discrete images as vectors **f** = [*f*1,..., *fn*], where the index *l* refers to the spatial position (like in a raster scanning). Most noise reduction methods to be reviewed in this Chapter, start from the following additive model of a discrete image **f** and noise $\boldsymbol{\vartheta}$

$\mathbf{v} = \mathbf{f} + \boldsymbol{\vartheta}$. (2.3.1)

The vector **v** is the input image. The noise $\boldsymbol{\vartheta}$ is a vector of random variables, while the unknown **f** is a deterministic signal. Some descriptions (Section 2.6) start from a fully stochastic model, considering **f** as well to be a specific realization of a random vector. One usually assumes that the noise has zero mean ($E(\boldsymbol{\vartheta}) = \mathbf{0}$), so that the covariance matrix is

$Q = E[(\vartheta - E(\vartheta))(\vartheta - E(\vartheta))^T] = E(\vartheta\vartheta\, T)$. (2.3.2)

On its diagonal are the variances $\sigma_l^2 = E(\vartheta_l^2)$. If the covariance matrix is diagonal, i.e., if $E(\vartheta_l \vartheta_k) = 0$ for $l \neq k$, the noise is uncorrelated and is called *white*. If all ϑ_l follow the same distribution, they are known to be *identically distributed*. This implies $\sigma_l^2 = \sigma^2$, for every l = 1 ..., n.

An important noise type is Gaussian with the probability density

$$p_\vartheta(\vartheta) = \frac{1}{(2\pi)^{n/2}\sqrt{\det(Q)}} e^{-\frac{1}{2}\vartheta^T Q^{-1}} \quad (2.3.3)$$

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If Gaussian noise variables are uncorrelated, as they are statistically independent $p\vartheta(\vartheta) = \Pi_l\, p\vartheta_l(\vartheta_l)$. The reverse implication (independent variables are uncorrelated) holds for all densities. A general guess is that the noise variables are independent, identically distributed. The majority of the methods in this chapter are specifically designed for the case of additive white Gaussian noise, which is often abbreviated as AWGN.

Noise in the wavelet domain

In the wavelet domain, the most essential information in a signal is compressed into relatively few, large coefficients, which coincide with the areas of major spatial activity (edges, corners, peaks ...) in the image. On the other hand, noise is spread over all coefficients, and at distinctive noise levels (that are of practical importance) the important coefficients can be well recognized. Now the assumed noise model in the wavelet domain formally. Owing to linearity of the wavelet transform, the additive model (2.3.1) remains additive in the transform domain as well:

$w = y + n,$ (2.3.4)

$w = W_d v$ Are the observed wavelet coefficients, $y = W_d f$ are noise-free coefficients, $n = W_d \vartheta$ is noise, and W_d is an operator that yields the discretized wavelet coefficients. An orthogonal wavelet transform maps the white noise in the input image into a white noise in the wavelet domain. Such an orthogonal transform, i.i.d. noise with a variance σ^2 remains i.i.d. with the same variance σ^2. One can express the signal to noise ratio (SNR) in terms of the mean squared error given below:

$$SNR = 10\,log10\,\frac{||\boldsymbol{f}\,||^2}{||\boldsymbol{f} - \hat{\boldsymbol{f}}\,||^2} = 10log10\,\frac{||\boldsymbol{f}\,||^2/N}{MSE},$$

Where SNR is in dB. In image processing, another common performance measure is the peak signal to noise ratio (PSNR), which is for grey scale images defined in dB as

$$PSNR = 10\,log10\,\frac{255^2/N}{MSE}.$$

III. Literature Survey

It is very necessary to remain the helpful data in the correct original form for additional processing and wavelet denoising being the newest method that has proved its control over this subject. The subsequent literature review discusses denoising using wavelet transforms in a wide scenario, i.e. by using a number of thresholding methods for a broad variety of test images.

John C. Wood, Kevin Johnson [1] did denoising of synthetic, phantom, and volunteer cardiac images either in the complex or magnitude domains. For superior edge resolution of real and imaginary images, authors suggested denoising prior to rectification. Magnitude and complex denoising significantly improved SNR.

Wilfred L. Rosenbaum, M. Stella Atkinsa and Gordon E. Sarty [2] applied wavelet shrinkage denoising algorithms and Nowak's algorithm for denoising the magnitude images. The wavelet shrinkage denoising methods were performed using both hard and soft thresholding. It was suggested that changes in mean relative SNR are statistically associated with type of threshold and type of wavelet. The data-adaptive wavelet filtering was found to provide the best overall performance as compared to direct wavelet shrinkage.

Fabrizio Argenti, Gionatan Torricelli [3] assumed Wiener-like filtering, for noise reduction, performed in a shift-invariant wavelet domain by means of an adaptive rescaling of the coefficients of undecimated octave decomposition calculated from the parameters of the noise model, and the wavelet filters. The proposed method resulted in excellent background smoothing as well as preservation of edge sharpness and well details. LLMMSE evaluation in an undecimated wavelet domain tested on both synthetically speckled images and ultrasonic images demonstrated an efficient rejection of the distortion due to speckle.

Jiecheng Xie [4] mentioned the denoising method based on a doubly stochastic process model of wavelet coefficients that gave a new spatially varying threshold using the MDL principle. This method outperformed the traditional thresholding method in both MSE error and compression gain.

Alle Meije Wink and Jos B.T.M.Roerdink [5] evaluated two denoising methods for the simulation of an fMRI series with a time signal in an active spot – by the average temporal SNR inside the original activated spot and by the shape of the spot detected by thresholding the temporal SNR maps. These methods were found to be better suited for low SNRs but for reasonable quality images they were not preferred as they introduced heavy decompositions. Therefore, wavelet based denoising methods were used as they preserved sharpness of the images, from the original shapes of active regions as well and produced a smaller total number of errors than Gaussian noise. But both Gaussian and wavelet based smoothing methods introduced severe deformations and blurred the edges of the active mark. For low SNR both techniques are found to be on par. For high SNR –Wavelet better than Gaussian giving a maximum output of above 10 db.

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Hyeokho Choi, Richard G.Baranuik [6] defined Besov Balls, a convex set of images whose Besov norms are bounded from above by their radii, in multiple wavelet domains and projected them onto their intersection using the projection onto convex sets (POCS) algorithm. It corresponded to a type of wavelet shrinkage for image denoising. This algorithm provided significant improvement over conventional wavelet shrinkage algorithm, based on a single wavelet domain such as hard thresholding in a single wavelet domain.

Byung-Jun Yoon and P. P. Vaidyanathan [7] proposed the custom thresholding scheme and demonstrated that it outperformed the traditional soft and hard-thresholding schemes, 6 since the custom thresholding function adapted well to the characteristics of the given signal, resulting in a smaller estimation error.

Tai-Chiu Hsung, Daniel Pak-Kong Lun and K.C.Ho [8] improved the traditional wavelet method by applying Multivariate Shrinkage on multiwavelet transform coefficients. 1stly a simple 2nd order orthogonal pre filter design method was used for applying multi wavelet of higher multiplicities (preserving orthogonal pre filter for any multiplicity). Then threshold selections were studied using Stein's unbiased risk estimator (SURE) for each resolution point, provided the noise constitution is known. Numerical experiments showed that a multivariate shrinkage of higher multiplicity usually gave better performance and (b) the proposed LSURE substantially outperformed the traditional SURE in multivariate shrinkage denoising, mainly at high multiplicity.

S.Poornachandra [19] used the wavelet-based denoising for the recovery of signal contaminated by white additive Gaussian noise and investigated the noise free reconstruction property of universal threshold. The process was known as Subband adaptive. Parameters were chosen by difference in mean method. The S-median-DM and S-median thresholds were found to have higher SNR and lower MSE than the universal threshold. This proposed technique found its application in denoising of biological and communication signals.

D.Giaouris, J.W.Finch [18] showed that the denoising scheme based on the WT did not distort the signal and the noise component after the process was found to be small. But this process imposed a certain delay on the signal and was relatively complicated. In fixed frequency case, no improvement had been noted. But WT was employed where the useful components existed at widely spread and varying frequencies and the bandwidths were uncertain.

IV. PROPOSED METHODOLOGY

There is a rising requirement of image processing in diverse application areas, such as multimedia computing, secured image data communication, biomedical imaging, biometrics, remote sensing, texture perceptive, pattern recognition, content-based image retrieval. And wavelet transform has been providing a major contribution in all the above mentioned areas since long time. But the betterment never ends. In our proposed system we would use the wavelet Decomposition Method with filtration method. In the below diagram firstly the noise is added with original image after that the wavelet Decomposition is used and for getting the satisfactorily results we proposed the filtration method for better results.

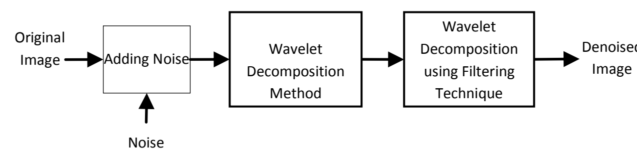

Fig.4.1 Show the block diagram of proposed system

V. CONCLUSION

This work presents a comparative analysis of various image denoising techniques using wavelet transforms. A various combinations have been applied in order to find the best method that can be followed for denoising intensity images. The study, demonstrates that UDWT outperforms DWT for denoising all of the above mentioned images (whether the low pass components are thresholded or are kept as such).

- UDWT denoises the images with more precision as compared to DWT because of its inborn quality of keeping the data intact to a greater extent.
- In UDWT, the step of down sampling the image in the forward run (decomposition process) and up sampling it in the reverse run (composition process) has been omitted. This way the useful data is not lost and a better denoised image is obtained.
- Both PSNR and MSSIM show an apprehensive improvement, if the noisy images are denoised using UDWT.

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