Implementation of Image Denoising Techniques using Novel Slantlet Transform

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ABSTRACT
Wavelets have been developed to analyze the frequency components of a signal according to a scale. They provide more information than the Fourier transform for signals which have discontinuities or sharp spikes. The modern techniques of digital signal processing such as MultiMate filtering, sub band coding and wavelet transform have been studied and applied effectively in science and technology fields nowadays. The discrete wavelet transform (DWT) is usually carried out by filter bank iteration; however, “for a fixed number of zero moments, this does not yield a discrete-time basis that is optimal with respect to time localization”. This project focuses on the “implementation and properties of an orthogonal DWT, with two zero moments and with improved time localization (wavelet bases generation)”, determining the relation between this transform and M –band wavelet theory, and its application in image coding is implemented. Shorter the scaling function spectrum, larger the number of wavelet co-efficient and hence more scale information (by designing filter of shorter length).The wavelet basis function is not on filter bank iteration; but on, different filters for each scale. Moment vectors are calculated based on input (either 1 – D or 2 – D Signal) signal and it is projected on wavelet basis to extract details of signal by using multi resolution analysis. The decomposition level is adapted to the length of signal as in case of fixed level in traditional discrete wavelet transform. For coarse scales, the support of the discrete-time basis function reduced (by a factor approaching one third for coarse scales).The implementation and properties of an orthogonal DWT, with two zero moments and with improved time localization are discussed in this project work. The wavelet representation of images using slantlet basis function is presented. The slantlet filter bank (wavelet bases generation) design technique where different filters for each level (scale or stage) is described will be implemented in this project work. The application of an image denoising using orthogonal discrete wavelet (slantlet) transform is presented in this project work. The various threshold methods which are used for image denoising is also discussed in this work. The signal estimation technique from the observed signal (that is corrupted by noise) that exploits the capabilities of wavelet (slantlet bases) transform for signal denoising is implemented in this project. The soft threshold technique which is useful in image enhancement coding (where noisy co-efficient are killed by fixing the threshold level) is also investigated.

Keywords
Wavelet Transform, Slantlet Transform, image denoising technique, soft thresholding, DWT, SLT

1. INTRODUCTION
Digital signal processing plays an important role in telecommunication network. MultiMate filtering, sub band coding and wavelet are now studied and applied effectively. Wavelet transform based on multiresolution analysis has exact local analysis capability. The closed connection between wavelet and sub band coding allows using filter bank for wavelet transform and that is one of the advantages of wavelet. Wavelet transform is applied effectively in a lot of fields such as signal noise filtering, speech processing and especially in image and video compression.

It is well known from Fourier theory that a signal can be expressed as the sum of a, possibly infinite, series of sine’s and cosines. This sum is also referred to as a Fourier expansion. The big disadvantage of a Fourier expansion however is that it has only frequency resolution and no time resolution. This means that although we might be able to determine all the frequencies present in a signal, we do not know when they are present. To overcome this problem in the past decades several solutions have been developed which are more or less able to represent a signal in the time and frequency domain at the same time.

The idea behind these time-frequency joint representations is to cut the signal of interest into several parts and then analyze the parts separately. It is clear that analyzing a signal this way will give more information about the when and where of different frequency components, but it leads to a fundamental problem as well: how to cut the signal? Suppose that we want to know exactly all the frequency components present at a certain moment in time. We cut out only this very short time window using a Dirac pulse, transform it to the frequency domain and ... something is very wrong.

The problem here is that cutting the signal corresponds to a convolution between the signal and the cutting window. Since convolution in the time domain is identical to multiplication in the frequency domain and since the Fourier transform of a Dirac pulse contains all possible frequencies the frequency components of the signal will be smeared out all over the Frequency axis. (Please note that we are talking about a two-dimensional time-frequency transform and not a one-dimensional transform.) In fact this situation is the opposite of the standard Fourier transform since we now have time resolution but no frequency resolution whatsoever

The WT or wavelet analysis is probably the most recent solution to overcome the shortcoming of the Fourier Transform. In wavelet analysis the use of a fully scalable modulated window solves the signal-cutting problem. The window is shifted along the signal and for every position the spectrum is calculated. Then this process is repeated many times with a slightly shorter (or longer) window for every new cycle. In the end result will be a collection of time- frequency representation of the signal, all with different resolution. Because of this collection of representation we can speak of a multiresolution analysis. In the case of wavelets we normally do not speak about time-frequency representation but about time-scale representation, scale being in a way the opposite of frequency, because the term frequency is reserved for the Fourier transform.

Wavelet transform (WT) represents an image as a sum of wavelet functions (wavelets) with different locations and scales. Any decomposition of an image into wavelets involves a pair of waveforms: one to represent the high frequencies corresponding to the detailed parts of an image (wavelet function) and one for the low frequencies or smooth parts of an image (scaling function). Fig. 1.0 shows two waveforms of a family discovered in the late 1980s by Daubechies: the right one can be used to represent detailed parts of the image and the left one to represent smooth parts of the image. The two waveforms are translated and scaled on the time axis to produce a set of wavelet functions at different locations and on different scales. Each wavelet contains the same number of cycles, such that, as the frequency reduces, the wavelet gets longer. High frequencies are transformed with short functions (low scale). Low frequencies are transformed with long functions (high scale). During computation, the analyzing wavelet is shifted over the full domain of the analyzed function. The result of WT is a set of wavelet coefficients, which measure the contribution of the wavelets at these locations and scales.

1.1 Orthogonal Discrete Wavelet Transform

The orthogonal discrete wavelet transform is called as Slantlet Transform [2]. The DWT described here is based on a filter bank structure where different filters are used for each scale. Nevertheless, a very simple efficient algorithm based on recursion is available. For the DWT filter bank described here, the support of the discrete-time basis functions is reduced (by a factor approaching one third for coarse scales) while retaining the basic characteristics of the two band iterated filterbank tree. This basis retains the octave-band characteristic and leads cleanly to a DWT for finite length signals (boundary issues do not arise, provided the data length is a power of 2). The filters are piecewise linear but are discontinuous—for coarse scales, they converge to piecewise linear, discontinuous functions. The basis, being piecewise linear, is reminiscent of the discrete wavelet transform approximation order 2 with improved time localization to which it is compared. However, the basis functions of the slant transform, like the Hadamard transform for example, are nonzero over all of the domain, whereas the basis functions described in this paper become progressively more narrow, giving a multiresolution decomposition. Hence, we have the name slantlet for the transform described here. The slantlet basis appears especially well suited for treating piecewise linear signals.

1.2 Problem Statement

The discrete wavelet transform (DWT) is usually carried out by filterbank iteration; however, for a fixed number of zero moments, this does not yield a discrete-time basis that is optimal with respect to time localization. In the application of wavelet bases to image compression, the time localization and number of zero moments of the basis are both important. Good time-localization properties lead to good representation of edges. Approximation order is important for sparse representation (compression) of smooth regions. This project focuses on the implementation and properties of an orthogonal discrete wavelet transform, with two zero moments and with improved time localization.

The wavelet bases described here should provide a good tradeoff between time localization (shorter filter length) and smoothness characteristics (number of zero moments). These two are competing criteria in designing wavelet bases.

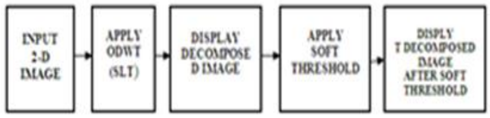
The basis described from a filter bank viewpoint, gives explicit solutions for the filter coefficients, and describes an efficient algorithm for the transform. The implemented orthogonal discrete wavelet transform will be applied on image and reconstructed image will be verified. An image enhancement (image denoising) will be done based on this transform using soft threshold method for various standard deviation ranges from 5 to 30 and mean zero.

1.3 Objective of Proposed Work

The objective of the project work is to implement or demonstrate efficient algorithm for an orthogonal DWT, with two zero moments and with improved time localization (wavelet bases generation) will be implemented. It by considering 2-D signal (i.e. on image) and experimental results will be verified. And also Image denoising using slantlet transform will be implemented. A threshold value is computed by observing mean, variance & standard deviation of the noisy image. A soft threshold method is applied to the slantlet co-efficients (after applying ODWT to the original image). Then threshold value is compared with wavelet co-efficient.

2. PROPOSED METHODOLOGY OF WORK

Fig 1: Analysis stage of proposed slantlet transform based



system

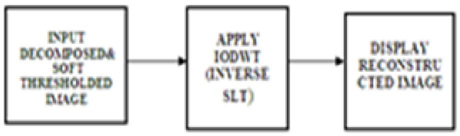


Fig 2: Synthesis stage of proposed slantlet transform based system

The Block Diagrams describe the proposed methodology of proposed work. it consists of Two stages, the first stage of work called the analysis stage, in the stage of analysis for the given input noisy image can be decomposed by SLT Transform and then this decomposed image is denoised by soft Threshold Technique, A threshold value is computed by observing mean, variance & standard deviation of the noisy image. In the stage of Synthesis the image can be reconstructed by applying Inverse orthogonal DWT (which uses slantlet bases). The performance of SLT Algorithm can be evaluated by computing MSE, PSNR for various SNR values, by considering original image and reconstructed image. Thus obtained performance is compare with existing algorithms performance such as discrete cosine transform, DFT, DWT and without & with soft threshold technique. The image denoising algorithms based on an orthogonal discrete wavelet and discrete cosine transform uses soft thresholding method discussed above on Lena picture.

2.1 Literature Review of Earlier Work

C. Valens in his published literature [4] on wavelets has stated an overview of Fourier theory and the disadvantages associated with Fourier transforms. It is well known from Fourier theory that a signal can be expressed as the sum of a possibly infinite series of sines and cosines. This sum is also referred to as Fourier expansion. Fourier expansion however is that it has only frequency resolution and no time resolution. The idea behind these time-frequency joint representations is to cut the signal of interest into several parts and then analyze the parts separately. It is clear that analyzing a signal this way will give more information about when and where the different frequency components exists, but it leads to a fundamental problem as well. Suppose, in order to know whether exactly all the frequency components are present at a certain moment in time or not, it is necessary to cut out only this very short time window using a Dirac pulse and transform it to the frequency domain. The problem here is that the cutting the signal corresponds to a convolution between the signal and the cutting window. Since convolution in the time domain is identical to multiplication in the frequency domain and the fourier transform of a Dirac pulse contains all possible frequencies, the frequency components of the signal will be smeared out all over the frequency axis. The big disadvantage of a fourier expansion is that it has only frequency resolution and no time resolution. This means that it is possible to determine all the frequencies present in a signal, but in time instant they are present cannot be determined [1].

To overcome this problem in the past decades several solutions have been developed which are more or less able to represent a signal in the time and frequency domain at the same time. Fourier expansion situation is opposite to the standard Fourier transform, since it is having time resolution, but no frequency resolution. The underlying principle of the phenomena just described is due to Heisenberg's uncertainty principle. In signal processing terms, it can be stated that it is impossible to know the exact frequency and the exact time of occurrence of this frequency in a signal. In other words, a signal can simply not be represented as a point in the time-frequency space [1].

Andrew B. Watson discusses about basic definition of discrete cosine transform. The discrete cosine transforms (DCT) is a technique for converting a signal into elementary frequency components. It is widely used in image or data compression [2].

Saied Belkasim describes the advantages and disadvantages of discrete cosine transform. The discrete cosine transform (DCT) gained popularity in signal compression for its energy compaction and optimal information representation properties. Sample folding into sums and differences has been used to improve computation of DCT, but has never been used to generate independent forward and inverse even or odd transforms. Although, resizing of signals has been successfully attempted using the DCT, it was not geared towards a general multi-resolution analysis procedure that allows local as well as global features to be captured in a wavelet-like structure [3].

The disadvantages of discrete cosine transform (DCT) are also stated by T. B. Littler and D. J. Morrow. For instance, DCT reconstruction reproduced the sinusoid signal, but not the transient component. This was attributed to the poor time localization of the DCT basis function. Also, additional noise was introduced in the DCT reconstruction. Wavelets are mathematical functions with advantages over fourier transforms and discrete cosine transform for the analysis of signals with transient features. Wavelet analysis is based on the decomposition of a signal according to *scale*, rather than frequency, using basis functions (samples) with adaptable scaling properties. This method of analysis is generally referred to as multiresolution analysis [4].

The wavelet analysis is probably the most recent solution to overcome the shortcoming of the discrete cosine transform. The advantages of wavelet compared to discrete cosine transform are stated by Chul Hwan Kim and Raj Aggarwal in their work [5].

S. Santoso and E. J. Powers have stated as to how compression is carried out using discrete wavelet transform and its disadvantage compared to slantlet transform. The compression is carried out in the wavelet domain by retaining wavelet transform coefficients associated with disturbance events and discarding all other disturbance-free coefficients. The most-smoothed version of the original recorded signal is also kept for reconstruction purposes. In order to recover the original disturbance signal, wavelet reconstruction techniques are utilized. Since the compression process discards about 90% of the total wavelet transform coefficients, some information will be lost. However, most of these coefficients are associated with noise. Therefore, the quality of the reconstructed disturbance signal is very high and most disturbance events are preserved nicely, since the wavelet transform coefficients associated with the disturbance are saved. To some extent, the reconstructed signal is actually a better signal, since it contains less electrical noise compared to the original signal, but maximum energy retainment is not achieved [9].

2.2 Scope of Present Work

The scope of present work is to overcome the disadvantages of discrete cosine transform and discrete wavelet transform by using slantlet transform for the denoising of image. Good time localization properties of slantlet transform are expected to result in good reconstruction of the signal. The scopes of the present work which includes Apply slant let transform method to the 2-D signals To the transformed coefficients of the signals, fix the threshold value. The coefficients which are below the threshold value are to be made zero, resulting in compression of the signal by reducing the number of coefficients. Compare and analyze the output of slantlet transform approach with that of discrete cosine transform and discrete wavelet transform approaches, in terms of post-reconstruction parameters such as amount of energy retained and the mean square error.

3. EXPERIMENTAL RESULTS

Following are the results of reconstructed image by applying orthogonal DWT (which uses slantlet bases) to the original Image with and without using soft threshold technique and running the denoising algorithms for the methods discussed above on Lena picture. The denoising is done after adding the Gaussian noise with standard deviation of 5, 10, 15, 20, 25, and 30 and mean 0 on original Lena picture. We estimated the threshold value which gives better denoised image by computing mean and variance. Then soft threshold technique is applied to wavelet co-efficient to remove the noisy co-efficient and inverse orthogonal DWT (ISLT) is applied to obtain the denoised image which contains less noise when compared to original noisy image. The PSNR is calculated for each denoised image with respect to original image and noisy image and also MSE is calculated for each and every denoised image (see Fig. 5.17). The results are tabulated (see Table 5.0). The deonised image figures and MSE are compared for the global and adaptive thresholding techniques. The denoised image results are shown for different noise variance (5, 10, 15, 20, 25 and 30) along with noisy image. Here soft threshold method is used to remove the noisy co-efficient.

3.1 Image Reconstruction without using Thresholding Technique

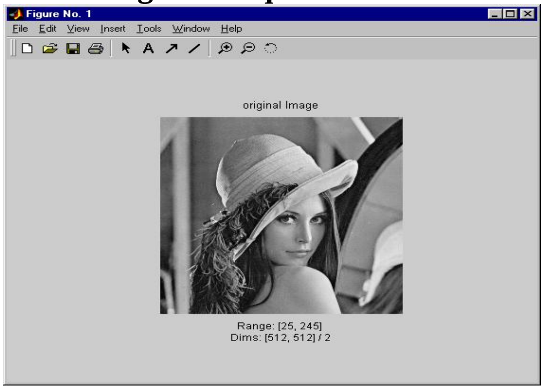


Fig 3: Original Lena Image

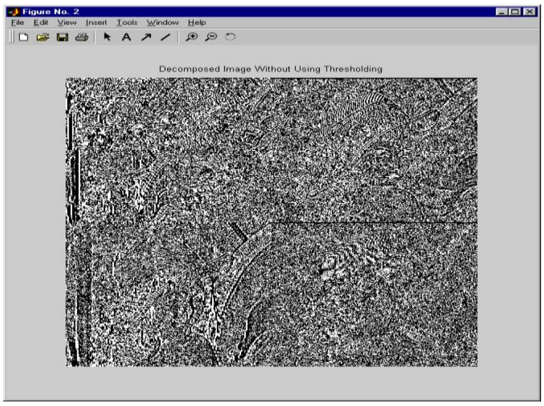


Fig 4: Decomposed Lena Image by SLT

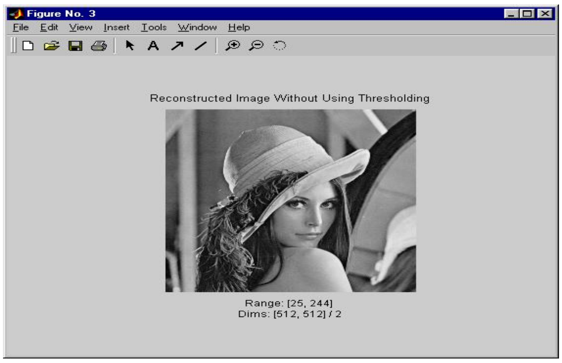


Fig 5: Reconstructed Lena Image by SLT before applying thresholding

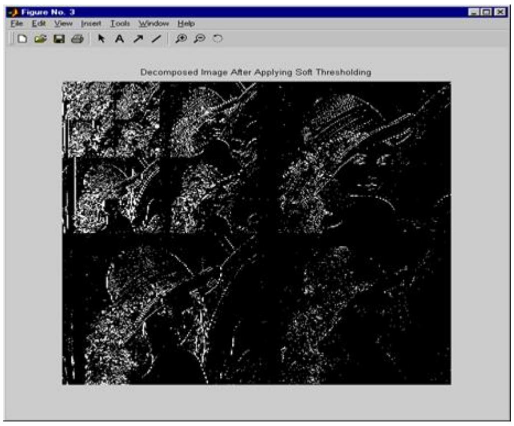


Fig 6: Decomposed image after applying soft thresholding

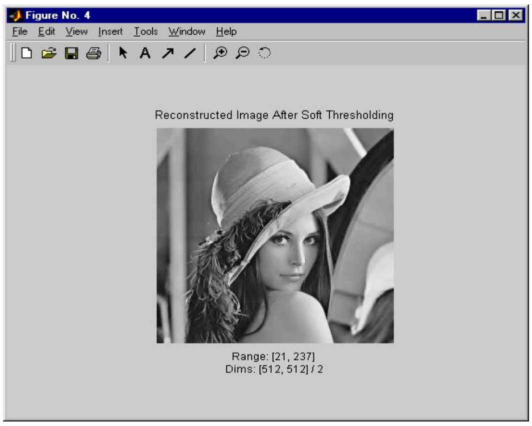


Fig 7: Reconstructed Image after applying thresholding technique

3.2 Image Denoising Using Soft Threshold Method

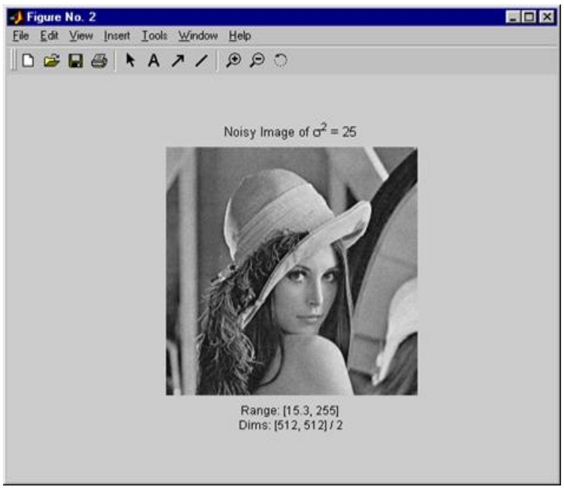


Fig 8: Noisy Lena Image of Variance 25 (σ=5)

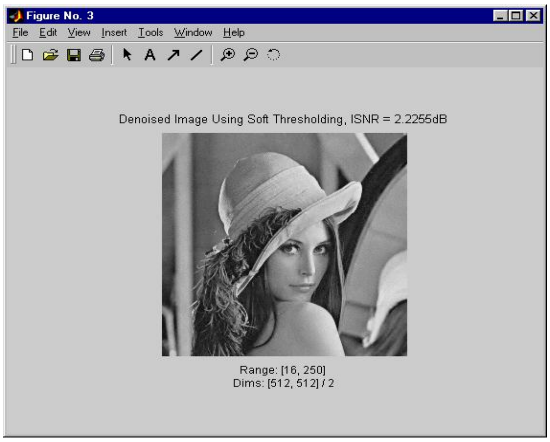


Fig 9: Denoised Lena Image of Variance 25 (SLTB, σ=5)

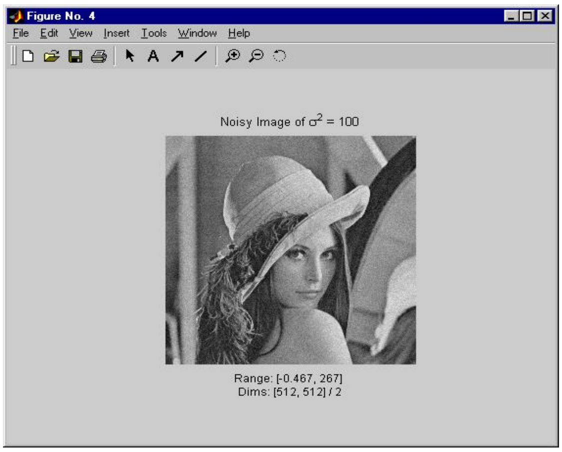


Fig 10: Noisy Lena Image of Variance 100 (σ=10)

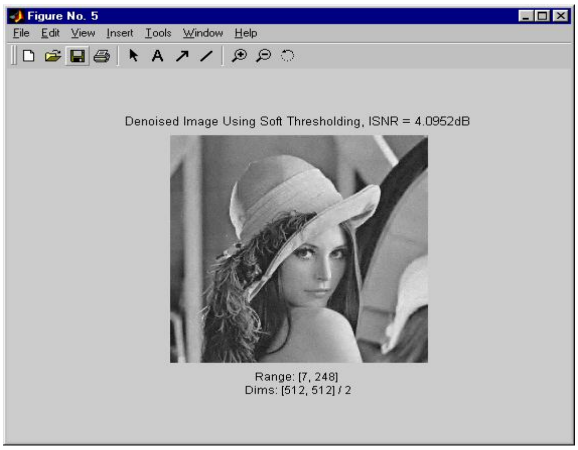


Fig 11: Denoised Lena Image of Variance 100 (SLTB, σ=10)

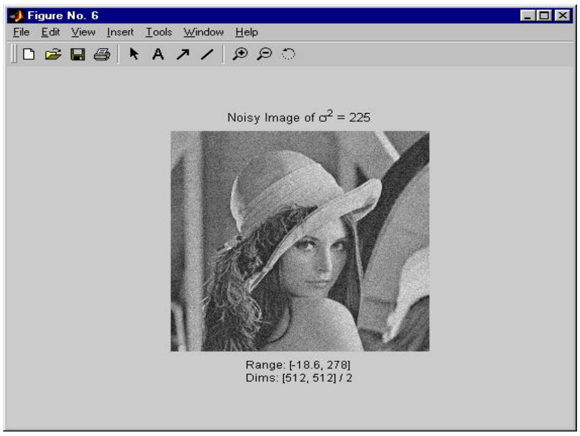


Fig 12: Noisy Lena Image of Variance 225 (σ=15)

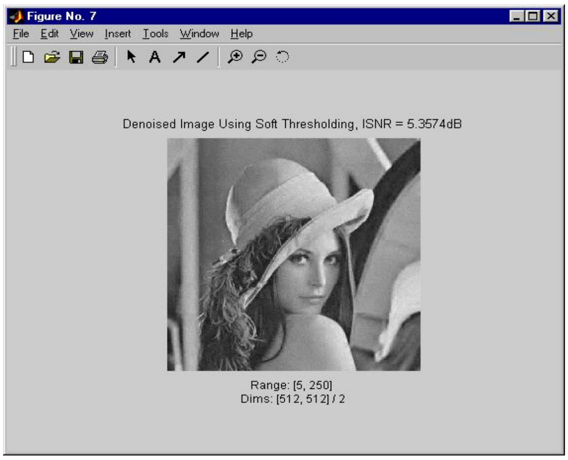


Fig 13: Denoised Lena Image of Variance 225 (SLTB, σ=15)

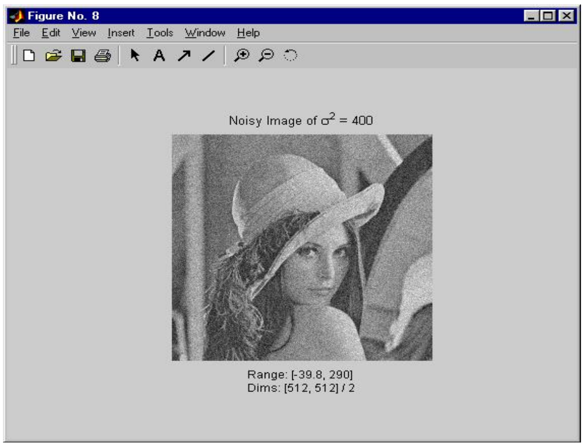


Fig 14: Noisy Lena Image of Variance 400 (σ=20)

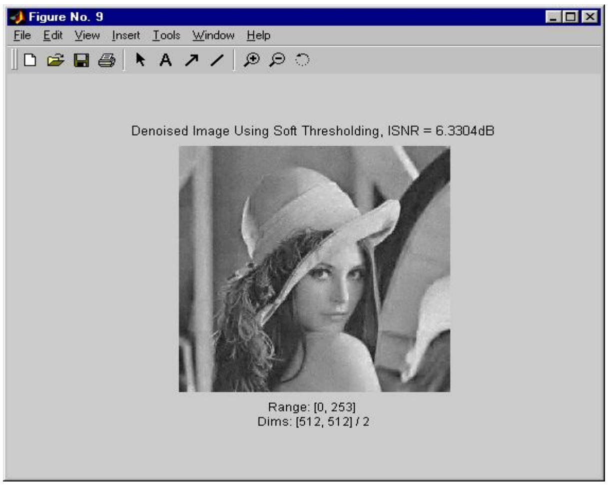


Fig 15: Denoised Lena Image of Variance 400 (SLTB, σ=20)

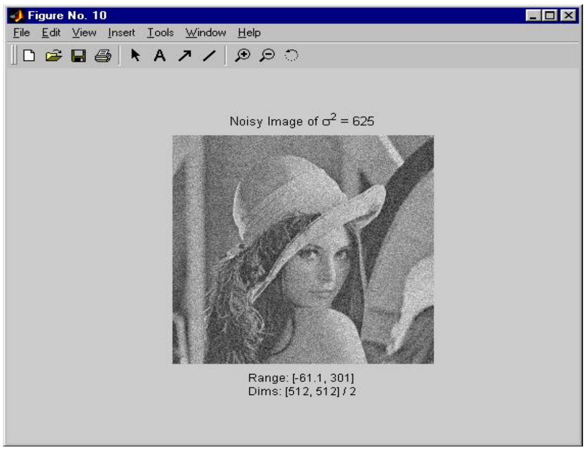


Fig 16: Noisy Lena Image of Variance 625 (σ=25)

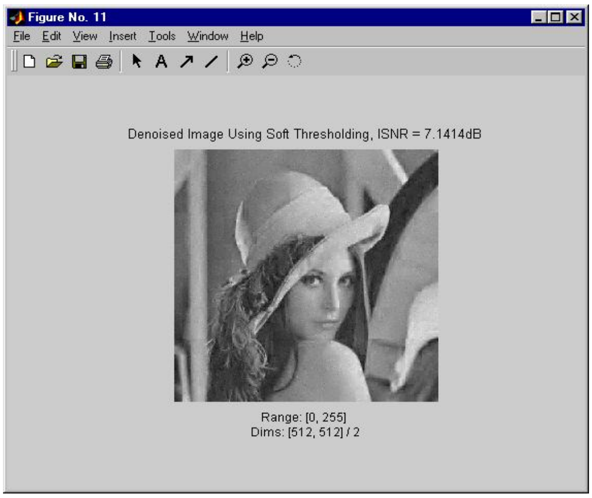


Fig 17: Denoised Lena Image of Noise Variance 625 (SLTB, σ=25)

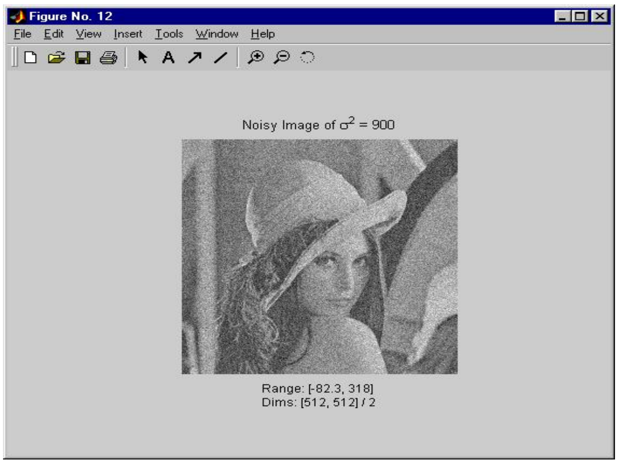


Fig 18: Noisy Lena Image of Variance 900 (σ=30)

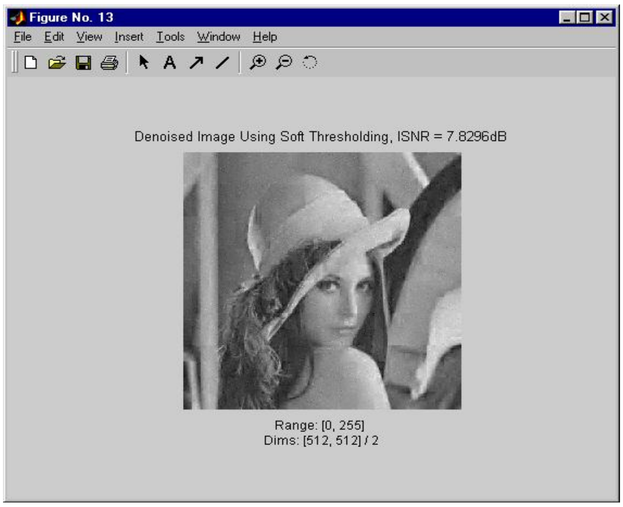


Fig 19: Denoised Lena Image of Noise Variance 900 (SLTB, σ=30)

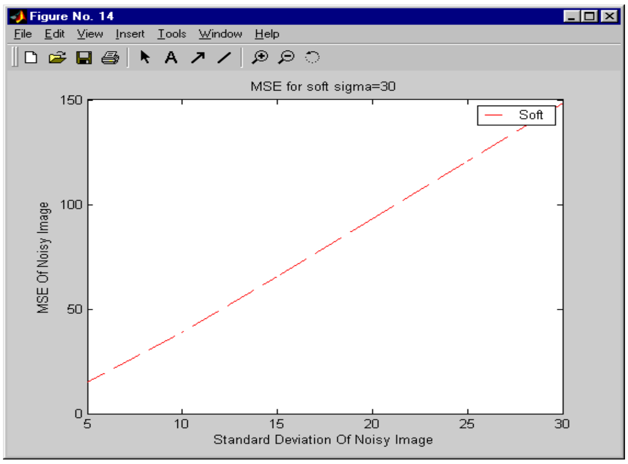


Fig 20: MSE for Denoised Image Using Soft Threshold Method

Table 1. Denoised Lena image Performance

Image Name	Threshold Value	Noise Variance	PSNR in db.
Lena	3.9766	25	36.3769
	11.5533	100	32.2260
	19.9299	225	29.9663
	29.9066	400	28.4407
	39.8838	625	27.3134
	49.9998	900	26.4180

4. CONCLUSIONS

This Paper works presents an orthogonal filter bank for the discrete wavelet transforms with two zero moments, where the filters are of shorter support than those of the iterated filter bank tree. Although not based on an iterated filter bank tree, the filter bank described in this project retains the main desirable characteristics of the usual DWT filterbank, namely, orthogonally, an octave-band characteristic, a scale-dilation factor of 2, and an efficient implementation. Table 1. Summarizes a comparison results of denoising of image using SLT transform. A transform for finite length signals based on this filter bank is particularly clean due to the filter lengths being exact powers of two. The basis appears particularly well suited for piecewise linear signals, as does the Haar basis for piecewise constant signals.

The newly designed an orthogonal filtebank (Slantlet Bases) provides better tradeoff between time – localization and smoothness characteristics. These wavelet bases supports shorter length when compared to existing discrete wavelet transform (shorter filter length improves the time – localization of the wavelet basis leads to good representation of edges without degrading the smoothness part). The same band pass filters are used for each scale in existing discrete wavelet transform (signal spectrum coverage is fixed). But the filter bank described here, uses different band-pass filters of having shorter length for each stage or level or scale. The decimation factor also varies in accordance with scale. The advantage of using many band-pass filters are that the width of every band can be chosen freely, in such a way that the spectrum of the signal to analyze is covered in the places where it might be interesting. The disadvantage is that we will have to design every filter separately and this can be a time consuming process and in turn increases the coding complexity.

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