DENOISING OF A COMPUTED TOMOGRAPHIC IMAGE USING WAVELET TRANSFORM AND IMAGE FUSION TECHNIQUE

A PROJECT REPORT

Submitted by

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CHAPTER 1
INTRODUCTION

Digital image processing is the use of computer algorithms to perform image processing on digital images. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing may be model in the form of multidimensional systems.

Almost every kind of data contains noise. Noise reduction is a required step for any sophisticated algorithms in computer vision and image processing. An efficient method is necessary for removing noise in the images.

Denoising attempts to remove whatever noise is present and retain whatever the signal is present regardless of the frequency content. Image denoising finds applications in fields such as medical imaging where the physical requirements for high quality imaging are needed for analyzing images of unique events, in astronomy where the resolution limitations are severe, and in forensic science where potentially useful photographic evidence is sometimes of extremely bad quality.

1.1 OBJECTIVE

In wavelet transform, the image is decomposed into many coefficients (approximate, horizontal, vertical, diagonal). Then the idea of thresholding is applied in which we set all high frequency sub-band coefficients that are less than a particular threshold to zero. These coefficients are used in an inverse wavelet transformation to reconstruct the data set. Therefore a better quality image is obtained.

The objective of this project is to compare the suitability of different thresholding methods such as Hard, Soft, Bayesshrink techniques and to find the best thresholding technique for different transforms such as discrete wavelet transform and stationary wavelet transform in terms of PSNR.

Wavelet families such as Haar, Daubechies(1 to 10), Symlet(2 to 8), Coiflet(1 to 5) are subjected to transforms(DWT/SWT).For individual algorithms, best family and best level are selected based on PSNR gain.

To enhance the PSNR gain, Image fusion method is also used. This project aims at finding the beat wavelet family of best decomposition level for various thresholding methods.

1.2 PROBLEM DESCRIPTION

The basic idea behind our project is the estimation of the uncorrupted image from the distorted or noisy image, and is also referred to as image “denoising”. There are various methods to help restore an image from noisy distortions. Selecting the appropriate method plays a major role in getting the desired image. The denoising methods tend to be problem specific.

The noisy image is visually unpleasant and it is difficult to perform various further analyses like segmentation, recognition and compression. Therefore, it is very important to reconstruct an original image from the corrupted observations. Noise is unwanted signal that interferes with the original signal and degrades the visual quality of digital image. Image denoising techniques are necessary to remove such noise while retaining as much as possible the important signal feature.

1.3 NOISE

Noise is an undesired information that corrupts the image. The noise degrades the quality of an image. It leads to information loss.Noise is always presents in digital images during image acquisition, coding, transmission, and processing steps. Noise produces undesirable effects such as artifacts, unrealistic edges, unseen lines, corners, blurred objects and disturbs background scenes. Noise is very difficult to remove it from the digital images without the prior knowledge of noise model. For effective denoising, information about the type of noise is essential.

1.3.1 Gaussian Noise

It is a random noise that has Gaussian distribution with zero mean and variance as noise power. Gaussian noise is evenly distributed over the signal. This means that each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value.

$$y(t)=x(t)+n(t)$$

Here noise is equally present with same power at all frequencies. In frequency domain the noise level is flat at every frequency.

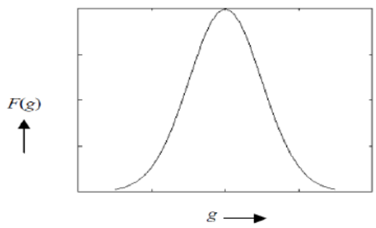


Fig1.1 Gaussian distribution

It has a bell shaped probability distribution function which is given by,

$$p_G(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}}$$

where "z" represents the gray level, "μ" is the mean or average of the function

"σ" is the standard deviation of the noise.

1.3.2 Poisson noise

The appearance of this noise is seen due to the statistical nature of electromagnetic waves such as x-rays, visible lights and gamma rays. The x-ray and gamma ray sources emitted number of photons per unit time. These rays are injected in patient's body from its source, in medical x rays and gamma rays imaging systems. These sources are having random fluctuation of photons. Result gathered image has spatial and temporal randomness. This noise is also called as quantum (photon) noise or shot noise. This noise obeys the Poisson distribution.

1.3.3 Noise Estimation

Thresholding Methods- Wave threshold is a signal estimation technique that exploits the capabilities of wavelet transform for image denoising. It removes noise by killing coefficients that are insignificant relative to same threshold.

Methods:

- Universal Thresholding
    a. Soft
    b. Hard
- Sub-band Adaptive
    a. Bayes shrink

This denoising mechanism involves Soft, hard and bayes thresholding methods. Bayes is an adaptive data driven threshold for image denoising via wavelet soft thresholding. Its effectiveness involves the selection of a threshold that minimizes Bayesian risk.

CHAPTER 2

WAVELET TRANSFORM

2.1 WAVELET TRANSFORM

Wavelet means small wave. It analyses with short duration, finite energy functions. They transform the image under investigation into another representation which presents it in a more suitable form. This transformation is called wavelet transform.

Wavelet transform provides time-frequency information. It leads to a multi-resolution analysis of signals. Spatial filters like mean and median filters smooth the data to reduce noise and also blur the edges. But Wavelet Transform preserves the edges

The use of wavelet transform for signal de-noising has been started in last decade. In mathematics, a wavelet series is a representation of a square-integrable(real-or complex-valued) function by a certain orthonormal series generated by a wavelet. Nowadays, wavelet transformation is one of the most popular of the time-frequency-transformations. Wavelets capability to give detail spatial-frequency information is the main reason for this investigation. This property promises a possibility for better discrimination between the noise and the real data. Successful exploitation of wavelet transform might lessen the blurring effect or even overcome it completely.

It involves three steps:

- a linear forward wavelet transform,
- nonlinear thresholding step and
- a linear inverse wavelet transforms.

Wavelet thresholding is a signal estimation technique that utilizes the capabilities of wavelet transform for signal denoising. It removes noise by killing coefficients that are inconsiderable 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 effectiveness of denoising.

Wavelet transform decomposes a signal into a set of basis functions. These basis functions are called wavelets. Wavelets are obtained from a single prototype wavelet y(t) called mother wavelet by dilations and shifting.

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right)$$

$\Psi_{s,\tau}(t)$ is the wavelet with scale s and time τ

Ψ is the mother wavelet

2.1.1 DISCRETE WAVELET TRANSFORM

The Discrete Wavelet Transform (DWT) of image signal produces a non-redundant image representation. Discrete Wavelet Transform has attracted more and more interest in image de-noising. The DWT can be interpreted as image decomposition in a set of independent, spatially oriented frequency channels. The image coefficients are passed through two complementary filters and emerge as approximation and detailed coefficients. This is called multi-scale decomposition or analysis. The components can be assembled back into the original image without loss of information. This process is called reconstruction or synthesis. The mathematical manipulation, which implies analysis and synthesis, is called discrete wavelet transform and inverse discrete wavelet transform.

The decomposition of the signal into different frequency bands is simply obtained by successive high pass and low pass filtering of the time domain signal.

First level decomposition Second level decomposition

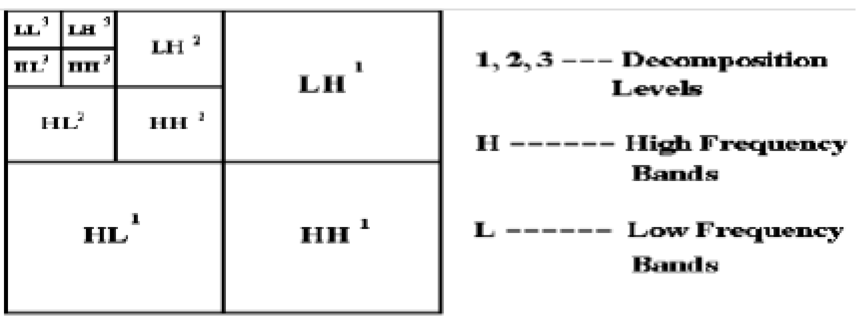


Fig 2.1Wavelet Decomposition

The original signal x[n] is first passed through a half band high pass filter g[n] and a low pass filter h[n]. After the filtering, half of the samples can be eliminated according to the Nyquist's rule, since the signal now has a highest frequency of π /2 radians instead of π. The signal can therefore be sub sampled by 2, simply by discarding every other sample. This constitutes one level of decomposition and can mathematically be expressed as follows:

$$y_{high}[k] = \sum_n x[n] \cdot g[2k - n]$$

$$y_{low}[k] = \sum_n x[n] \cdot h[2k - n]$$

where, yhigh[k] and ylow[k] are the outputs of the high pass and low pass filters respectively, after subsampling by 2.

The decomposed components can be assembled back into the original signal without loss of information. This process is called *reconstruction*, or *synthesis*. The mathematical manipulation that effects synthesis is called the *inverse discrete wavelet transforms* (IDWT).

Wavelet analysis involves filtering and down sampling, whereas the wavelet reconstruction process consists of up sampling and filtering.

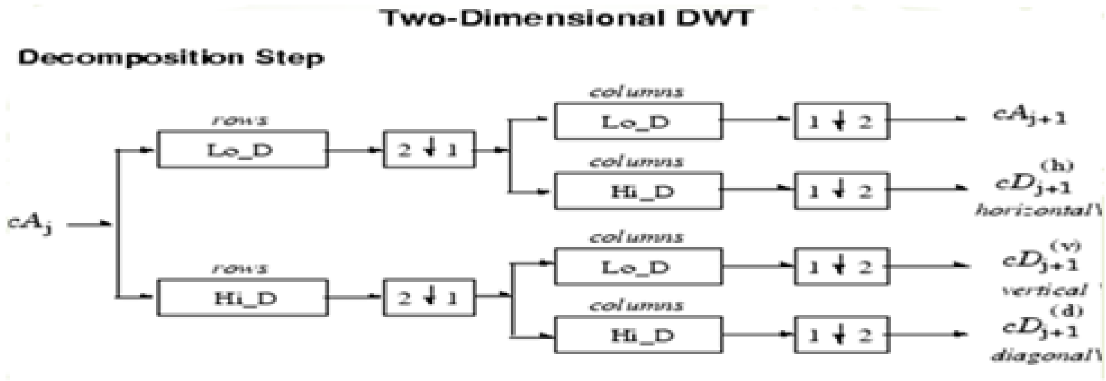


Fig 2.2 Decomposition of 2D-DWT

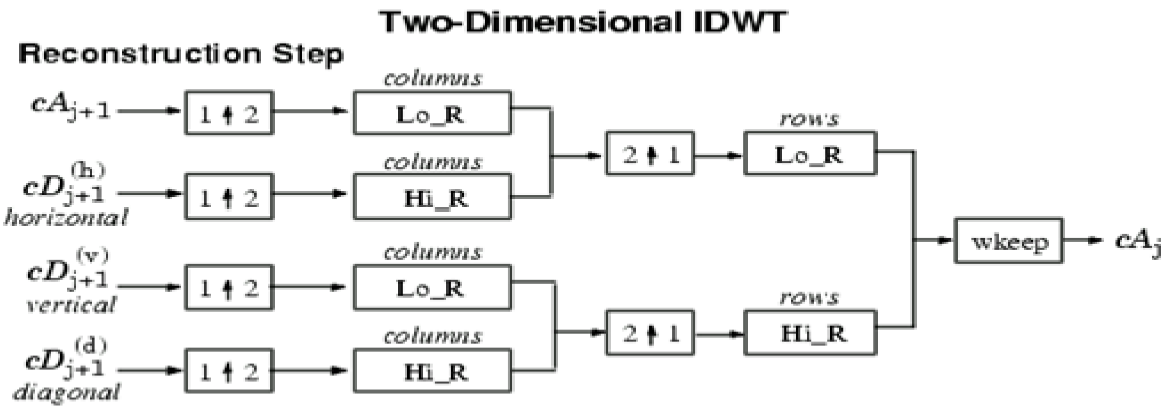


Fig 2.3Reconstruction of 2D-DWT

2.1.2 STATIONARY WAVELET TRANSFORM

The Stationary wavelet transform (SWT) is similar to the DWT except the signal is never sub-sampled and instead the filters are up sampled at each level of decomposition. It is also known as Undecimated wavelet transform. The SWT is an inherent redundant scheme, as each set of coefficients contains the same number of samples as the input. So for a decomposition of N levels, there is a redundancy of 2N.

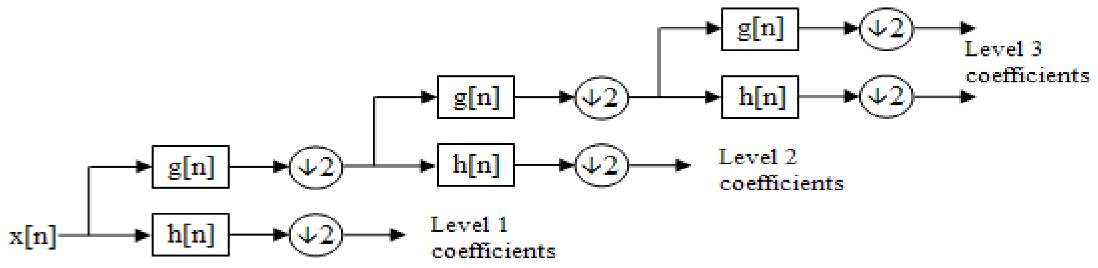


Fig 2.4 Wavelet filter bank

DWT is not translation invariant which leads to block artifacts and aliasing during the fusion process between the wavelet coefficients. For this reason, the Stationary Wavelet Transform (SWT) is used.The general idea behind stationary wavelet transform is that it doesn't decimate the image (i.e.) it never sub sample but up samples the image.

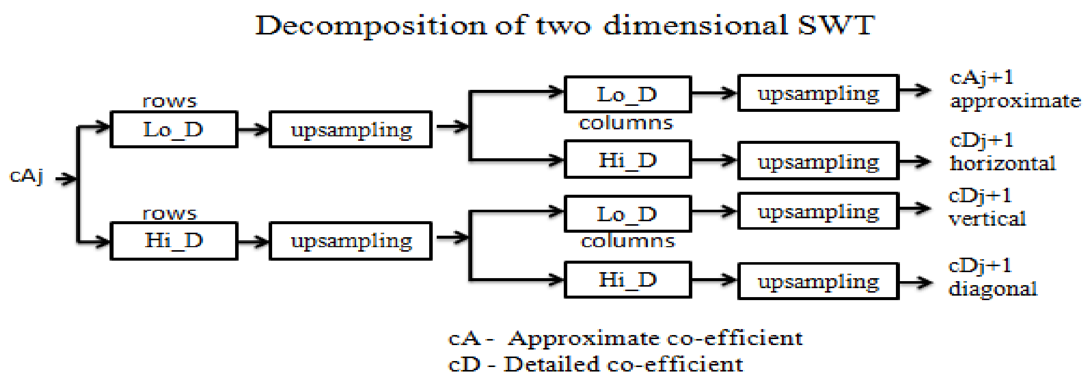


Fig 2.5 Decomposition of 2D-SWT

To achieve shift invariance, SWT is used. Thus it produces more precise information for frequency localization. SWT gives increased amount of information about the transformed signal compared to DWT.

SWT is an inherent redundant scheme as each set of co-efficient contains the same number of samples as the input. So for a decomposition of N levels, there is a redundancy of 2N. In SWT output signals at each stage are redundant because there is no signal down sampling, insertion of zero between the taps of filters is used. But from the computational point of view the SWT has larger storage space requirements and involves more computations.SWT is bigger in memory cost as well as redundancy in coefficients.

For the SWT scheme , the output signals at each stage are redundant because there is no signal down- sampling; insertion of zeros between taps of the filters are used instead of decimation. In SWT, artifacts and aliasing are less compared to DWT.

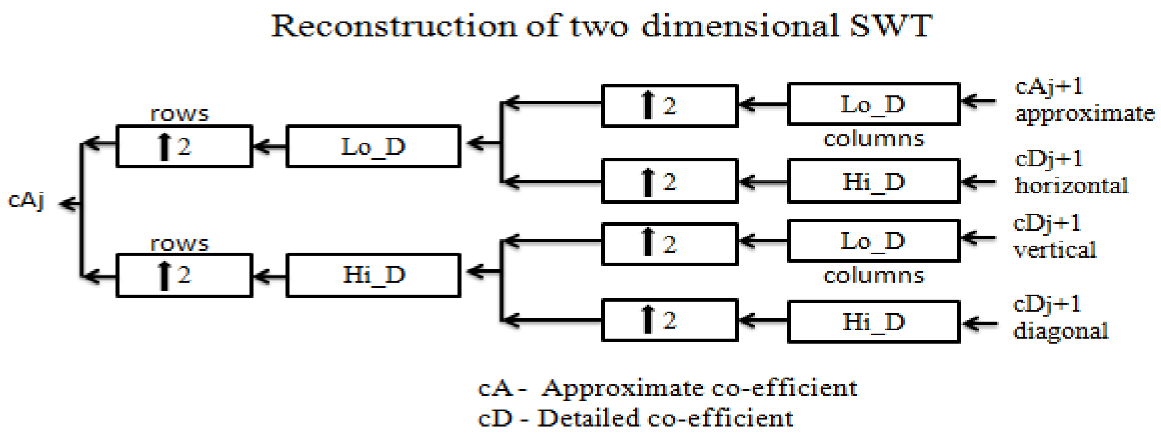


Fig 2.6 Reconstruction of 2D-SWT

This is the reason, why SWT is preferred over DWT. More precisely, it applies the transform at each point of the image and saves the detail coefficients and uses the low frequency information at each level.

The main application of the SWT is de-noising. Also, the stationary wavelet decomposition structure is more tractable than the DWT.

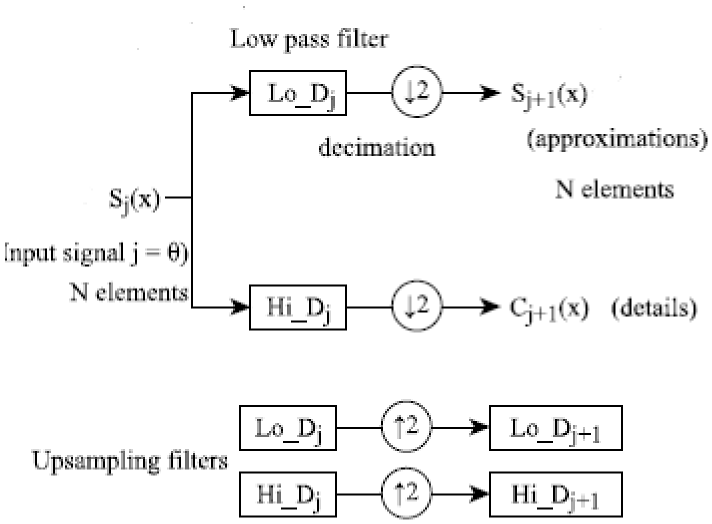


Fig 2.7 Decomposition through DWT and SWT

CHAPTER 3

WAVELET FAMILIES

3.1 WAVELET

A wavelet is a wave-like oscillation that is localized in the sense that it grows from zero, reaches maximum amplitude, and then decreases back to zero amplitude again. It thus has a location where it maximizes, a characteristic oscillation period, and also a scale over which it amplifies and declines. Wavelets can be used in signal analysis, image processing and data compression. They are useful for sorting out scale information, while still maintaining some degree of time or space locality. Wavelets are used to compress and store fingerprint information by the FBI.

3.1.1 Haar wavelet

Haar wavelet is discontinuous and resembles a step function. It represents the similar wavelet as Daubechies db1. The Haar wavelet transform may be considered to pair up input values, store the difference and passing the sum. This process is repeated again and again, pairing up the sums to provide the next scale, finally results in differences and one final sum. The Haar wavelet is a simple form of compression which involves average and difference terms, storing detail coefficients, eliminating data, and reconstruct the matrix so that the resulting matrix is similar to the initial matrix [10]. Haar wavelet is the only wavelet that is compactly supported, orthogonal and symmetric. The compact support of the haar wavelets enables the haar decomposition to have a good time localization. Specifically, this means that the haar coefficients are effective for locating jump discontinuities and also for the efficient representation of signals with small support.

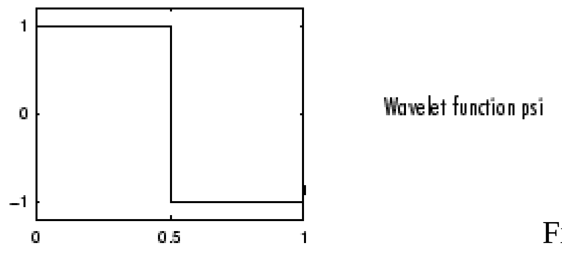


Fig 3.1Haar Wavelet

Disadvantages

However, the fact that they have jump discontinuities in particular in the poorly decaying haar coefficients of, smooth functions and in the blockiness of images reconstructed from subsets of the haar coefficients

3.1.2 Daubechies Wavelet

The Daubechies family wavelets are written as dbN, where N is the order, and db the "surname" of the wavelet. The db1 wavelet is the same as Haar wavelet. The Daubechies wavelets are orthogonal in nature which is energy preserving,compactly-supported, orthogonal wavelets. This wavelet use overlapping windows so that high frequency coefficient reflects all high frequency changes. This wavelet is smoother than Haar wavelet since Daubechies averages over more pixels.

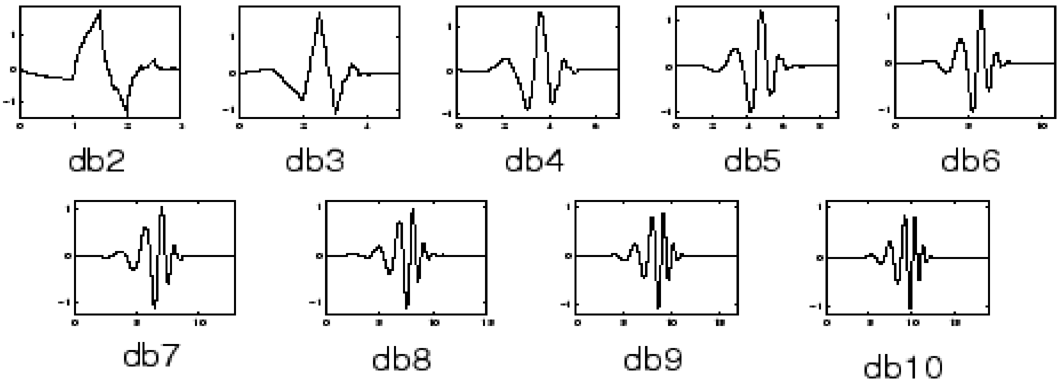


Fig 3.2 Daubechies wavelets

Disadvantage:

This wavelet is more complicated than Haar wavelet.

3.1.3 Symlet wavelet

The family of symlet wavelet is short of "symmetrical wavelets". The symN wavelets are also known as Daubechies' least-asymmetric wavelets. The symlets are more symmetric than the extremal phase wavelets. In symN, *N* is the number of vanishing moments. The symlets are nearly symmetrical wavelets proposed by Daubechies as modifications to the db family. The properties of the two wavelet families are similar. They are designed so that they have the least asymmetry and maximum number of vanishing moments for a given compact support.There are 7 different symlet functions from sym2 to sym8.

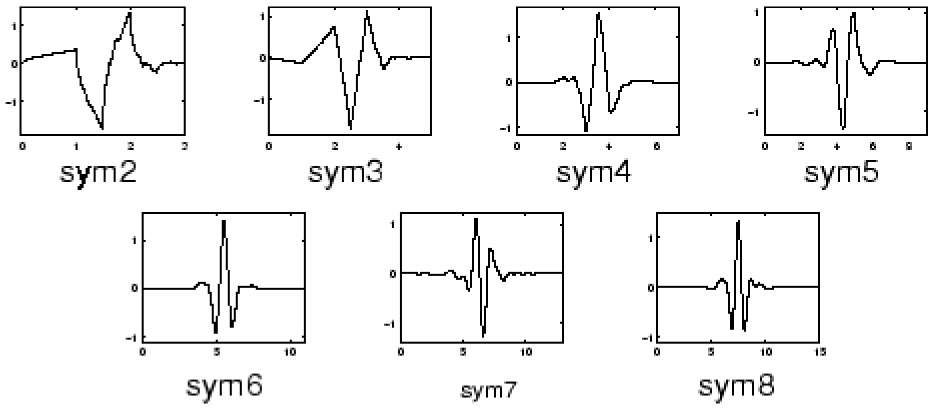


Fig 3.3 Symlet wavelets

3.1.4 Coiflets Wavelet

This wavelet function has 2N moments equal to 0 and its scaling function has 2N-1 moments equal to 0. The two functions have support of length 6N-1. The coifIets wavelets have nearly symmetric graphs. Coiflets wavelet are similar to daubechies wavelet they have a maximum number of vanishing moments. This wavelet uses windows that overlap more. Increase in pixel averaging and differencing leads to a smoother wavelet.

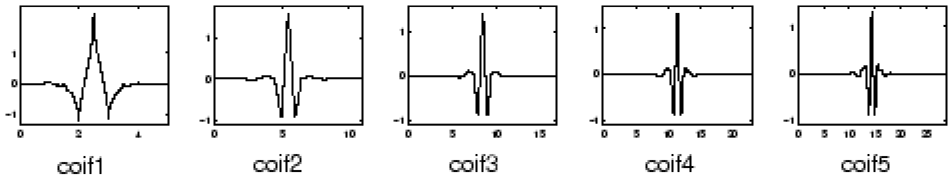


Fig 3.4 Coiflet wavelets

Disadvantages

a) There is no any formula for coiflets for arbitrary genus, and there is no formal proof of their existence for arbitrary genus at this time.

CHAPTER 4

WAVELET THRESHOLDING

Thresholding is a simple non-linear technique, which operates on one wavelet coefficient at a time. In its most basic form, each coefficient is thresholded by comparing against threshold, if the coefficient is smaller than threshold, set to zero; otherwise it is kept or modified. Replacing the small noisy coefficients by zero and inverse wavelet transform on the result may lead to reconstruction with the essential image pixels and with less noise.

4.1 THRESHOLDING

The threshold plays an important role in the denoising process. Finding an optimum threshold is a tedious process. A small threshold value will retain the noisy coefficients whereas a large threshold value leads to the loss of coefficients that carry image signal details.

Researchers have developed various techniques for choosing denoising parameters and so far there is no "best" universal threshold determination technique. Types are

- Universal or Global Thresholding
  - Hard
  - Soft
  - Visu shrink
- Sub Band Adaptive Thresholding
  - Neigh shrink SURE
  - Bayes shrink

4.2 SELECTION OF THRESHOLD VALUE

4.2.1Global Threshold: A single value T is to be applied globally to all empirical wavelet coefficients at different scales. T=constant.

The threshold $\lambda_{UNIV} = \sigma\sqrt{2\log N}$ is well known in wavelet literature as the Universal threshold.
Where,
σ = noise variance N = size of image pixels

4.2.2 Level dependent Threshold: A different threshold value T is selected for each wavelet analysis level (scale). J is the coarsest level for wavelet expansion to be processed. T=T(j),j=1,2,3,….J

4.2.3 Spatial Adaptive Threshold: Threshold value T varies spatially depending on local properties of individual wavelet coefficients. Usually T is also level-dependent. T=Tj(x,y,z)

4.3 THRESHOLDING METHODS

The most frequently used thresholding methods are soft and hard thresholding. These thresholding functions might be a good choice because large coefficients remain nearly unaltered.

4.3.1 HARD THRESHOLD

Hard thresholding is a keep or kill rule. Hard thresholding can be described as the usual process of setting to zero the elements whose absolute values are lower than the threshold. The hard thresholding also ignores the signals below the noise threshold but there is sharp transition from on/off.

$$S\sigma(x) = \begin{cases} x & x \geq \sigma \\ 0 & x < \sigma \end{cases}$$

which keeps the input if it is larger than the threshold ; otherwise, it is set to zero.

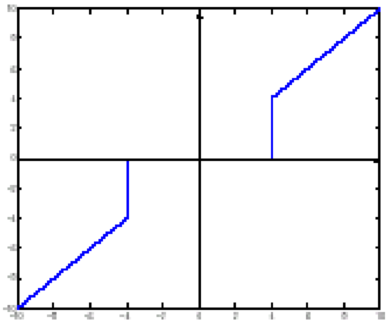


Fig 4.1 Hard Threshold

4.3.2 SOFT THRESHOLD

Soft thresholding shrinks the coefficients above the threshold in absolute value. It is a shrink or kill rule.The soft-threshold function (also called the shrinkage function-shrinks coefficients above the threshold in absolute value.) . The soft thresholding ignores signals below noise threshold and attenuates low level signals. There is a smooth transition between on/off. Soft Thresholding is defined by a fixed threshold σ

$$S\sigma(x) = \begin{cases} x-\sigma & x \geq \sigma \\ 0 & x < \sigma \\ x+\sigma & x \leq \sigma \end{cases}$$

In Soft thresholding, thresholding sets any coefficient less than or equal to the threshold to zero. The threshold is subtracted from any coefficient that is greater than the threshold. It takes the argument and shrinks it toward zero by the threshold. The wavelet thresholding procedure removes noise by thresholding only the wavelet coefficients of the detail sub-bands, while keeping the low resolution coefficients unaltered.

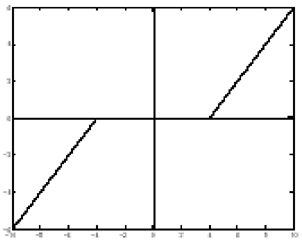


Fig 4.2-Soft Threshold

The soft-thresholding rule is chosen over hard thresholding for several reasons. The soft-thresholding method yields more visually pleasant images over hard-thresholding because the latter is discontinuous and yields abrupt artifacts in the recovered images, especially when the noise energy is significant. Soft thresholding shrinks coefficients above the threshold in absolute value. The continuity of soft thresholding has some advantages. Sometimes, pure noise coefficients may pass the hard threshold and appear as annoying ’blips’ in the output. Soft thesholding shrinks these false structures.

4.3.3 BAYES SHRINK THRESHOLD:

The goal of the BayesShrink is to minimizes the Bayesian risk, and hence its name, BayesShrink. It uses soft thresholding and is subband-dependent, which means that the thresholding is done at each band of resolution in the wavelet decomposition. Like the SureShrink procedure, it is smoothness-adaptive. In Bayesian approach the formulation is grounded on the empirical observation that the wavelet coefficients in a sub-band of a natural image can be summarized adequately by a Generalized Gaussian Distribution (GGD). To make this threshold data driven, the parameters are estimated from the observed data, one set for each sub-band. To achieve simultaneous denoising and compression, the nonzero thresholded wavelet coefficients need to be quantized.

The Bayes soft threshold has been calculated by the observation model is, Y=X+V, with X and V independent of each other, hence

$$\sigma_Y^2 = \sigma_X^2 + \sigma^2$$

where, σ_Y^2 is the variance of Y.

Since Y is modeled as zero mean, σ_Y^2 can be found empirically by

$$\hat{\sigma}_Y^2 = \frac{1}{n^2} \sum_{i,j=1}^{n} Y_{ij}^2$$

Where n x n is the size of the sub-band under consideration

$$\hat{T}_B(\hat{\sigma}_X) = \frac{\hat{\sigma}^2}{\hat{\sigma}_X} \qquad \hat{\sigma}_X = \sqrt{\max(\hat{\sigma}_Y^2 - \hat{\sigma}^2, 0)}.$$

CHAPTER 5

IMAGE FUSION

Image Fusion is defined as the task or technique of combining two or more images into a single image. The new single image retains important information from each input image. Image fusion is a powerful tool used to increase the quality of image. Image fusion increases reliability, decreases uncertainty and storage cost by a single informative image than storing multiple images Image fusion can take place at three different levels pixel feature,decisionlevel. The principle of image fusion using wavelets is to merge the wavelet decompositions of the two original images using fusion methods applied to approximations coefficients and details coefficients. The two images must be of the same size.

General process of image fusion using DWT

Step 1. Implement Discrete Wavelet Transform on both the source images to create wavelet lower decomposition.

Step 2. Fuse each decomposition level by using different fusion rule like simple average, simple maximum, simple minimum ,etc .

Step 3. Carry Inverse Discrete Wavelet Transform on fused decomposed level, for reconstruction of final fused image.

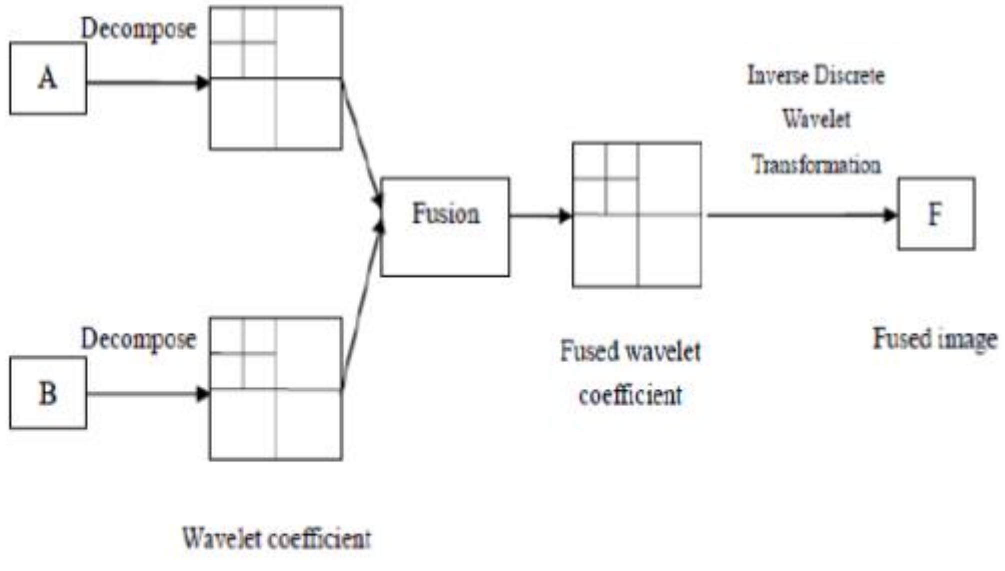


Fig 5.1 Wavelet based Image Fusion

Two reconstructed images of discrete wavelet transforms are subjected to fusion. The two images are from best family at its best level of decomposition. Same type of Thresholding is applied. It is tested for various thresholding methods such as soft, hard, bayesthresholding.

Fusion-1:

The block diagram of image fusion using DWT is represented in Fig 5.2

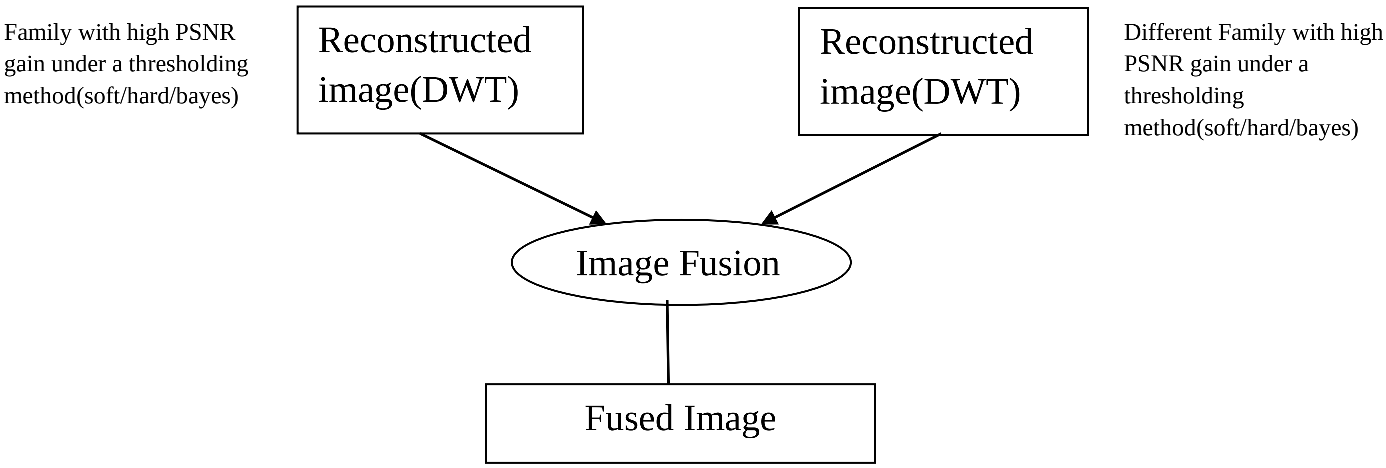


Fig5.2 Image Fusion of DWT

The figure depicts the fusion of two reconstructed images obtained from DWT. The wavelet families (haar,daubechies,symlet,coiflet) with highest PSNR gain is selected. A single thresholding (Soft/Hard/Bayes) is applied i.e same type of thresholding is used for both the reconstructed images. But the wavelet families are different. In this approach, two different wavelet families with high PSNR gain are selected at its best level of decomposition and are thresholded, reconstructed and finally subjected to image fusion.

Fusion-2:

The diagram fig5.3 represents the image fusion of a different wavelet transforms

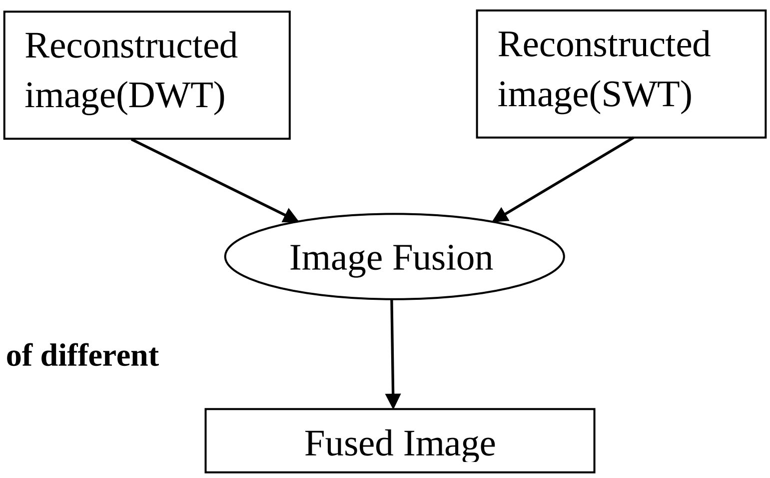


Fig5.3 Image fusion of different

Transform images

The figure depicts the fusion of two reconstructed images obtained from different wavelet transforms. The wavelet families(haar,daubechies,symlet,coiflet) with highest PSNR gain are selected at its best level of decomposition. A single thresholding is applied i.e same type of thresholding is used for both the reconstructed images(Soft/Hard/Bayes). But the wavelet families are different. In this approach, two different wavelet families with high PSNR gain are selected at its best level of decomposition and they are treated with different wavelet transforms(DWT and SWT). Then a singe threshold method (Soft/Hard/Bayes) is applied and reconstruction is performed. Finally, two differently transformed images of two wavelet families at its best level of decomposition under a single thresholding method(Soft/Hard/Bayes) are subjected to image fusion to get the fused image.

CHAPTER 6

DENOISING ALGORITHM

6.1 IMAGE DENOISING WITH DISCRETE WAVELET TRANSFORM

Step 1

Input image is read.

Step 2

Colour conversion is performed.

Step 3

The gray image is now subjected to resizing inorder to get the desired pixel size.

Step 4

Noise is added to the image(Gaussian,Poisson).

Step 5

Perform the forward wavelet transform of the noisy image.

Step 6

Threshold value is estimated. It depends on the type of thresholdingi.e soft, hard, bayes.

Step 7

Application of threshold to the horizontal, vertical, diagonal coefficients.

Step 8

Perform the inverse wavelet transform to reconstruct the denoised image.

Step 9

Estimate the mean square error for the noisy and reconstructed image.

Step 10

Evaluate PSNR value of noisy image and reconstructed image.

6.2 IMAGE DENOISING WITH STATIONARY WAVELET TRANSFORM

Step 1

Input image is read.

Step 2

Colour conversion is performed.

Step 3

The gray image is now subjected to resizing inorder to get the desired pixel size.

Step 4

Noise is added to the image.

Step 5

Perform the stationary wavelet transform of the noisy image.

Step 6

Threshold value is estimated. It depends on the type of thresholdingi.e soft, hard, bayes.

Step 7

Application of threshold to the horizontal, vertical, diagonal coefficients.

Step 8

Resize the thresholded coefficients.

Step 9

Perform the inverse stationary wavelet transform to reconstruct the denoised image.

Step 10

Estimate the mean square error for the noisy and reconstructed image.

Step 11

Evaluate PSNR value of noisy image and reconstructed image.

6.3 DENOISING ALGORITHM

The following figure6.1 depicts the basic steps of denoising algorithm.

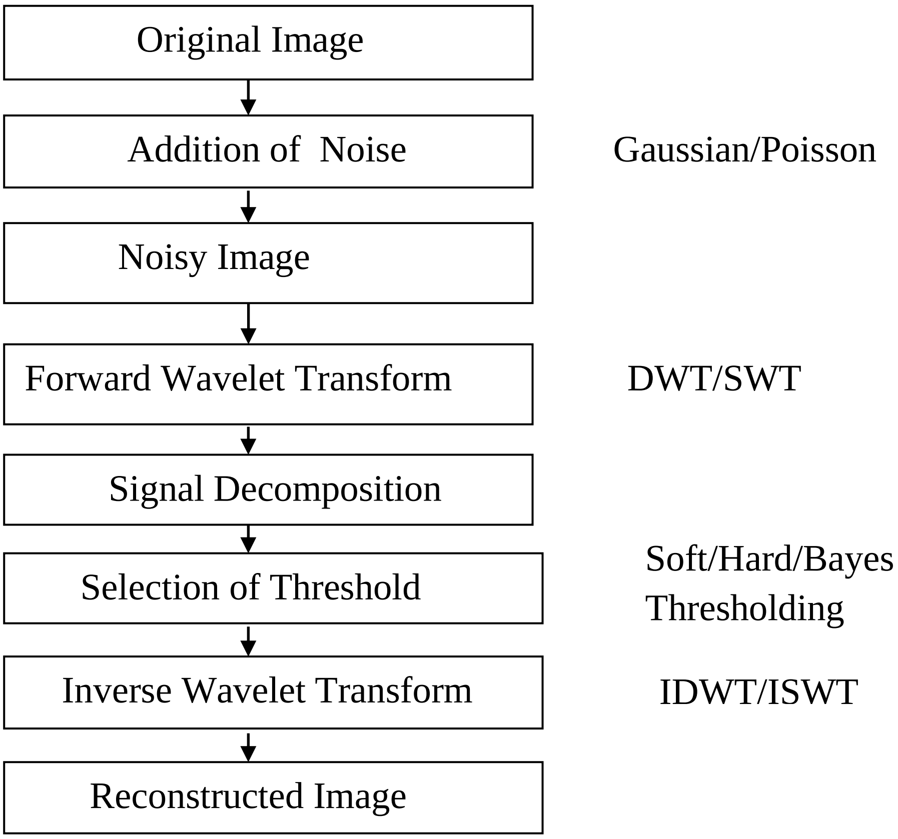


Fig 6.1 Flow Diagram of Denoising Algorithm

This figure represents the steps that are followed in denoising algorithm. To the original image, noise is added that may be poisson or Gaussian. Forward wavelet transform is applied inorder to get the filter coefficients to which thresholding is applied i.e soft or hard or bayes. Finally, inverse wavelet transform is applied to that thresholded coefficients to get the reconstructed image.

CHAPTER 7

PERFORMANCE EVALUATION

The effectiveness of image denoising method was calculated by two important parameters.

The performance of Hard, Soft, Bayes shrink thresholding are calculated by the following parameters

- Mean Squared Error (MSE)
- Peak Signal to Noise Ratio (PSNR)

These are the two error metrics used to compare image quality.

7.1 MEAN SQUARED ERROR(MSE)

The MSE represents the cumulative squared error between the noisy and the original image.

The objective quality of the reconstructed image is measured by

$$MSE = \frac{1}{IxJ}\sum_{i=1}^{I}\sum_{j=1}^{J} [x(i,j) - x(i,j)]^2$$

Where MSE is the mean square error between the original and the de-noised image with size I×J.

7.2 PEAK SIGNAL TO NOISE RATIO(PSNR)

PSNR represents a measure of the peak error. Peak Signal to Noise Ratio which is calculated using the formula,

$$PSNR = 10\log_{10}\frac{255^2}{mse} \text{ dB}$$

MSE is the mean squared error between the original image and the reconstructed de-noised image..

CHAPTER 8
SOFTWARE

The project was implemented using MATLAB 12 with Windows 7 as the platform.

8.1 MATLAB 12

MATLAB is an interactive system whose basic element is an array that does not need dimensioning. It was originally written by Dr.Cleve Moler, Chief scientist at math works, Inc., to provide easy access to matrix software developed in the LINPACk and EISPACK project.

8.1.1 FEATURES OF MATLAB

- Advanced algorithm for high performance numerical computations, especially in the field of matrix algebra.
- A large collection of predefined mathematical functions and the ability to define one's own functions.
- 2D and 3D graphics for plotting and displaying the data.
- A complete online help system.
- Powerful, matrix/vector-oriented, high level programming language for individual applications.
- Ability to cooperate with programs written in other languages and for importing and exporting formatted data.
- Tool boxes available for solving advanced problem in several application areas.
- MATLAB 12 that is aimed at speeding up the processing of M-file functions and scripts.

8.1.2 APPLICATIONS OF MATLAB

- Math and computational.
- Algorithm development.
- Modeling, simulation and prototyping.
- Data analysis, exploration and visualization.
- Scientific and Engineering graphics.
- Application development, including graphical user interface building.

CHAPTER 9

SOURCE CODE

9.1 DWT Soft Thresholding program for Gaussian Noise

```
clc;
clear all;
close all;
[x y]=uigetfile('*.jpg');
A=strcat(y,x);
a=imread(A);
B = imresize(A,[256 256]);
f = rgb2gray(B);
f=uint8(f);
va=0.01;
wv='coif4';sorh = 'h';
g=imnoise(f,'gaussian',0,va);

%DISCRETE WAVELET TRANSFORM
[cA1,cH1,cV1,cD1] = dwt2(g,'coif4');
h=[cA1,cH1;cV1,cD1];
[thr,sorh,keepapp] = ddencmp('den','wv',h);
xd=wdencmp('gbl',h,'coif4',3,thr,sorh,keepapp);

%THRESHOLDING
cH1 = wthresh(cH1,sorh,thr);
cV1 = wthresh(cV1,sorh,thr);
cD1 = wthresh(cD1,sorh,thr);

%RECONSTRUCTION
z = idwt2(cA1,cH1,cV1,cD1,'coif4');

subplot(2,2,1);
imshow(A);
title('original image');
```

```
subplot(2,2,2);
imshow(uint8(g));
title('noisy image');

subplot(2,2,3);
imshow(uint8(z));
title('reconstructed image');



%PSNR CALCULATION
s=double(f);
x=double(g);

 %PSNR DENOISED
     rms=0;
     for i=1:256
      for j=1:256
         rms=rms+((s(i,j)-z(i,j))*(s(i,j)-z(i,j))/(256*256));
      end
     end
psnr_restored_dwt=(10*log10((255*255)/rms));
disp(['PSNR_denoised=',num2str(psnr_restored_dwt)]);

%PSNR noised
     rms=0;
     for i=1:256
      for j=1:256
         rms=rms+((s(i,j)-x(i,j))*(s(i,j)-x(i,j))/(256*256));
      end
     end
psnr_noisy=(10*log10((255*255)/rms));
disp(['PSNR_noised=',num2str(psnr_noisy)]);

  PSNR_gain=psnr_restored_dwt-psnr_noisy;
       disp(['psnr_gain=',num2str(PSNR_gain)]);
```

9.2 SWT Bayes thresholding Program for Gaussian Noise

```
clear all;
clc;
%%% NL-means Filter Parameters.
ksize=7; %%% Neighbor Window Size (should be odd).7
ssize=21; %%% Search Window Size (should be odd).21
sigmas=5; %%% Sigma for Gaussian Kernel Generation.5

%%% Wavelet Transform Parameters.
Nlevels=3;
NoOfBands=3*Nlevels+1;
wname='coif1'; %% db8 sym8 db16 coif5 bior6.8
sorh='s';
level=1;
[x y]=uigetfile('*.jpg');
A=strcat(y,x);
a=imread(A);

b = imresize(a,[256 256]);
x=rgb2gray(b);
[a b]=size(x);

%%% Gaussian Noise addition.
n=imnoise(x,'gaussian',0,0.01);
xn=double(n);
xn = max(0,min(xn,255));

 %%% Noise Level Estimation using Robust Median Estimator.
 [ca,ch,cv,cd]=swt2(xn,level,wname);
tt1=cd(:)';
 median_hh2=median(abs(tt1)); %% HH1->Subband containing finest level diagonal details.
std_dev2=(median_hh2/0.6745);
```

```
%%% NL-means Filtering.
tic
im_nl=nlmeans_filt2D(xn,sigmas,ksize,ssize,std_dev2);
toc
yd=double(xn)-im_nl;
%%% General Wavelet Decomposition.
dwtmode('per');
[C,S]=wavedec2(yd,Nlevels,wname);
k=NoOfBands;
CW{k}=reshape(C(1:S(1,1)*S(1,2)),S(1,1),S(1,2));
k=k-1;
st_pt=S(1,1)*S(1,2);
for i=2:size(S,1)-1
slen=S(i,1)*S(i,2);
CW{k}=reshape(C(st_pt+slen+1:st_pt+2*slen),S(i,1),S(i,2)); %% Vertical
CW{k-1}=reshape(C(st_pt+1:st_pt+slen),S(i,1),S(i,2)); %% Horizontal
CW{k-2}=reshape(C(st_pt+2*slen+1:st_pt+3*slen),S(i,1),S(i,2)); %% Diagonal
st_pt=st_pt+3*slen;
k=k-3;
end
%%%% BayesShrink Technique.
tt2=CW{1}(:)';
median_hh2=median(abs(tt2)); %% HH1->Subband containing finest level diagonal details.
std_dev2=(median_hh2/0.6745);
cw_noise_var=std_dev2^2; %% var=std^2
for i=1:NoOfBands-1
thr = bayesthf(CW{i},cw_noise_var);
yw{i} = threshf(CW{i},sorh,thr,2);
end
yw{i+1}=CW{i+1};
%%% General Wavelet Reconstruction.
k=NoOfBands;
xrtemp=reshape(yw{k},1,S(1,1)*S(1,2));
k=k-1;
for i=2:size(S,1)-1
```

```
xrtemp=[xrtemp reshape(yw{k-1},1,S(i,1)*S(i,2)) reshape(yw{k},1,S(i,1)*S(i,2)) reshape(yw{k-2},1,S(i,1)*S(i,2))];
k=k-3;
end
ydr=(waverec2(xrtemp,S,wname));
nl_mnt=im_nl+ydr;
nl_mnt8=uint8(nl_mnt);
toc
%%%% MSE Computation
%%% PSNR Computation of Noisy Image.
xn_mse=sum(sum((double(x)-double(xn)).^2))/(a*b);
xn_psnr=10*log10(255^2./xn_mse);

ynl_mnt_mse=sum(sum((double(x)-double(nl_mnt8)).^2))/(a*b);
%%%% PSNR Computation.


%psnr_nl=10*log10(255^2./ynl_mse);
psnr_nl_mnt=10*log10(255^2./ynl_mnt_mse);
PSNR=psnr_nl_mnt-xn_psnr;
disp(['PSNR=',num2str(PSNR)]);

subplot(1,3,1),imshow(uint8(x)),colormap gray
subplot(1,3,2),imshow(uint8(xn)),colormap gray
subplot(1,3,3),imshow(uint8(nl_mnt8)),colormap gray,title('NL-means Filtering');
```

9.3 DWT-SWT Fusion Program for Poisson Noise

```
clc;
clear all;
close all;
[x y]=uigetfile('*.jpg');
A=strcat(y,x);
a=imread(A);
B = imresize(A,[256 256]);
f = rgb2gray(B);
```

```
f=uint8(f);
[a b]=size(f);
va=0.01;
g=imnoise(f,'poisson');
poi=double(g);
%Variable Stabilising Transformation
for i=0:a-1
    for j=0:b-1
        poi(i+1,j+1)=2*sqrt(poi(i+1,j+1)+(3/8));
    end
end
wv='db10';level=6;
%WAVELET TRANSFORM-Image1
[cA1,cH1,cV1,cD1] = dwt2(poi,wv);
h=[cA1,cH1;cV1,cD1];
sorh = 'h';
[thr,sorh,keepapp] = ddencmp('den','wv',h);
xd1=wdencmp('gbl',h,wv,level,thr,sorh,keepapp);

%THRESHOLDING
cH1 = wthresh(cH1,sorh,thr);
cV1 = wthresh(cV1,sorh,thr);
cD1 = wthresh(cD1,sorh,thr);

%Reconstructed Image1
z1 = idwt2(cA1,cH1,cV1,cD1,wv);
%Inverse Variable Stabilisation
for i=0:a-1
    for j=0:b-1
        z1(i+1,j+1)=((( z1(i+1,j+1)/2).^2) - (3/8));
    end
end;

wv='db2';
%decomposition
[swa,swh,swv,swd] = swt2(poi,1,wv);
```

```
%soft threshold
[thr,sorh,keepapp] = ddencmp('den','wv',g);
%Sorh=sorh;
sorh = 'h';
 swh = wthresh(swh,sorh,thr);
 swv = wthresh(swv,sorh,thr);
 swd = wthresh(swd,sorh,thr);
 swh=imresize(swh,[256 256]);
swv=imresize(swv,[256 256]);
swd=imresize(swd,[256 256]);

%reconstructio6/
z2=iswt2(swa,swh,swv,swd,wv);
%Inverse Variable Stabilisation
for i=0:a-1
    for j=0:b-1
        z2(i+1,j+1)=((( z2(i+1,j+1)/2).^2) - (3/8));
    end
end;

%fusion
fu = wfusimg(z1,z2,wv,5,'min','min');

subplot(2,2,1);
imshow(uint8(z1));
title('Reconstructed image1');

subplot(2,2,2);
imshow(uint8(z2));
title('Reconstructed image2');

subplot(2,2,3);
imshow(uint8(fu));
title('Fused image');
```

```
s=double(f);
x=double(g);
 %PSNR denoised
         rms=0;
         for i=1:256
           for j=1:256
              rms=rms+((s(i,j)-fu(i,j))*(s(i,j)-fu(i,j))/(256*256));
           end
         end
psnr_restored_dwt=(10*log10((255*255)/rms));
disp(['PSNR Denoised=',num2str(psnr_restored_dwt)]);

%PSNR noised
         rms=0;
         for i=1:256
           for j=1:256
              rms=rms+((s(i,j)-x(i,j))*(s(i,j)-x(i,j))/(256*256));
           end
         end
psnr_noisy=(10*log10((255*255)/rms));
disp(['PSNR noised=',num2str(psnr_noisy)]);

 PSNR_gain=psnr_restored_dwt-psnr_noisy;
            disp(['PSNR Gain=',num2str(PSNR_gain)]);
```

CHAPTER 10

RESULTS AND DISSCUSION

This paper proposes an image denoising scheme using different thresholding techniques. The performance of the proposed method has been evaluated using the quality measure PSNR. In this project, an important challenge is to improve the visual quality of images through image denoising which is the adaptive process.Inorder to find the effective type of thresholding and the best level of decomposition this project is focused on different wavelet families for both poisson and Gaussian noises.The wavelet families used are haar,daubechies,symmlet,coiflet.

Various wavelet transforms like Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT) are investigated using various thresholding techniques such as universal thresholding (Hard, Soft) and Subband adaptive thresholding (Bayesshrink) on noisy versions of the various 2-D images The simulated results show that subband adaptive thresholding(Bayesshrink) performs better than a universal thresholding(Hard,Soft).

- It has been concluded from the observation that Bayesshrink has better PSNR gain than Hard thresholding which in turn has better PSNR gain than Soft thresholding.
- On comparing DWT with SWT, the SWT holds good for both Poisson and Gauusian Noise

However the wavelet families with high PSNR gain varies for different noises at different thresholds.

- In SWT the best of daubechies,symmlet,coiflet is level 1 of db1, sym2, coif1 respectively for both Poisson and Gaussian noises.
- In DWT the best of daubechies, symmlet is db10, sym8 repectively for Gaussian and Poisson Noise.
- In coiflet families the high PSNR gain is found in coif4 for Gaussian noise and coif5 for Poisson Noise.

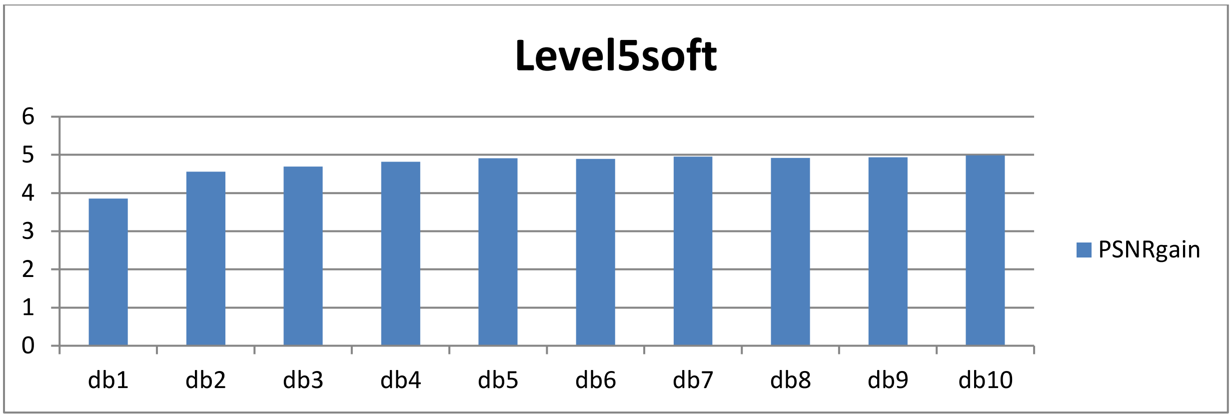
The PSNR gain for various thresholding of various families are compared in tables given below and graphs are drawn for each test set.

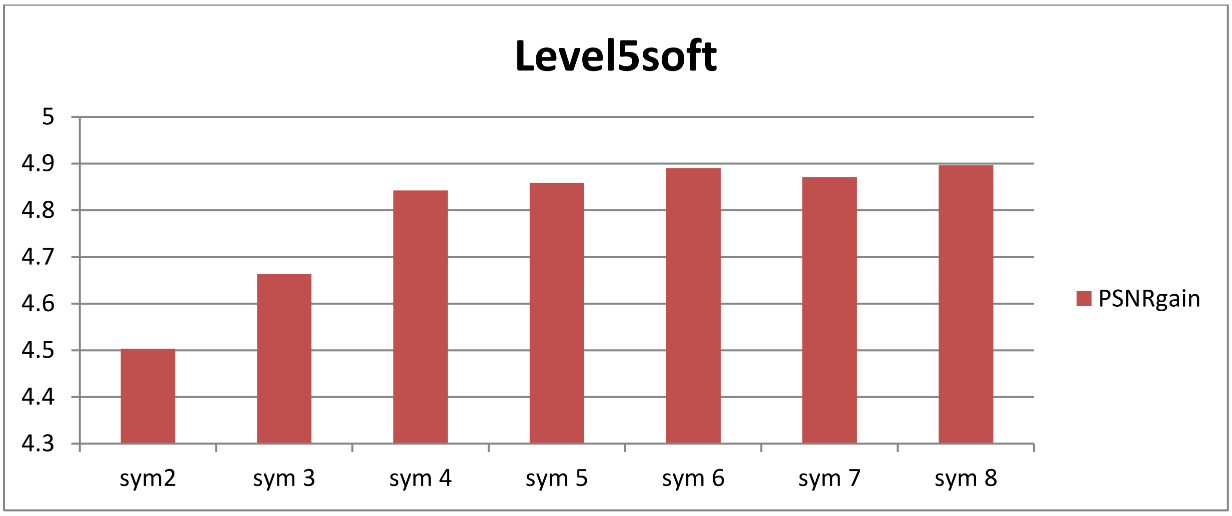
TABLES AND GRAPHS

The PSNR gain of various families for different soft thresholding at various level of decomposition is represented in the table 10.1

TABLE 10.1 DE-NOISING OF GAUSSIAN NOISE BY SOFT THRESHOLDING USING DWT

CT5	soft thresholding(PSNR gain in db)					
	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
haar	3.824	3.8033	3.7489	3.844	3.8192	3.7694
db1	3.8094	3.8484	3.7845	3.7954	3.8572	3.7789
db2	4.5435	4.4875	4.5326	4.4435	4.5563	4.5156
db3	4.6998	4.7056	4.6751	4.6791	4.6938	4.6387
db4	4.7552	4.7839	4.7645	4.7893	4.8171	4.7754
db5	4.7852	4.8447	4.888	4.837	4.9097	4.8928
db6	4.8602	4.8456	4.8336	4.8725	4.8968	4.8917
db7	4.9111	4.9492	4.8907	4.9645	4.95	4.9424
db8	4.8825	4.9493	4.9019	4.8999	4.9214	4.9103
db9	4.8579	4.9261	4.9309	4.9113	4.94	4.9003
db10	4.9267	4.9344	4.8722	4.8928	4.9871	4.9472
sym2	4.4596	4.5288	4.499	4.5333	4.5029	4.4744
sym 3	4.5563	4.7002	4.6638	4.6527	4.6634	4.7251
sym 4	4.7932	4.8479	4.855	4.7974	4.8426	4.8134
sym 5	4.8526	4.8727	4.8583	4.8872	4.8587	4.8599
sym 6	4.9052	4.838	4.9104	4.9077	4.8904	4.8592
sym 7	4.9056	4.897	4.8674	4.9371	4.8713	4.8793
sym 8	4.9788	4.8876	4.9639	4.9318	4.8967	4.9189
coif 1	4.5883	4.6092	4.5924	4.5578	4.5647	4.5688
coif 2	4.8322	4.7848	4.8379	4.783	4.7796	4.7887
coif 3	4.8694	4.8618	4.9251	4.8508	4.8687	4.9068
coif 4	4.9491	4.9179	4.9602	4.9045	4.8745	4.9334
coif 5	4.9559	4.9216	4.9178	4.993	4.963	4.9256





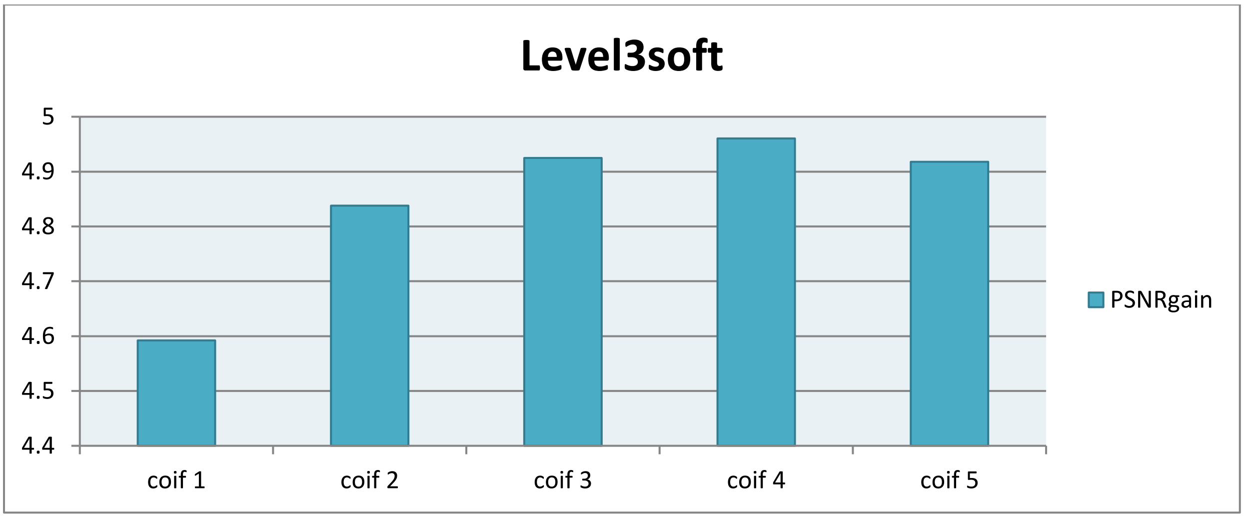


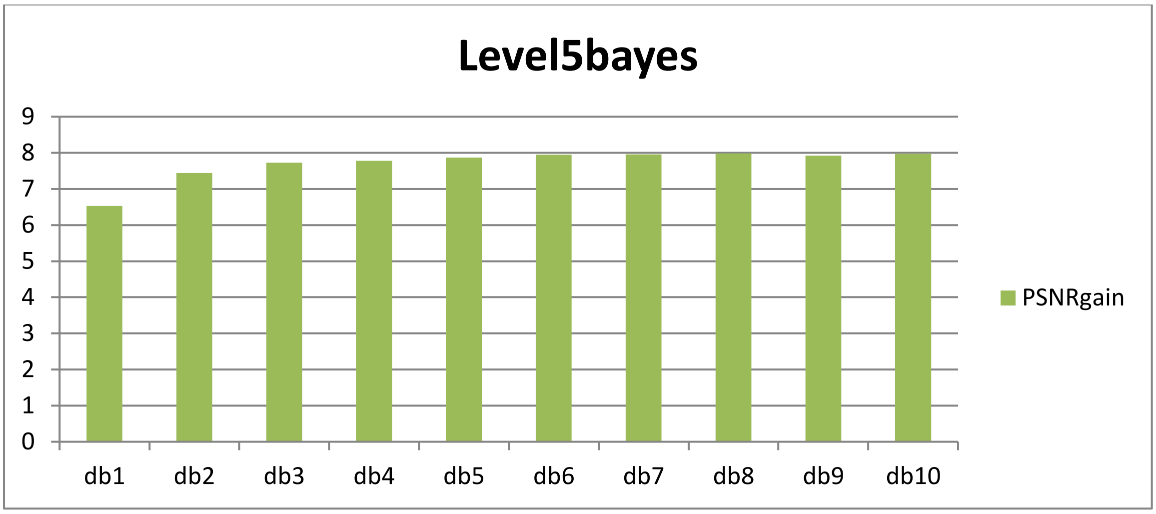
Figure 10.1 Comparison chart on denoising results for gaussain noise using soft thresholding with DWT

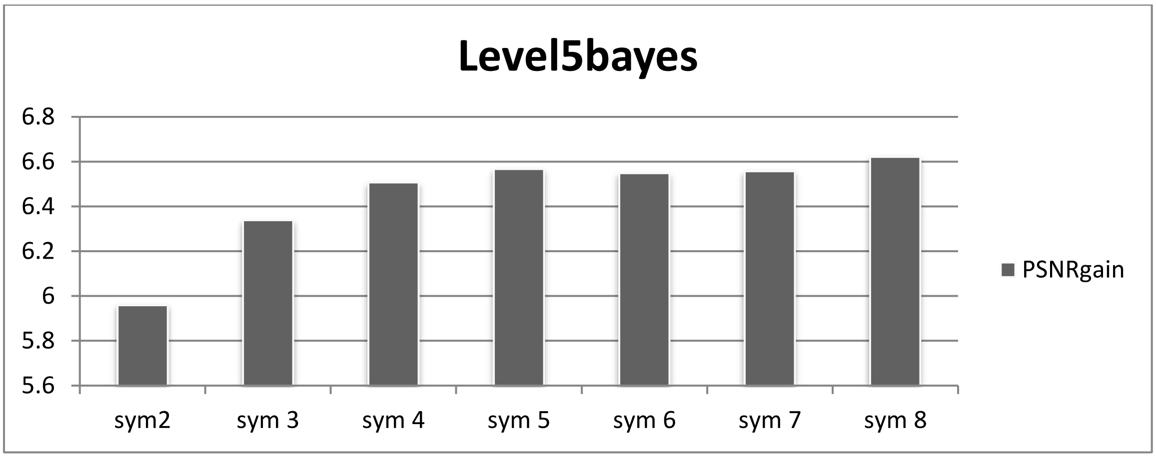
From the graphs it is observe dthat db10 and sym8 offers high PSNR gain at level 5 whereas coif4 at level3 for soft thresholding

The PSNR gain of various families for different bayes thresholding at various level of decomposition is represented in the table 10.2

TABLE 10.2 DE-NOISING OF GAUSSIAN NOISE BY BAYESTHRESHOLDING USING DWT

CT5	Bayes(PSNR gain in db)					
	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
haar	4.6862	6.3614	6.5413	6.5633	6.5983	6.566
db1	4.6878	6.4429	6.5357	5.158	6.5286	6.5553
db2	5.1223	7.2007	7.4354	7.4225	7.4432	7.4332
db3	5.1927	7.427	7.6859	7.7105	7.7238	7.6875
db4	5.2794	7.6232	7.8333	6.4372	7.7766	7.7621
db5	5.2895	7.6571	7.8769	7.8391	7.8656	7.8234
db6	5.2855	7.6599	7.9071	6.6407	7.9463	7.9104
db7	5.2914	7.6807	7.9281	6.6574	7.953	7.9255
db8	5.3741	7.667	7.9405	6.5923	7.9836	7.913
db9	5.3603	7.7341	7.9024	7.915	7.9198	7.9247
db10	5.3491	7.7865	7.9522	7.9869	7.975	7.9679
sym2	4.5734	5.8925	5.9882	5.988	5.9588	6.055
sym 3	4.6987	6.0481	6.304	6.3236	6.3385	6.2962
sym 4	4.8786	6.3241	6.4261	6.5344	6.5066	6.5195
sym 5	4.8908	6.406	6.4934	6.4892	6.5664	6.4733
sym 6	4.9082	6.4171	6.6358	6.5907	6.5485	6.6618
sym 7	4.8782	6.4767	6.6523	6.6207	6.5574	6.6275
sym 8	4.9068	6.5654	6.6528	6.5772	6.6208	6.6176
coif 1	4.6589	5.9764	6.1372	6.1144	6.1055	6.1521
coif 2	4.8626	6.4495	6.5934	6.4996	6.5383	6.5154
coif 3	4.9261	6.4885	6.5711	6.657	6.6764	6.6312
coif 4	4.9339	6.5527	6.6948	6.7174	6.6629	6.6368
coif 5	4.9588	6.5457	6.689	6.6295	6.7122	6.6905





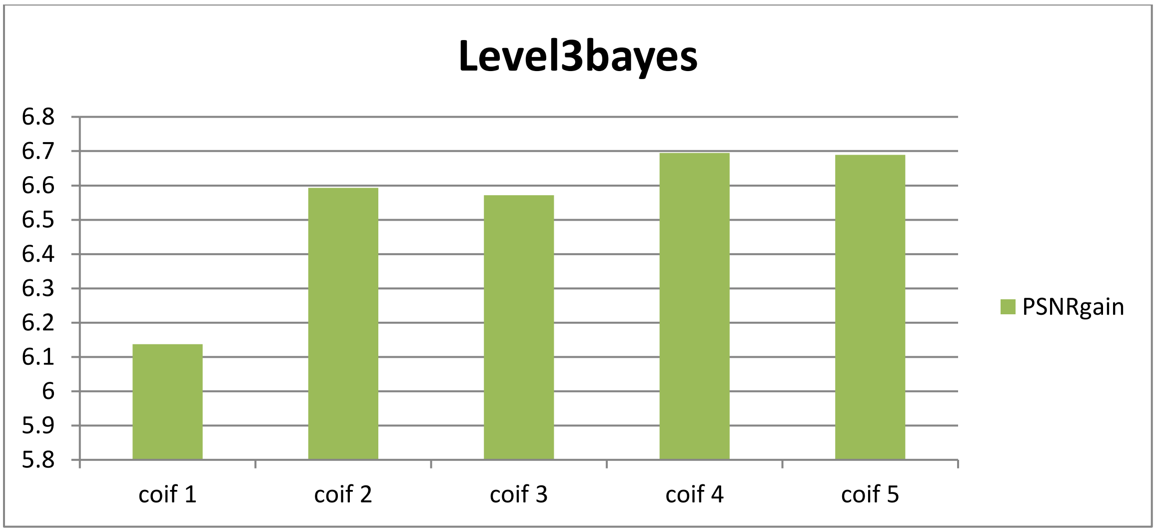


Figure 10.2 Comparison chart on denoising results for gaussain noise using bayes thresholding with DWT

From the graphs it is observe dthat db10 and sym8 offers high PSNR gain at level 5 whereas coif4 at level3 for bayes thresholding.

The PSNR gain of various families for different bayes thresholding at various level of decomposition is represented in the table 10.3

TABLE 10.3 DE-NOISING OF GAUSSIAN NOISE BY HARDTHRESHOLDING USING DWT

CT5	Hard thresh					
	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
haar	3.772	3.8265	3.8052	3.849	3.8209	3.7874
db1	3.8011	3.7838	3.884	3.8435	3.8186	3.82
db2	4.4846	4.4668	4.536	4.5725	4.5166	4.5123
db3	4.7123	4.7319	4.6775	4.6535	4.6819	4.6942
db4	4.7642	4.7713	4.772	4.8627	4.7621	4.8485
db5	4.8429	4.8515	4.798	4.8081	4.8795	4.7914
db6	4.8324	4.8791	4.847	4.8302	4.8852	4.8799
db7	4.9289	4.9319	4.8909	4.8619	4.9031	4.927
db8	4.8686	4.9425	4.9324	4.9091	4.9538	4.9148
db9	4.9382	4.9296	4.9447	4.9123	4.8978	4.9688
db10	4.9246	4.9421	4.9266	4.9222	4.9456	4.919
sym2	4.5083	4.4461	4.5254	4.4673	4.7721	4.5039
sym 3	4.6659	4.6845	4.6747	4.6638	4.703	4.656
sym 4	4.8175	4.8535	4.7863	4.8307	4.8412	4.7656
sym 5	4.8222	4.8603	4.8483	4.8554	4.8843	4.8045
sym 6	4.8759	4.8543	4.909	4.925	4.9113	4.8812
sym 7	4.8616	4.8187	4.866	4.835	4.88	4.8774
sym 8	4.9268	4.9378	4.9234	4.8643	4.9328	4.9052
coif 1	4.5441	4.5802	4.5964	4.5429	4.5312	4.5474
coif 2	4.8316	4.8463	4.8503	4.8236	4.7634	4.8225
coif 3	4.8037	4.8766	4.888	4.869	4.8974	4.8967
coif 4	4.9358	4.8513	4.907	4.8892	4.9197	4.9343
coif 5	4.9544	4.9625	4.8985	4.91	4.8737	4.9323

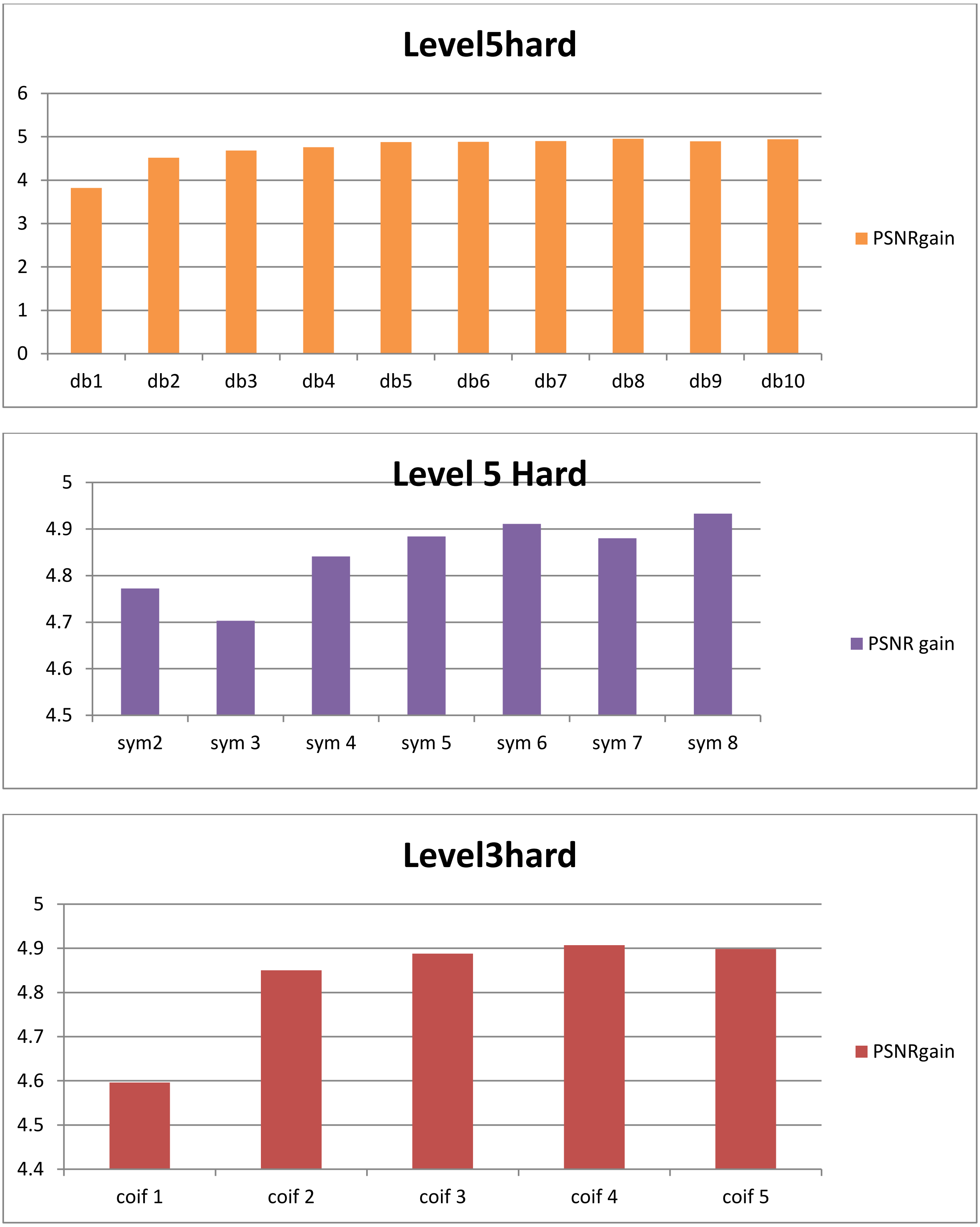


Figure 10.3 Comparison chart on denoising results for gaussain noise using hard thresholding with DWT

From the graphs it is observed that db10 and sym8 offers high PSNR gain at level 5 whereas coif4 at level3 for hard thresholding.

The denoising results of various types of thresholding for best wavelet families at its best decompsition level based on PSNR gain are tabulated in 10.4

TABLE 10.4 DE-NOISING RESULTS OF SOFT,HARD,BAYES THRESHOLDING FOR BEST WAVELET FAMILIES USING DWT

	soft	hard	bayes	Level
db10	4.9871	4.9456	7.975	5
sym 8	4.8967	4.9328	6.6208	5
coif 4	4.9602	4.907	6.6948	3

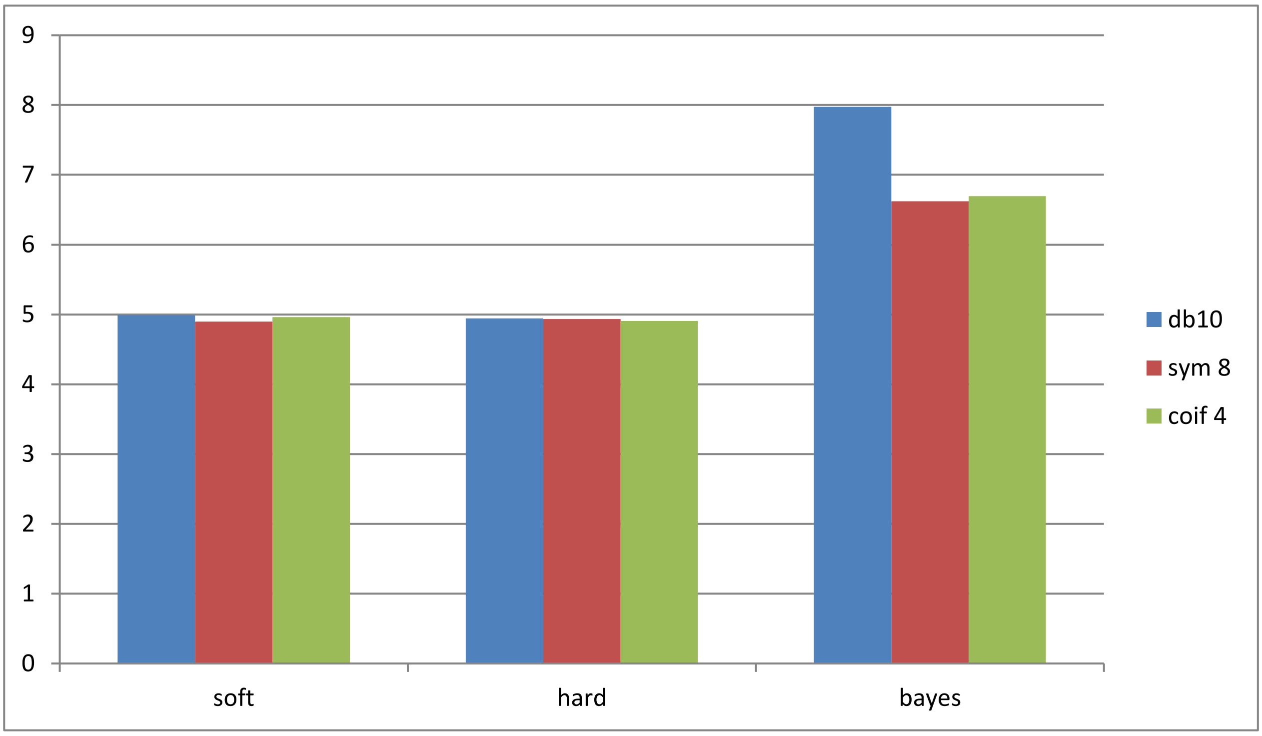


Figure 10.4 Comparison chart of various thresholding methods for best wavelet families on denoising AWGN using DWT

INFERENCE:

- On denoising using dwt the best of daubechies, symlet is level 5 of db10, level 5 of sym8 respectively. In coiflet family the best is level 3 of coif4.

- As the number of vanishing moments increases, number of coefficients also increases. Hence, a better thresholding process is accomplished at higher order(N) which in turn produces a better reconstructed image.

The PSNR gain of various families for different soft thresholding at various level of decomposition is represented in the table 10.5

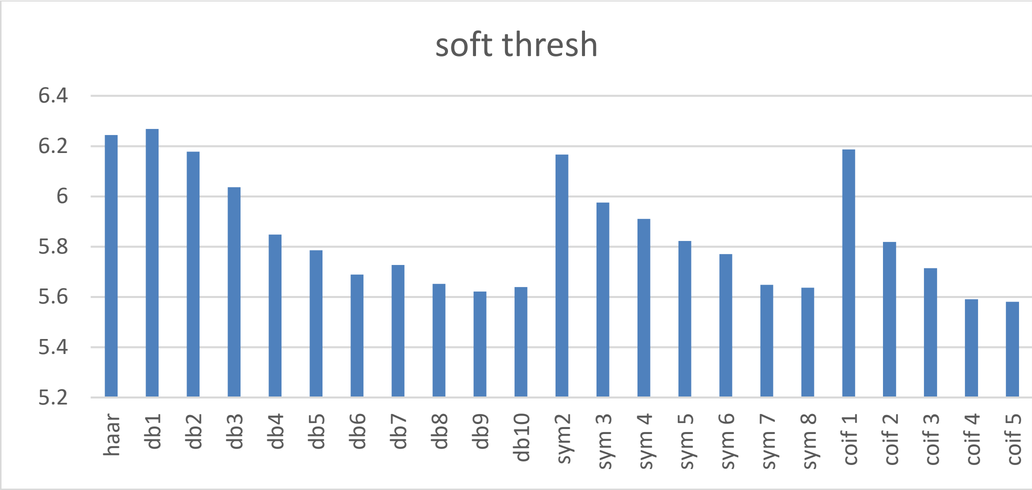
TABLE 10.5 DE-NOISING OF GAUSSIAN NOISE BY SOFT THRESHOLDING USING SWT

CT5	soft thresholding(PSNR gain in db)					
	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
haar	6.2435	5.1033	2.8647	1.6261	1.2362	1.0987
db1	6.2682	5.128	2.8621	1.6779	1.2495	1.1344
db2	6.1774	5.5895	3.3131	2.1597	1.7138	1.6141
db3	6.0368	5.6649	3.4523	2.2894	1.8512	1.7579
db4	5.8483	5.5632	3.3998	2.2717	1.9125	1.7773
db5	5.7852	5.5637	3.4227	2.2741	1.8345	1.6891
db6	5.6893	5.4925	3.3712	2.2065	1.8414	1.7306
db7	5.7265	5.4664	3.3844	2.2159	1.8499	1.6694
db8	5.6517	5.4554	3.3357	2.1832	1.7436	1.7121
db9	5.6212	5.4572	3.2642	2.1643	1.7396	1.6118
db10	5.6397	5.4284	3.3759	2.1441	1.7674	1.6654
sym2	6.1658	5.5228	3.2803	2.1639	1.7179	1.618
sym 3	5.9753	5.5464	3.4185	2.2104	1.8397	1.7392
sym 4	5.91	5.6247	3.4634	2.4221	1.9811	1.8479
sym 5	5.8225	5.6005	3.4732	2.3064	1.9348	1.828
sym 6	5.7701	5.4772	3.4459	2.3859	1.9224	1.9253
sym 7	5.6479	5.5424	3.4588	3.4495	1.9071	1.8504
sym 8	5.6367	5.5999	3.3511	2.3055	1.9128	1.8597
coif 1	6.1864	5.6187	3.344	2.1593	1.7432	1.6159
coif 2	5.8191	5.6045	3.4905	2.3532	1.9242	1.8102
coif 3	5.7142	5.517	3.4169	2.2379	1.9414	1.8774
coif 4	5.5906	5.4891	3.4311	2.3306	1.9886	1.8807
coif 5	5.5806	5.4451	3.3998	2.3145	1.8953	1.8754

The PSNR gain of various families for different hard thresholding at various level of decomposition is represented in the table 10.6

TABLE 10.6 DE-NOISING OF GAUSSIAN NOISE BY HARD THRESHOLDING USING SWT

CT5	hard threshold					
	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
haar	6.2619	5.7604	4.8001	4.5218	4.5022	4.4978
db1	6.3237	5.7982	4.7455	4.5123	4.4967	4.113
db2	6.2006	6.0706	5.0025	4.8055	4.6845	4.7772
db3	6.0264	6.1222	5.1608	4.8262	4.7982	4.8117
db4	5.9125	6.0705	5.1339	4.8917	4.8707	4.9286
db5	5.9054	6.0069	5.084	4.8572	4.7478	4.8567
db6	5.8099	5.949	4.9723	4.8402	4.8051	4.743
db7	5.7096	5.829	4.0291	4.7831	4.7609	4.7753
db8	5.6801	5.941	4.9254	4.9376	4.769	4.6578
db9	5.6361	5.8515	4.9443	4.9796	4.6959	4.6485
db10	5.654	5.8159	4.8967	4.6351	4.6382	4.575
sym2	6.2477	6.0503	5.0116	4.8294	4.727	4.738
sym 3	6.0641	6.1215	5.1236	4.8565	4.8447	4.8995
sym 4	5.8998	6.0748	5.1984	4.9627	4.994	4.877
sym 5	5.8519	6.0905	5.213	4.9736	4.9482	4.9013
sym 6	5.8016	6.0261	5.1652	4.9498	4.8503	4.9041
sym 7	5.773	5.9945	5.1115	4.9866	4.9393	4.9281
sym 8	5.6712	5.961	5.1712	4.9498	4.8661	4.9288
coif 1	6.2266	6.1072	5.0189	4.888	4.8957	4.8132
coif 2	5.9066	6.0843	5.1943	5.0589	4.8817	4.9771
coif 3	5.7641	6.0679	5.0967	4.8822	4.9185	4.932
coif 4	5.6346	5.9201	5.218	4.9045	4.8791	4.8704
coif 5	5.6261	5.9604	5.1062	4.9949	4.844	4.8627



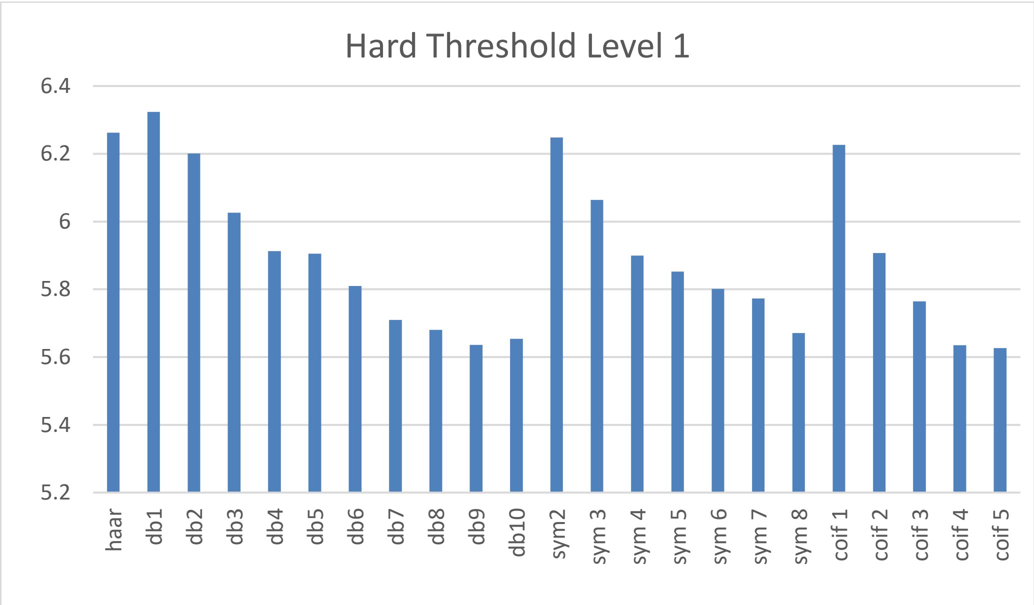


Figure 10.5 Comparison chart on denoising results for gaussain noise using soft & hard thresholding with SWT

The PSNR gain of various families for different bayes thresholding at various level of decomposition is represented in the table 10.6

TABLE 10.7 DE-NOISING OF GAUSSIAN NOISE BY BAYES THRESHOLDING USING SWT

Bayes	
CT5	Level1(PSNR gain in db)
db1	7.0184
sym2	7.2429
coif1	7.1942

INFERENCE

- On denoising using swt, level 1 has high PSNR gain for soft, hard, bayes.
- Comparing the PSNR gain of all wavelet families, db1 of daubechies, sym2 ofsymlet, coif1 of coiflet is found to be high.

The PSNR gain of various families for different soft thresholding at various level of decomposition with poisson noise using DWT is represented in the table 10.8

TABLE 10.8 DE-NOISING OF POISSON NOISE BY SOFT THRESHOLDING USING DWT

CT5	soft thresholding(PSNR gain in db)					
	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
haar	0.3181	0.3388	0.2714	0.306	0.3911	0.2938
db1	0.3173	0.3481	0.3322	0.3376	0.3218	0.3211
db2	1.7628	1.669	1.7147	1.695	1.7285	1.7534
db3	2.129	2.1421	2.1662	2.1604	2.165	2.1397
db4	2.3829	2.342	2.4349	2.3866	2.4147	2.4163
db5	2.4734	2.4934	2.517	2.5131	2.4901	2.4798
db6	2.5651	2.5199	2.5433	2.555	2.5107	2.5569
db7	2.6092	2.566	2.57	2.6258	2.635	2.5887
db8	2.6127	2.6124	2.6075	2.6275	2.6398	2.5892
db9	2.572	2.6435	2.7073	2.63	2.6041	2.6221
db10	2.7016	2.6999	2.6811	2.7163	2.7122	2.7447
sym2	1.6948	1.7382	1.7635	1.7044	1.6713	1.71
sym 3	2.1547	2.1282	2.1563	2.1413	2.1623	2.1473
sym 4	2.4035	2.4105	2.3587	2.3875	2.4284	2.3497
sym 5	2.4802	2.4663	2.497	2.4831	2.5063	2.5071
sym 6	2.5009	2.4866	2.5373	2.5304	2.5443	2.5543
sym 7	2.6091	2.6113	2.601	2.6149	2.6409	2.6058
sym 8	2.6398	2.6695	2.6481	2.6697	2.5987	2.6188
coif 1	1.8908	1.8194	1.8264	1.8324	1.8187	1.8919
coif 2	2.4489	2.4353	2.4606	2.4172	2.4244	2.3695
coif 3	2.5363	2.5567	2.6031	2.5533	2.5654	2.6071
coif 4	2.6654	2.6709	2.5906	2.6303	2.6258	2.6536
coif 5	2.6891	2.6355	2.7084	2.7155	2.7318	2.7013

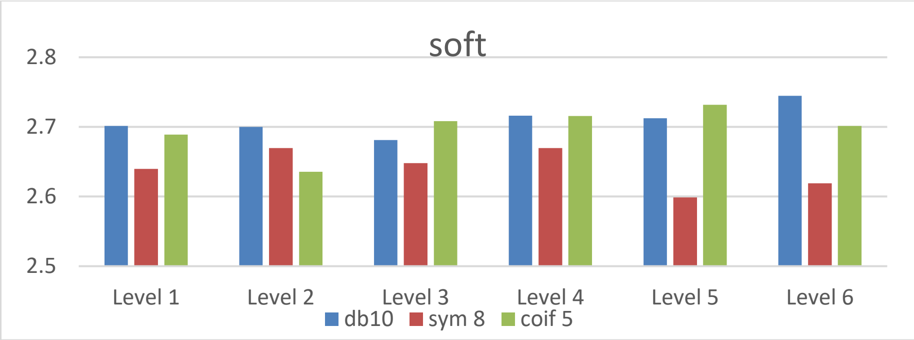


Figure 10.6 Comparison chart on denoising performance of various wavelet families with poisson noise using soft thresholding

The PSNR gain of various families for different bayes thresholding at various level of decomposition with poisson noise using DWT is represented in the table 10.8

TABLE 10.9 DE-NOISING OF POISSON NOISE BY SOFT THRESHOLDING USING DWT

	Bayes(PSNR gain in db)					
	Level1	Level 2	Level 3	Level 4	Level 5	Level 6
haar	2.377	2.6382	2.6694	2.6216	2.5995	2.6345
db1	2.3645	2.5801	2.6344	2.6043	2.6352	2.5958
db2	2.8881	3.2803	3.2993	3.2666	3.2362	3.2844
db3	3.1322	3.5096	3.5202	3.5807	3.5281	3.5376
db4	3.2726	3.6498	3.6674	3.7112	3.6967	3.7564
db5	3.3058	3.7454	3.7682	3.7655	3.7826	3.7708
db6	3.4258	3.8203	3.8576	3.8354	3.8733	3.8179
db7	3.4494	3.8558	3.8529	3.8341	3.871	3.8275
db8	3.3899	3.8251	3.8519	3.8639	3.8012	3.8415
db9	3.3965	3.8284	3.7914	3.8634	3.8594	3.8999
db10	3.4019	3.8425	3.8371	3.8616	3.8737	3.8486
sym2	2.9309	3.2427	3.2445	3.2805	3.297	3.2788
sym 3	3.146	3.5182	3.523	3.537	3.5292	3.5583
sym 4	3.2689	3.703	3.7633	3.7233	3.7546	3.7478
sym 5	3.3561	3.7684	3.7756	3.7888	3.775	3.7416
sym 6	3.4135	3.8008	3.8453	3.849	3.8332	3.8455
sym 7	3.438	3.8639	3.856	3.8818	3.8636	3.8521
sym 8	3.4567	3.3908	3.9852	3.8882	3.9025	3.8978
coif 1	2.9493	3.4294	3.2698	3.3394	3.2959	3.3228
coif 2	3.292	3.7372	3.6998	3.7495	3.7354	3.7918
coif 3	3.4564	3.8447	3.8284	3.8672	3.8818	3.8471
coif 4	3.4423	3.8935	3.932	3.9557	3.9061	3.9212
coif 5	3.5253	3.943	3.9387	3.9289	3.9756	3.9624

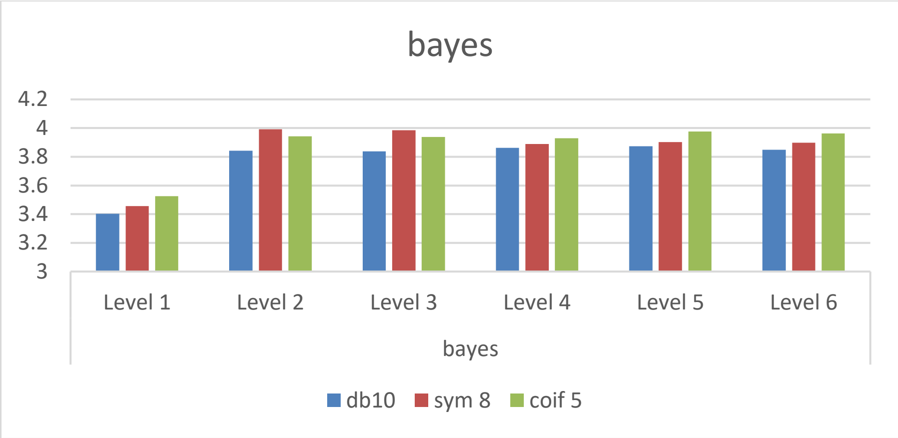


Figure 10.7 Comparison chart on denoising performance of various wavelet families with poisson noise using soft thresholding

The PSNR gain of various families for different hard thresholding at various level of decomposition with poisson noise using DWT is represented in the table 10.8

TABLE 10.10 DE-NOISING OF POISSON NOISE BY HARD THRESHOLDING USING DWT

CT5	hard thresh(PSNR gain in db)					
	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
haar	0.3545	0.32221	0.28258	0.35025	0.36263	0.35048
db1	0.34909	0.33327	0.32373	0.36253	0.32358	0.27655
db2	1.661	1.741	1.7335	1.7124	1.7157	1.7041
db3	2.15	2.1173	2.1874	2.1823	2.1263	2.1177
db4	2.406	2.346	2.3944	2.3615	2.42	2.387
db5	2.5106	2.4851	2.4658	2.5026	2.4652	2.4785
db6	2.5693	2.5836	2.5054	2.5864	2.5798	2.5116
db7	2.6368	2.5841	2.5821	2.6259	2.5628	2.6158
db8	2.5965	2.6049	2.6196	2.5688	2.615	2.5883
db9	2.6334	2.6131	2.6032	2.6522	2.6244	2.6731
db10	2.732	2.6883	2.6745	2.7216	2.6739	2.7416
sym2	1.7317	1.7568	1.7055	1.7589	1.7476	1.7054
sym 3	2.1314	2.1292	2.1602	2.1729	2.1652	2.1505
sym 4	2.386	2.3899	2.3806	2.3446	2.4046	2.4004
sym 5	2.4403	2.4805	2.4622	2.5176	2.4898	2.5219
sym 6	2.5702	2.5551	2.5432	2.5197	2.5596	2.5646
sym 7	2.6219	2.6279	2.644	2.601	2.6228	2.6272
sym 8	2.5971	2.6467	2.6812	2.6089	2.6167	2.6573
coif 1	1.8463	1.8329	1.8502	1.8496	1.8729	1.8313
coif 2	2.4031	2.4121	2.4286	2.4271	2.4142	2.4083
coif 3	2.5856	2.608	2.5935	2.6281	2.5683	2.58

coif 4	2.7185	2.703	2.6763	2.6528	2.6694	2.7014
coif 5	2.6865	2.7174	2.6995	2.6914	2.7448	2.6923

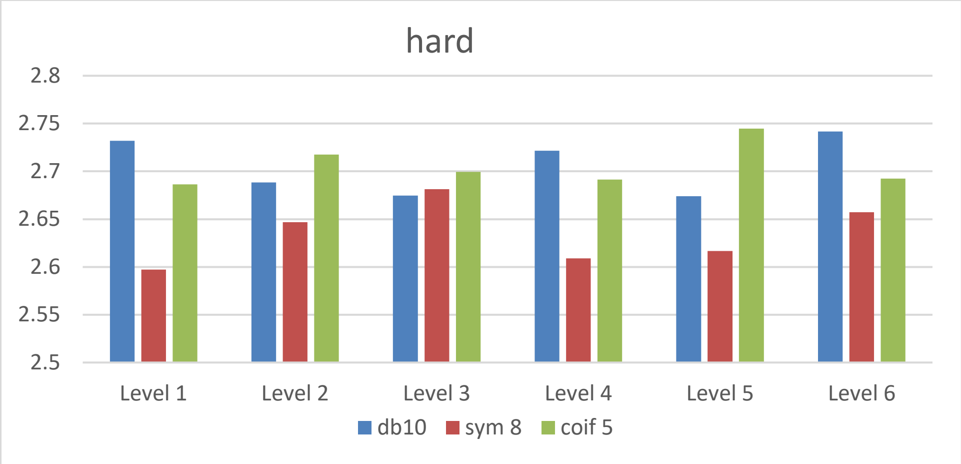


Figure 10.8 Comparison chart on denoising performance of various wavelet families with poisson noise using hard thresholding

INFERENCE

On denoising ct5 image using dwt

- level 6 of db10
- level 3 of sym8
- level5 of coif5 has high PSNR gain

The PSNR gain of various families for different bayes thresholding at various level of decomposition with poisson noise using DWT is represented in the table 10.11

TABLE 10.11 DE-NOISING OF POISSON NOISE BY BAYESTHRESHOLDING USING SWT

CT5	soft	hard
	Level 1	Level 1
haar	3.4613	3.4579
db1	3.3923	3.4331
db2	3.7626	3.7488
db3	3.7115	3.7267
db4	3.6139	3.5936
db5	3.5767	3.5802
db6	3.5838	3.5493
db7	3.4842	3.4527
db8	3.4534	3.4392
db9	3.3509	3.4561
db10	3.3672	3.3876
sym2	3.8179	3.7806
sym 3	3.7017	3.6357
sym 4	3.6317	3.6533
sym 5	3.6187	3.6011
sym 6	3.6068	3.5867
sym 7	3.5029	3.5333
sym 8	3.4877	3.5196
coif 1	3.7777	3.7623
coif 2	3.6358	3.6102
coif 3	3.5553	3.5316
coif 4	3.4873	3.4493
coif 5	3.395	3.4206

The experimental results on denoising poisson noise with SWT by soft and hard thresholding is tabulated in 10.12

TABLE10.12 PSNR GAIN OF SOFT & HARD THRESHOLDING USING SWT FOR DENOISING POISSON NOISE

	soft	hard
db1	3.3923	3.4331
sym2	3.8179	3.7806
coif 1	3.7777	3.7623

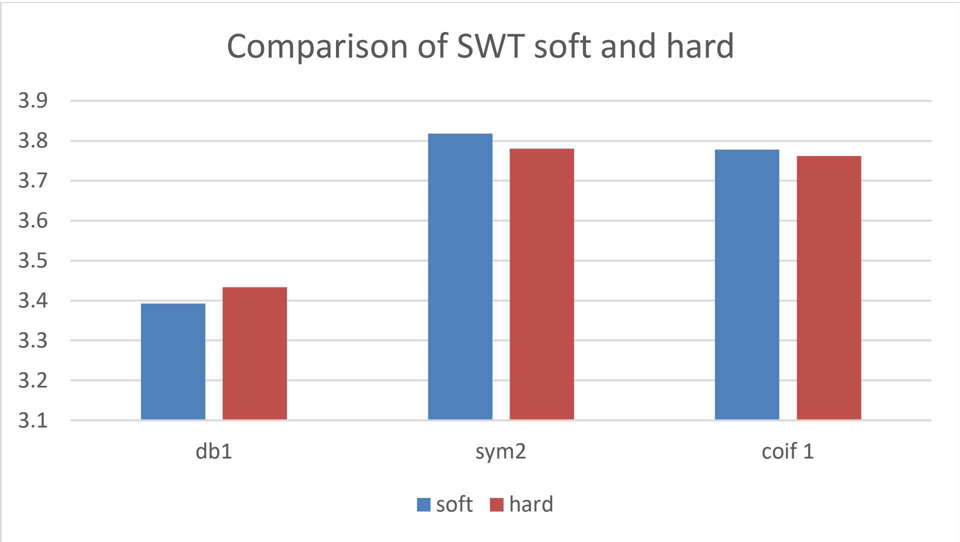


Figure 10.9 Chart for comparison on denoising performance of best families at best level with Poisson noise using SWT by soft and hard thresholding

INFERENCE

On denoising ct5 image using swt, level 1 of all families have high PSNR gain. Of which the best of daubechies, symlet, coiflet are db1, sym2, coif1 respectively.

The results of image fusion of best wavelet families on denoising gaussain noise under various type of threholding with DWT are tabulated in 10.13

TABLE 10.13 DWT FUSION OF BEST WAVELET FAMILIES AT BEST LEVEL OF DECOMPOSITION UNDER VARIOUS THRESHOLDING METHODS

	PSNR Gain Hard	Hard	PSNR Gain Soft		PSNR Gain Bayes	Bayes
db10	4.9456		4.9871		7.975	
sym8	4.9328	6.5085	4.8967	6.5806	6.6948	7.8549
db10	4.9456		4.9871		7.975	
coif4	4.907	6.4311	4.9602	6.4664	6.6208	7.897
coif4	4.907		4.9602		6.6948	
sym8	4.9328	6.4872	4.8967	6.3528	6.6208	7.7343

INFERENCE:

Image fusion is applied among the best of wavelet families for all the three types of threshold and following conclusions are declared. It is found that PSNR gain has improvement of approximately 20% for soft and hard and approximately 50% for bayes.

The results of image fusion of best wavelet families on denoising gaussain noise under various type of threholding with SWT are tabulated in 10.14

TABLE 10.14 SWT FUSION OF BEST WAVELET FAMILIES AT BEST LEVEL OF DECOMPOSITION UNDER VARIOUS THRESHOLDING METHODS

	PSNR Gain Hard	Hard	PSNR Gain Soft	Soft
db1	6.3237		6.2682	
sym2	6.2477	6.6334	6.1658	6.5494
sym2	6.2477		6.1658	
coif1	6.2266	6.3398	6.1864	6.2734
coif1	6.2266		6.1864	
db1	6.3237	6.5566	6.2682	6.4859

INFERENCE:

On fusing images of different wavelet families for different threshold with SWT, only a slight improvement is achieved.

The results of image fusion of best wavelet families on denoising gaussain noise under various type of threholding with SWT and DWT are tabulated in 10.15

TABLE 10.15 IMAGE FUSION OF TWO WAVELET TRANSFORMS

	swt	dwt	fussion
	db2(1)	db10(5)	SOFT
	6.1774	4.9871	5.8732
			HARD
Gauss	6.2006	4.9456	5.7967
	swt	**dwt**	**fusion**
	db2(1)	db10(6)	soft
	3.7626	2.7447	3.465
			hard
poisson	3.7488	2.7416	3.5021

From the table,it is observed that the PSNR gain obtained from Discerte Wavelet Transform for soft and hard thresholding undergoes a distinct inflation.Hence Image fusion is a successful technique that increase the PSNR gain of soft and hard thresholding.It is applicable to both poisson and Gaussian noise.

The results of image fusion of best wavelet families on denoising poisson noise under various type of threholding with DWT are tabulated in 10.16

TABLE 10.16 DWT FUSION OF BEST WAVELET FAMILIES AT BEST LEVEL OF DECOMPOSITION UNDER VARIOUS THRESHOLDING METHODS

level		PSNR Gain	soft	PSNR Gain Soft	hard	PSNR Gain Bayes	Bayes
6	db10	2.7447		2.7416		3.8486	
3	sym8	2.6481	2.9207	2.6812	2.8463	3.9852	5.6863
6	db10	2.7447		2.7416		3.9852	
5	coif5	2.7318	2.9225	2.7448	2.8496	3.9756	5.7998
5	coif5	2.7318		2.7448		3.9756	
3	sym8	2.6481	2.8374	2.6812	2.8502	3.9852	5.4701

INFERENCE:

There is only a slight improvement on image fusion of soft and hard threshold whereas on bayes threshold 35% improvement is achieved on fusion.

The results of image fusion of best wavelet families on denoising poisson noise under various type of threSholding with SWT are tabulated in 10.17

TABLE 10.17 SWT FUSION OF BEST WAVELET FAMILIES AT BEST LEVEL OF DECOMPOSITION UNDER VARIOUS THRESHOLDING METHODS

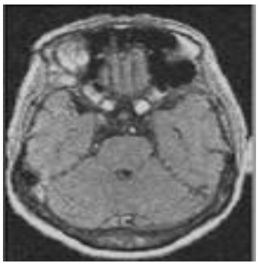
level		PSNR Gain	soft	PSNR Gain Soft	hard
	db2	3.7626		3.7488	
	sym2	3.8179	2.3655	3.7806	2.3693
	db2	3.7626		3.7488	
	coif1	3.7777	2.3568	3.7623	2.3369
	coif1	3.7777		3.7623	
1	sym2	3.8179	2.6474	3.7806	2.669

INFERENCE:

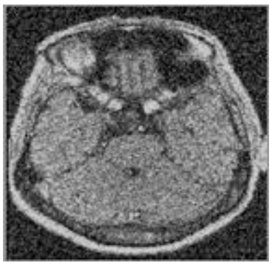
On fusing images of different wavelet families for different threshold, only a slight improvement is achieved.

IMAGES

The figure 10.10 shows the images of various wavelet families at its best level of decomposition that offers high PSNR gain for Gaussian noise



(a)

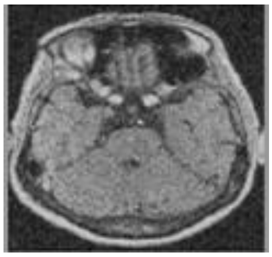


(b)

(c)

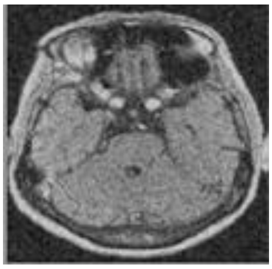
(d)

(e)



(f)

(g)



(h)

Fig.10.10 Denoising of CT image for gaussian noise with DWT and SWT

(a) original image (b) noisy image(gaussian noise)

using DWT(c) db10 level5 image (d)sym8 level5 image (e) coif4 level3 image

using SWT (f) db1 level1 image (g) sym2 level1 image (h) coif1 level1 image

The figure 10.11 shows the images of various wavelet families at its best level of decomposition that offers high PSNR gain for poisson noise.

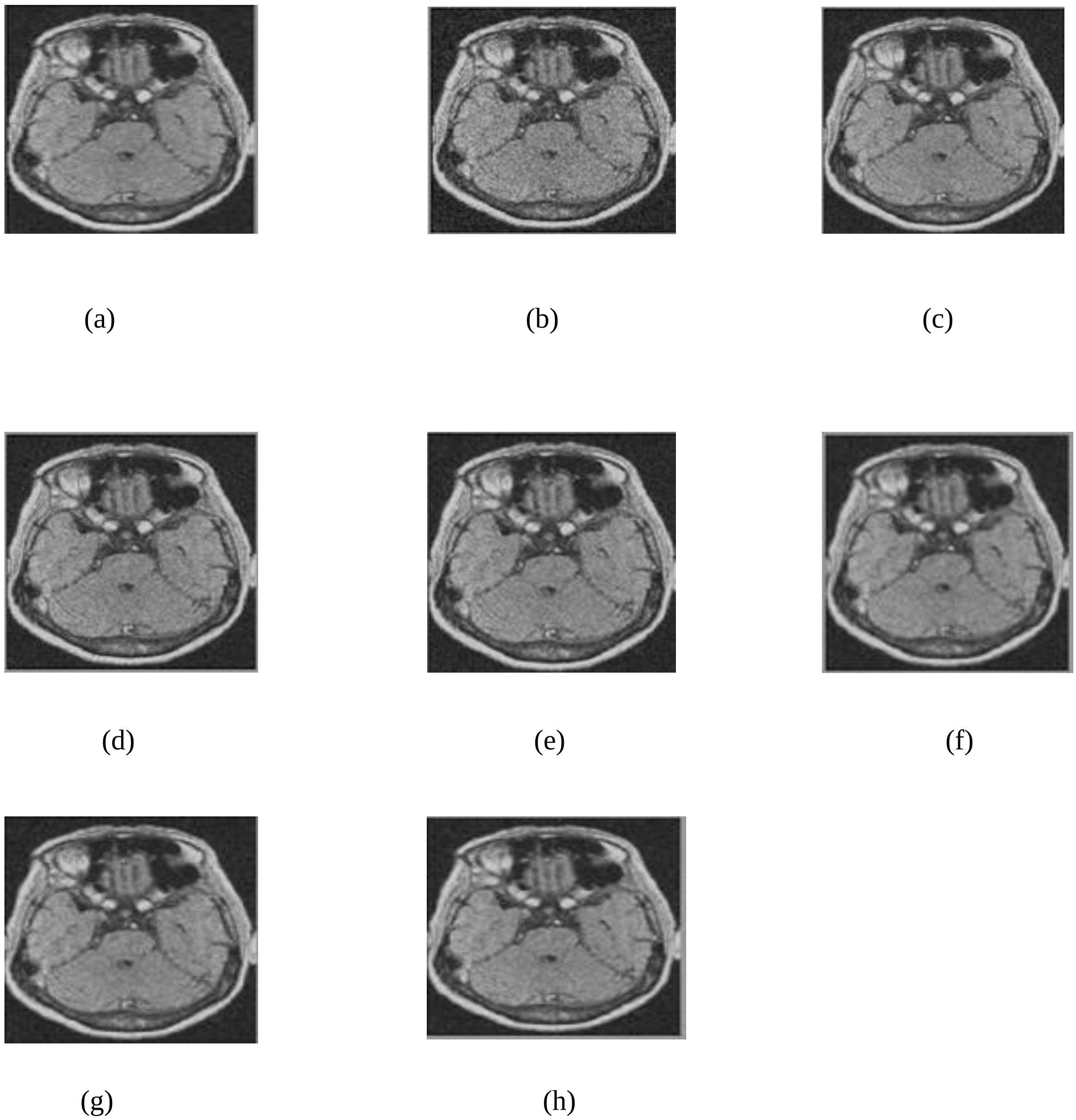


Fig.10.11 Denoising of CT image for poisson noise with DWT and SWT

(a) original image (b) noisy image(poisson noise)

using DWT(c) db10 level6 image (d)sym8 level3 image (e) coif5 level5 image

using SWT (f) db1 level1 image (g) sym2 level1 image (h) coif1 level1 image

CHAPTER 11
CONCLUSION

In this project, we have compared Wavelet Transforms like Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT) using Hard, Soft, Bayesshrink thresholding methods for denoising Gaussian and Poisson noise added images.From this paper, it is concluded that for DWT as the number of vanishing moments increases, number of coefficients also increases. Hence, a better thresholding process is accomplished at higher order(N) which in turn produces a better reconstructed image. However for SWT the performance is good for lower order of N.

While comparing the performance of different types of thresholding, bayes threshold provides better performance than hard which is better than soft thresholding method.

The advantage of proposed technique is that it has not only improvement in image characteristics such as PSNR & MSE but also in image quality (Visual image). This technique is tested with medical images.The algorithm tested with Computed Tomography images aids the doctors in a better and accurate diagnosis. The lesions (tumours or any other abnormality) obscured by noise is thus removed, thus enabling the physicians to differentiate the contrast in figures, so that the benign and malignant tumours are easily identified, thus saving the lives of humans.

FUTURE SCOPE:

This can be extended by performing denoising using other wavelet families like biorthogonal. It can also be extended to thresholding methods such as Neigh shrink SURE threshold, Visu shrink threshold to check on their performance measures. Rather than fusing images on same threshold on same level with same families, this project can be further extended by image fusion of different threshold different level and different transform to attain the best performance.

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