Chapter 3

Image Denoising using Wavelet and Bilateral Filters based Hybrid Denoising Models

3.1 Introduction

Digital images can play an important role in daily life applications such as satellite television, magnetic resonance imaging, computer tomography as well as in the areas of research and technology such as geographical information systems and astronomy. Data sets collected by image sensors are generally contaminated by different types of noises [14].

There are different sources of noise that may contaminate a digital image. Among them, dark current noise is due to the thermally generated electrons at sensor sites. It is proportional to the exposure time and highly dependent on the sensor temperature. Shot noise, which has the characteristics of Poisson distribution, is due to the quantum uncertainty in photoelectron generation. Amplifier noise and quantization noise occur during the conversion of number of electrons to pixel intensities. The overall noise characteristics in an image depends on many factors, which include sensor type, pixel dimensions, temperature, exposure time, and ISO speed [8]. In addition, imperfect instruments, problems with the data acquisition process, and interfering natural phenomena all can degrade the data of interest. Furthermore, noise can be introduced by transmission errors and com-
Noise is also channel dependent. Typically, green channel is the least noisy and blue channel is the noisiest channel. In single-chip digital camera, demosaicking algorithms are used to interpolate missing color components. That means, noise is in general not white. Noise in a digital image has low-frequency as well as high frequency components. Though the high-frequency components can easily be removed, it is challenging to eliminate low frequency noise as it is difficult to distinguish between real signal and low-frequency noise. Most of the natural images are assumed to have additive random noise, which is modeled as Gaussian type. Speckle noise [87] is observed in ultrasound images, whereas Rician noise [88] affects MRI images. Thus, denoising is often a necessary and the first step to be considered before the image data is analyzed. It is necessary to apply an efficient denoising technique to compensate for any data corruption [14]. The goal of denoising is to remove the noise while preserving the important image features as much as possible.

Linear filtering techniques, such as Wiener filter or match filter, have been used for this purpose for many years. But linear filters may result in some problems, such as blurring sharp edges, destroying lines and other fine image details, and fail to effectively remove heavy tailed noise. This calls for alternatives, like nonlinear filtering. Many works [2]-[4] are reported on image denoising using nonlinear filters. Thresholding algorithm in an orthogonal transform domain, such as subband or wavelet transform, is a nonlinear filter. Subband transform with orthogonal perfect reconstruction filter-banks is an orthogonal transform. It is known that the subband filters act as a set of discrete time based functions in a vector space and the decomposition of signal is just to project the signal onto these base functions. As for a signal with noise, there are some differences between the coefficients of original signal and noise because of their different features. In general, if an orthogonal transform with high-energy compaction and de-correlation properties is used, most of the energy of the original signal will be compacted into a few high magnitude coefficients [5], [6]. If the image data is corrupted by additive white noise, components that correspond to noise will be distributed among low magnitude high frequency components. Most of the coefficients of noise are
of smaller amplitudes. So, it is reasonable to eliminate the noise by comparing all the coefficients with a threshold and cutting off those coefficients with smaller than the threshold values [49], [85].

In recent years, lots of works have been reported on the use of wavelet transform not only in image processing but also in various fields of signal processing. It has the advantage of using variable size time-windows for different frequency bands. This results in a high frequency resolution in low bands and low frequency resolution in high bands. Consequently, wavelet transform is a powerful tool for modeling non-stationary signals that exhibit slow temporal variations in low frequency and abrupt temporal changes in high frequency [89]. Many denoising methods have been proposed over the years, such as the Wiener filter, wavelet thresholding [49], anisotropic filtering [90], bilateral filtering [7], total variation method [91], and non-local methods [92]. Among these methods, wavelet thresholding has been reported to be a highly successful method. In wavelet thresholding, a signal is decomposed into approximation (low-frequency) and detail (high-frequency) subbands, and the coefficients in the detail subbands are processed via hard or soft thresholding [49], [50], [85], [93]. The hard thresholding eliminates (sets to zero) coefficients that are smaller than a threshold as discussed earlier while the soft thresholding shrinks the coefficients that are larger than the threshold as well. The main task of the wavelet thresholding is threshold selection and the effect of denoising depends on the selected threshold: a bigger threshold will throw off the useful information and the noise components at the same time while a smaller threshold can not eliminate the noise effectively. Donoho [49] gave a general estimation method of threshold, but the best threshold cannot be found by this method. Chang et al. [56] have used predictive models to estimate the threshold. It is a spatially adaptive threshold based on context modeling. They also presented data-driven threshold for image denoising in a Bayesia framework [77]. In the SURE Shrink approach [93], the optimal threshold value based on the Stein's Unbiased Estimator for Risk (SURE) is estimated. A major strength of the wavelet thresholding is the ability to treat different frequency components of an image separately; this is important, because noise in real scenarios may be frequency dependent. But, in wavelet thresholding the problem experienced is
generally smoothening of edges.

The bilateral filter was proposed in [7] as an alternative to wavelet thresholding. It applies spatial weighted averaging without smoothing edges. This is achieved by combining two Gaussian filters; one filter works in spatial domain, the other filter works in intensity domain. Therefore, not only the spatial distance but also the intensity distance is important for the determination of weights [14]. Hence, these types of filters can remove the noise in an image while retaining its images. However, the filter may not be very efficient in removing any noise in the texture part of the image. It is not being able to remove salt and pepper type of noise. Also there is no theoretical works on the optimal values of the filter parameters.

In this thesis works a hybrid denoising method is proposed to find the best possible solution, so that PSNR [94] and IQI [86] of the image after denoising are optimal. The proposed approach to denoise an image is based on wavelet thresholding and bilateral filtering, which exploits the potential features of both wavelet thresholding and bilateral filters at the same time their limitations are overcome.

In view of the above the main objectives of this chapter are:

(i) To develop hybrid filters through hybridization of wavelet thresholding and bilateral filters in different configurations and to tune the different parameters of the hybrid filters to optimize the performance of the tuned hybridized filters for denoising different types of images,

(ii) To tune the parameters of both the wavelet based filter and the bilateral filter to optimize their performance for filtering the same types of images as in step (i).

(iii) To compare the performance of the filters developed in step (i) with those in step (ii) in denoising different types of images.

This chapter is organized as follows:

Section 3.2 introduces the concept of wavelet decomposition and thresholding and reported works on it. Section 3.3 explains concepts of bilateral filtering along with its working principle. Performance measurement criteria are discussed
in section 3.4. Sections 3.5, 3.6, 3.7 and 3.8 describe the proposed hybrid denoising models and all the working models considered for the work. Experimental results and discussions are given in section 3.9. Finally the conclusions are drawn in section 3.10.

3.2 Wavelet Decomposition

A wavelet is simply a small wave, which has its energy concentrated in time to give a tool for the analysis of transient, non-stationary or time varying phenomena. Mathematical expression of the wavelet is defined in equation (2.6) of chapter 2.

For the function to be a wavelet it should be time limited. For a given scaling parameter $a$, the wavelet is translated by the parameter $b$. A mother wavelet is the unique prototype function from which a family of wavelets is generated through change of scale, $a$ (compression or dilation) and shift, $b$ (translation) of the mother wavelet.

The continuous wavelet transform is defined by equation (2.7) in chapter 2. According to equation (2.7), for every $(a, b)$, there is a wavelet coefficient, representing how much the scaled wavelet is similar to the function at location $t = b/a$. The wavelet coefficients obtained from signal correlations with mother wavelet, stretched to large scale, reveal the approximate (low frequency) features, while those coefficients with small scale provides the fine features (high frequency) of the image. So, for wavelet decomposition, while a signal or image is scanned with the mother wavelet, the scale and position of the wavelet is varied continuously (in continuous wavelet transform) or in discrete steps (discrete wavelet transform).

Generally, in signal processing, the way of representing a signal should be such that the task of extracting certain properties of the signal is important for specific application, like denoising, becomes easier. Also, the building blocks, required for processing and representing a signal with a given accuracy, are as few as possible for faster computation. Another important aspect in signal processing especially, image processing, are the detail features, which are dependent on different scales of resolution. Multi-resolution representation as in wavelet decomposition enables one to analyze different details at different resolution scales.

The wavelet decomposition process involves three basic steps as follows:
3.2. Wavelet Decomposition

(i) a linear forward wavelet transform

(ii) nonlinear thresholding step and

(iii) a linear inverse wavelet transform.

3.2.1 Wavelet Representation of Image

Let \( f = \{ f_{ij}, \ i, \ j = 1, 2 \ldots M \} \) denote the \( M \times M \) matrix of the original image and \( M \) is some integer power of 2. During transmission the image \( f \) is corrupted by white Gaussian noise with independent and identically distributed (i.i.d) zero mean, and standard deviation \( \sigma \) i.e. \( n_{ij} \sim N(0, \sigma^2) \). So, the noisy image received at the receiver end is \( g_{ij} = f_{ij} + \sigma n_{ij} \). The goal is to estimate the signal \( f \) from noisy observations \( g_{ij} \) such that Mean Squared Error (MSE) is minimum and Peak Signal to Noise Ratio (PSNR) is maximum as well as image quality index (IQI) is also maximum within its range \([0, 1]\). Let \( W \) and \( W^{-1} \) denote the two dimensional orthogonal discrete wavelet transform (DWT) matrix and its inverse respectively. Then \( Y = W g \) represents the matrix of wavelet coefficients of \( g \) having four subbands (LL, LH, HL and HH). The subbands \( HH_k, HL_k, \) and \( LH_k \) are called details, where \( k \) is the scale varying from \( 1, 2 \ldots J \) and \( J \) is the total number of decompositions. The size of the subband at scale \( k \) is \( N/2^k \times N/2^k \). The subband \( LL_J \) is the low-resolution residue. The wavelet thresholding denoising method processes each coefficient of \( Y \) from the detail subbands with a soft threshold function to obtain \( \hat{X} \) \([95]\). The denoised estimate is inverse transformed to \( \hat{f} = W^{-1} \hat{X} \). The decomposition is shown in fig. 2.5(b).

3.2.2 Wavelet Thresholding

It has been observed that in many signals energy is mostly concentrated in a small number of dimensions and the coefficients of these dimensions are relatively large compared to other dimensions or to any other signal (specially noise) that has its energy spread over a large number of coefficients. Hence, in wavelet thresholding, each coefficient is thresholded (set to zero) by comparing against a threshold to eliminate noise, while preserving important information of the original signal \([96]\). Usually two types of thresholding techniques are used:
3.2. Wavelet Decomposition

3.2.1 Hard Thresholding

The hard thresholding operator is defined in equation (3.1).

\[ D(U, \lambda) = \begin{cases} U, & \text{for all } |U| > \lambda \\ 0, & \text{otherwise} \end{cases} \quad (3.1) \]

Hard threshold is a "keep or kill" procedure and is more intuitively appealing. The transfer function is shown in fig. 3.1.

3.2.2 Soft Thresholding

The soft thresholding operator is defined as equation (3.2).

\[ D(U, \lambda) = \begin{cases} (|U| - \lambda), & \text{for all } |U| > \lambda \\ 0, & \text{otherwise} \end{cases} \quad (3.2) \]

Soft thresholding shrinks coefficients above the threshold in absolute value. The transfer function of the same is shown in fig. 3.2.

3.2.3 Procedure of Wavelet Thresholding

The procedure of wavelet thresholding can be discussed in three steps as follows:

1. Calculate the wavelet coefficient matrix \( w \) by applying a wavelet transform \( W \) to the data: \( w = Wg = Wf + Wn \)
3.2. Wavelet Decomposition

2. Thresholding the wavelet coefficients to obtain the estimate of the wavelet coefficients of $\hat{X}$: $w \rightarrow \hat{X}$

3. Inverse transform the modified coefficients to obtain the denoised estimate: $\hat{f} = w^{-1}\hat{X}$

Consequently, wavelet coefficients are compared to a threshold and it is determined which coefficients must be set to zero. Determination of the value of the threshold is crucial as larger value may result into loss of information while smaller one may allow noise to continue. The proper value of threshold can be determined in many ways. The different methods that are used for the determination of the threshold value may be as given below:

(i) Universal thresholding

(ii) Visu Shrink

(iii) Sure Shrink

(iv) Bayes Shrink

**Universal or Global Thresholding**

The universal threshold can be defined in equation (3.3).

$$\lambda_{UNIV} = \sqrt{2\ln N\sigma}$$ (3.3)
where $N$ is the signal length, and $\sigma$ is the noise variance. In the asymptotic sense, it is the optimal threshold and minimizes the cost function of the difference between the function and the soft thresholded version of the same. It is very useful to obtain a starting value when nothing is known about the conditions of the signal condition.

**Visu Shrink**

In this method the Universal threshold proposed by Donoho and Johnstone is used. This threshold is given in equation (3.4).

$$\lambda_{VISU} = \sigma \sqrt{2 \log M} \quad (3.4)$$

where $\sigma$ is the noise variance and $M$ is the number of pixels in the image. Denoising of images with this method results into overly smoothed estimate of the images.

**SURE Shrink**

This is a thresholding method, where subband adaptive threshold is applied. It is based on Stein’s Unbiased Estimator for Risk (SURE), a method for estimating the loss in an unbiased fashion. Let wavelet coefficients in the $j^{th}$ subband be $X_i : i = 1, \ldots, d$. For the soft threshold estimator $\hat{X}_i = \eta_t(X_i)$ we have

$$SURE(t; X) = d - 2\{i : |X_i| \leq t\} + \sum_{i=1}^{d} \min(|X_i|, t) \quad (3.5)$$

The threshold $t_S$ can be obtained by:

$$t_s = \arg\min_{c \leq t \leq \sqrt{2 \log M}} SURE(t; X).$$

**Bayes Shrink**

It is also an adaptive data-driven threshold for image denoising where soft-thresholding technique is used. Generalized Gaussian distribution (GGD) is assumed for the wavelet coefficients in each detail subband. Then the threshold $T$ will be found out, which minimizes the Bayesian Risk. In all these methods, the noise variance $\sigma$ is present as a parameter. But in practice, for a noised image, the exact noise variance is not known. Noise variance may be estimated by the robust median estimator $\hat{\sigma} = \frac{\text{Median}(|Y_{ij}|)}{0.6745}$, $Y_{ij} \in \text{subband } HH_1$. 
3.3. Bilateral Filter

The thresholding techniques have some underlying disadvantages. For instance, the estimated wavelet coefficients by the hard-thresholding method are not continuous at the threshold \( \lambda \) which may lead to the oscillation of the reconstructed signal. In the soft-thresholding case, there are deviations between image coefficients and thresholded coefficients which directly influence the accuracy of the reconstructed signal. Retention of the edges is also a problem here. Different edge detection algorithm may be used to extract the contour feature of cell images. Bilateral filter may help in achieving the objective of edge retention.

3.3 Bilateral Filter

The bilateral filter was proposed in [7] as an alternative to wavelet thresholding for image denoising. It applies spatial weighted averaging without smoothing edges. This is achieved by combining two Gaussian filters; one filter works in spatial domain, the other filter works in intensity domain. Therefore, not only the spatial distance but also the intensity distance is important for the determination of weights. At a pixel location \( x \), the output of a bilateral filter can be represented by the equations (2.46) and (2.47) in the previous chapter.

The bilateral filter is a special case of the Jacob algorithm. This single iteration of Jacob algorithm, which is known as the diagonal normalized steepest descent, yields the bilateral filter. One weakness of the bilateral filter is not being able to remove salt-and-pepper type of noise. A second drawback of the bilateral filter is its single resolution nature. Unlike the wavelet filter, the bilateral filter may not access to the different frequency components of a signal. Although it is effective in removing high-frequency noise, the bilateral filter fails to remove low-frequency noise. Another issue with the bilateral filter is that there is no theoretical work on the optimal values of the parameters, \( \sigma_d \) and \( \sigma_r \).

3.3.1 Parameter Selection for the Bilateral Filter

There are two parameters that control the behaviour of the bilateral filter. Referring to equation (2.46), \( \sigma_d \) and \( \sigma_r \) characterize the spatial and intensity domain behaviours, respectively. Although these parameters should be related to the noise
3.4 Measurement of Performance

To judge the performance of a denoising technique it requires to decide upon using the error criterion. The error criteria commonly used may be classified into two broad groups:

(i) Objective criteria

(ii) Subjective criteria

The first group of measures needs mathematical formulation and restricted to statistical sense only, while it is very difficult to standardize the second group of measures as it involves human observers.

3.4.1 Objective Criteria

For objective measurement we can use Mean Squared Error (MSE) and Peak Signal to Noise Ratio (PSNR). Good PSNR does not imply that the visual quality of the image is good. To overcome this problem Image Quality Index (IQI) [86] is considered as the second parameter for judging the quality of denoised images. MSE is defined in equation (2.48) in the previous chapter. If we wanted to find the MSE between the denoised and the original image, then we would take the difference between the two images pixel-by-pixel, square the results, and average the results. The PSNR is defined in equation (2.49).

The IQI, Q, is proposed by Wang and Bovik [86] as a product of three different factors: loss of correlation, luminance distortion, and contrast distortion and is defined in equations (2.50) and (2.51).

The first component of equation (2.50) is the correlation coefficient between $f$ and $g$, which measures the degree of linear correlation between $f$ and $g$ and
3.5. Proposed Approach

its dynamic range is [-1, 1]. The second component, with a value range of [0, 1], measures how close the mean luminance is between \( f \) and \( g \). \( \sigma_f \) and \( \sigma_g \) can be viewed as estimates of the contrast of \( f \) and \( g \), so the third component with a value range of [0, 1] measures how similar the contrasts of the images are.

The dynamic range of \( Q \) is [-1, 1]. The best value is 1 which means that the tested image is exactly equal to the original image. The best value is achieved, if and only if, \( g_i = f_i \) for all \( i = 1, 2, \ldots, M \). The lowest value of -1 occurs when \( g_i = 2f_i - f_i \) for all \( i = 1, 2, \ldots, M \).

3.4.2 Subjective Criteria

For subjective measurement the original image and the denoised image are shown to a large group of examiners. Each examiner assigns a grade to the denoised image with respect to the original image. These grades may be drawn from a subjective scale and may be divided as excellent, good, reasonable, poor and unacceptable. Based on grades assigned by examiners, an overall grade is assigned to the denoised image. Complement of this grade gives an idea of the subjective error [94]. However, this method is not used in the proposed work, as its effectiveness is highly susceptible to sensibility of the human viewers.

3.5 Proposed Approach

In this thesis works an exhaustive study of the different possible models by hybridizing bilateral and wavelet based principles for image denoising has been carried out along with the existing models designed using the concepts of wavelet, or bilateral or wavelet and bilateral both. The performances of the models in different configurations and with variation of model parameters are investigated for arriving at the optimum hybrid structure for denoising of images. The models investigated and experimented in this study fall into four different categories:

1. Model with Wavelet based denoising method only (model no. 1).

2. Model with Bilateral filter only (model no. 2).
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3. Model proposed by Ming Zhang and Bahadur Gunturk (Zhang-Gunturk method) (model no. 3).

4. Hybridized models (model nos. 4 to 51) in different configurations.

While designing a model, the parameters $w$, $\sigma_d$ and $\sigma_r$ of bilateral filters are varied over a wide range of values as there is no explicit rules that can guide the tuning of these parameters. The threshold value for the wavelet based filter is also varied.

These four categories may be clubbed into 2 groups:

(i) Existing Denoising Models and

(ii) Newly Designed Models.

3.5.1 Existing Denoising Models:

Model nos. 1, 2 and 3 are the existing denoising models based on wavelet, bilateral and both wavelet and bilateral filtering respectively.

1. Wavelet decomposition and thresholding based model: model no. 1

The model is designed by using only the wavelet decomposition of the input image into the four subbands of detail and approximation. The wavelet based soft thresholding technique is applied on all the decomposed subbands. The errors are chopped out due to this thresholding and after the chopping out of the information, the available information is combined into an image again. This image is considered here as the denoised output image that is generated through the wavelet based denoising model. The model is depicted in fig. 3.3.

Here LL, LH, HL and HH are the four decomposed subbands of the input image. The wavelet based thresholding technique represented by $W$ in the model is used on all of the subbands.

2. Bilateral filtering model: model no. 2

The bilateral filter was proposed in [7] as an alternative to wavelet decomposition and thresholding base models. Two types of domain filters are used
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Figure 3.3: Model No. 1

Input image \[ \xrightarrow{\text{Bilateral filter}} \] \[ \xrightarrow{\text{Wavelet thresholding}} \] Output image

Bilateral filter

Wavelet thresholding

Figure 3.4: Model No. 2

Bilateral Filter is represented by B in the fig. 3.4.

3. Zhang-Gunturk method: model no. 3

The model was first proposed by Ming Zhang and Bahadur Gunturk in 2008. Among the existing hybrid model, this is the best one that outperforms the other models as per the report of Zhang and Gunturk [8]. The structure of the model as proposed by the authors are presented in the fig. 3.5.

In this model, Bilateral filter is applied first on the input image. Then, the wavelet decomposition is performed on the image and the decomposed
3.5. Proposed Approach

detail and approximation subbands are ready for any other type of work. The bilateral filter is applied again in the high frequency domain whereas in the other domains only wavelet thresholding is used. After the application of the filters, the subbands are combined to form the image. Again bilateral filter is applied on the image that is produced through the inverse wavelet decomposition process.

3.5.2 New Proposed Models:

In this thesis, a number of working models are designed and experimented over a number of images and the results are examined to get the best denoising model.

Initially 48 different models have been designed using wavelet and bilateral filtering techniques. The models are represented as model nos. 4 to 51. The designed models are of three categories:

1. Category I:

   The image is decomposed first using discrete wavelet transform function and bilateral or wavelet thresholding based filtering is used in each of the decomposed component. After filtration these components are again recombined into one image by using inverse discrete wavelet transform (idwt). Now, bilateral filter is used on the image to get the ultimate desired denoised one. The model is illustrated in fig. 3.6.

2. Category II:
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In this category, at first the image is denoised by using bilateral filter. After the first stage of denoising, the image is decomposed using the same discrete wavelet transform function that is used in category I and bilateral or wavelet thresholding based filtering is used in each of the decomposed component. These components are again recombined into one image by using inverse discrete wavelet transform (idwt). At last, bilateral filter is used on the image to get the ultimate desired denoised one. The model is shown in fig. 3.7.

3. Category III:

In this category, first the image is denoised by using bilateral filter as in category II. After this, the image is decomposed using the same discrete wavelet
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transform function as of category I and bilateral or wavelet thresholding based filtering is used in each of the decomposed component. These components are again combined into the desired output image by using inverse discrete wavelet transform (idwt). The model is shown in fig. 3.8.

![Diagram of model](image)

Figure 3.8: Category III

The functions defined by B in the figs. 3.6, 3.7 and 3.8 of category I, II and III respectively are the bilateral filtering technique whereas the function F may be bilateral filter or wavelet thresholding and all the possible structures of the three categories are considered and experimented. Programs are developed in Matlab command line using wavelet and image processing tool boxes of Matlab7. At the time of decomposition, the subbands are downsampled by 2. Then the filtering techniques are applied on the subbands followed by the upsampling process by 2. So, the ultimate denoised image can retain its size. The programs are tested on different types of images that are considered throughout this work. General images are considered along with telescopic and satellite images for the testing of the efficiency and capability of the models.

The models that are designed with the structure of the category I are illustrated as model nos. 4 to 19 in section 3.6.

The models that are designed with the structure of the category II are illustrated as model nos. 20 to 35 in section 3.7.

The models that are designed with the structure of the category III are illustrated as model no. 36 to 51 in section 3.8.
At the time of construction of the models, the following facts are considered:

(i) Different standard available images along with some unpublished images are considered throughout this work. All the models are applied on each and every image.

(ii) For a particular image and a model, a wide range of values for the $w, \sigma_d$ and $\sigma_r$ are considered.

(iii) After wavelet decomposition, soft thresholding or bilateral technique is applied on each and every subband of the image.

(iv) The value of soft thresholding cut off is also considered as a variable here to get the best result with the suitable models.

The PSNR is calculated by equation (2.49) and IQI by equation (2.50) for all the considered models with the considered parameters as already discussed.

### 3.6 Models of Category I:

The models that are designed with the structure of the category I are illustrated here as model nos. 4 to 19.

![Figure 3.9: Model No. 4](image-url)
3.6. Models of Category I:

Input image → LL → B → W → Output image

Input image → LH → W → Output image

Input image → HL → W → Output image

Input image → HH → W → Output image

B Bilateral filter

W Wavelet thresholding

Figure 3.10: Model No. 5

Input image → LL → W → Output image

Input image → LH → B → W → Output image

Input image → HL → W → Output image

Input image → HH → W → Output image

B Bilateral filter

W Wavelet thresholding

Figure 3.11: Model No. 6

Input image → LL → W → Output image

Input image → LH → W → Output image

Input image → HL → B → Output image

Input image → HH → W → Output image

B Bilateral filter

W Wavelet thresholding

Figure 3.12: Model No. 7
3.6. Models of Category I:

Figure 3.13: Model No. 8

Figure 3.14: Model No. 9

Figure 3.15: Model No. 10
3.6. Models of Category I:

![Diagram of Model No. 11]

- **B**: Bilateral filter
- **W**: Wavelet thresholding

**Figure 3.16: Model No. 11**

![Diagram of Model No. 12]

- **B**: Bilateral filter
- **W**: Wavelet thresholding

**Figure 3.17: Model No. 12**

![Diagram of Model No. 13]

- **B**: Bilateral filter
- **W**: Wavelet thresholding

**Figure 3.18: Model No. 13**
3.6. Models of Category I:

Input image → Input image

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**Figure 3.19: Model No. 14**

- LL → W → B → B → Output image
- LH → B → Output image
- HL → B → Output image
- HH → W → Output image

- B: Bilateral filter
- W: Wavelet thresholding

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**Figure 3.20: Model No. 15**

- LL → W → B → B → Output image
- LH → B → Output image
- HL → B → Output image
- HH → B → Output image

- B: Bilateral filter
- W: Wavelet thresholding

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**Figure 3.21: Model No. 16**

- LL → B → B → Output image
- LH → W → B → Output image
- HL → B → Output image
- HH → B → Output image

- B: Bilateral filter
- W: Wavelet thresholding
3.6. Models of Category I:

- **Figure 3.22: Model No. 17**
  - Input image
  - Bilateral filter
  - Wavelet thresholding

- **Figure 3.23: Model No. 18**
  - Input image
  - Bilateral filter
  - Wavelet thresholding

- **Figure 3.24: Model No. 19**
  - Input image
  - Bilateral filter
  - Wavelet thresholding
3.7 Models of Category II:

The models that are designed with the structure of the category II are illustrated as model nos. 20 to 35.

Figure 3.25: Model No. 20

Figure 3.26: Model No. 21
3.7. Models of Category II:

Figure 3.27: Model No. 22

Figure 3.28: Model No. 23

Figure 3.29: Model No. 24
3.7. Models of Category II:

- **Bilateral filter**
- **Wavelet thresholding**

**Figure 3.30: Model No. 25**

**Figure 3.31: Model No. 26**

**Figure 3.32: Model No. 27**
3.7. Models of Category II:

Figure 3.33: Model No. 28

Figure 3.34: Model No. 29

Figure 3.35: Model No. 30
3.7. Models of Category II:

Figure 3.36: Model No. 31

Figure 3.37: Model No. 32

Figure 3.38: Model No. 33
3.7. Models of Category II:

Bilateral filter

Wavelet thresholding

Figure 3.39: Model No. 34

Figure 3.40: Model No. 35
3.8 Models of Category III:

The models that are designed with the structure of the category III are illustrated as model nos. 36 to 51.

Figure 3.41: Model No. 36

Figure 3.42: Model No. 37
3.8. Models of Category III:

Figure 3.43: Model No. 38

Figure 3.44: Model No. 39

Figure 3.45: Model No. 40
3.8. Models of Category III:

Figure 3.46: Model No. 41

Figure 3.47: Model No. 42

Figure 3.48: Model No. 43
3.8. Models of Category III:

Figure 3.49: Model No. 44

Figure 3.50: Model No. 45

Figure 3.51: Model No. 46
3.8. Models of Category III:

Figure 3.52: Model No. 47

Figure 3.53: Model No. 48

Figure 3.54: Model No. 49
3.8. Models of Category III:

Figure 3.55: Model No. 50

Figure 3.56: Model No. 51
3.9 Experimental Results and Discussions

The first model is developed with wavelet based thresholding algorithm as shown in fig. 3.3. In this algorithm, the images are decomposed into four subbands. The soft thresholding method is then employed on each of the four subbands by varying the thresholding values from 0.001 to 0.1 and the best thresholding result is found with the threshold value as 0.01 using db8 filters available in Matlab. As most of the researchers have used dbS filters for image denoising, the same has been considered in this work too. Though the lowering of thresholding value below 0.01 yields better PSNR but the visual quality of the denoised images are not as good as with the threshold value of 0.01. The second model is the bilateral filter as shown in fig. 3.4. The parameters, $w$, $\sigma_d$ and $\sigma_r$ are tuned for finding the optimal performance. The parameter, $\sigma_d$ is varied from 0.01 to 2.2, the window size, $w$, is varied from 1 to 11, and $\sigma_r$ is varied from 10 to 60. The third one is the model proposed by Ming Zhang and Bahadur Gunturk in [8]. As proposed by the authors, the images are decomposed into four subbands and the both wavelet based and bilateral filters are used as shown in fig. 3.5.

The models from four to fifty one are the newly proposed hybridized ones for the experimentation. For these models, db8 filters available in Matlab are used for one-level wavelet decomposition. The value of soft-thresholding is set at the same value obtained for model no. 1 with wavelet thresholding only.

All the models are experimented with standard pictures like Lena, Barbara, Einstein, satellite picture like pyramid and two astronomical telescopic images Astrol and Astro2. The PSNR and IQI values obtained for all the models considering the image Lena, are given in table 3.1. The values of PSNR and IQI for other images namely Barbara, Einstein, Pyramid, Astrol and Astro2 are presented in this chapter in tables 3.2, 3.3, 3.4, 3.5 and 3.6 respectively.

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Table 3.4: Performance of all the models on image “Pyramid” in terms of PSNR and IQI

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Table 3.6: Performance of all the models on image “Astro2” in terms of PSNR and IQI

The models 1, 2, 3, 4, 20, and 36 have been found to be more capable in denoising all the images as compared to other models. Again, these models are executed over the considered images to fine-tune the values of the parameters. The fine-tuned values are shown in table 3.7.
## 3.9. Experimental Results and Discussions

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Table 3.7: Fine-tuned performance of the best performing models in terms of PSNR and IQI

However, there is some difference in the performance of these six models in terms of PSNR and IQI. For standard image Lena, model 4 achieved the best PSNR as well as IQI values very closely followed by model 36. Models 20, 2, 1 and 3 follow in descending order in terms of PSNR as is evident in figs. 3.57 and 3.58 and in table 3.8. In the case of Barbara, again the performance of the model 4 is the best in terms of PSNR but in terms of IQI, the performance of model 36 is at par with model 4. For image Einstein, model 36 generates the best PSNR whereas model 4 generates best IQI.

When the satellite image, Pyramid is considered, the best model in terms of PSNR and IQI is 36 followed by model 20. Models 2 and 4 follows them but the performance of the other two models (1 & 3) are comparatively poorer. For two astronomical telescopic images, Astro1 and Astro2, model 36 gives the best results, except model 20 that achieves better IQI for image Astro1 even though its PSNR is less.

Model no. 3 is behaving in a very inconsistent manner. Even though its performance is well for standard images, in case of satellite image the performance deteriorates with further fall in performance for astronomical telescopic images.

Model nos. 12, 13, 16, 17, 18, 19, 28, 29, 32, 33, 34, 35, 43, 44, 45, 48, 49,
Table 3.8: Performance of the best six models in terms of PSNR and IQI

50 and 51 are not performing well for all the images.

From the above discussion and the structure of the models, it is observed that the models, whose performance is not good enough, are having bilateral filtering technique in the decomposed frequency subbands.

From the results of the experiments in terms of PSNR and IQI as reported in table 3.7 and 3.8, the models 4, 20 and 36, as depicted in figs. 3.9, 3.25 and 3.41 respectively, are considered as the better models than the other ones.

In model 4, the images are decomposed first into four subbands using $db8$ filters in Matlab. In this level the wavelet based soft thresholding is applied on all the subbands. The results so obtained after thresholding are then used to reconstruct the image. In the next level, bilateral filter is applied to get the final denoised image. In model 20, first the image is denoised with bilateral filter followed by decomposition into four subbands using $db8$ filters. And wavelet thresholding is applied on all the subbands as applied in model 4. The results obtained after thresholding are then used to reconstruct the image. In the last level, again bilateral filter is applied to get the final denoised image.

Model 36 is similar to model 20 except there is no bilateral filter at the
output side of model 36. The wavelet thresholding is applied on all the subbands. The results obtained after thresholding are then used to reconstruct the denoised image.

Figure 3.57: Performance Comparison of the best six models in terms of PSNR

Figure 3.58: Performance Comparison of the best six models in terms of IQI

Observation of the results reveals that when only the wavelet based thresholding filter is used on all the decomposed subbands of any image, then it results
in good PSNR and IQI. But when bilateral filter is applied in different ways along with wavelet based thresholding filters, the performance deteriorates. When the bilateral filter is used before or after or both sides of the decomposition of an image, the performance improves.

But out of the best three models, 4, 20 and 36, the performance of model 36 is almost uniform and consistent for all the different types of images that are considered. The values of both the parameters, PSNR and IQI, are reasonably well for this model as is evident from figs. 3.57 and 3.58 respectively.

![Figure 3.59: Performance Comparison of the best six models with respect to Lena](image)

3.10 Conclusion

Hybrid denoising models designed through hybridization in different configurations are developed and their performances are tested on different types of noisy images. The performance of the models is evaluated in terms of PSNR and IQI and comparison is drawn. Out of 48 models experimented with only three models (models 4, 20 and 36) are found to be comparatively better than all other models. It is observed that the model 36 is more uniform and consistent in its performance in all the types of images tested with in terms of PSNR and IQI. It is also observed that application of bilateral filters on wavelet decomposed subbands in any
Figure 3.60: Performance Comparison of the best six models with respect to Barbara

Figure 3.61: Performance Comparison of the best six models with respect to Einstein

combination with wavelet thresholding deteriorates the performance of the model, whereas, application of bilateral filters before or after or on both before and after decomposition enhances the performance. So, the model 36, wherein the bilateral filter is applied before decomposition, is found to be the most consistent. Thus,
Figure 3.62: Performance Comparison of the best six models with respect to Pyramid

model 36 is recommended as a well competent model for denoising any type of images.

The visual quality of the images can also be viewed from the figs. 3.59, 3.60, 3.61, 3.62, 3.63 and 3.64 where the original image and its noisy one is depicted...
3.10. Conclusion

![Image of image comparison](image.png)

Figure 3.64: Performance Comparison of the best six models with respect to Astro2 along with the denoised counterparts by the existing models 1, 2, 3 and the proposed model i.e., model no. 36.