CHAPTER I
INTRODUCTION

This chapter describes the sources of noise and image denoising problem including the statistical characteristics of the noise and the images. It also describes the motivation and objectives of the thesis. Finally, a short outline of the thesis is also presented.

1.1 SOURCES OF NOISE

Digital images are naturally embedded with essential geometric structures of lines, contours and edges. Nowadays, these images play a vital role in day-to-day life. Their applications now widen from the documentation of events and satellite television to the various scientific and technological research areas like surveillance, weather prediction and medical diagnosis. This has driven to an ever growing demand for precise and visually pleasant images.

In the past decades, images picked up by the cameras had been developed by making use of the photochemical processes in paper form. Any deterioration of the images in the paper form is now rectified by scanning the photographs and bringing them back to the original image by numerical algorithms. Still, these images account for most of the flaws like noise and blur in photochemical photographs.

Recently, numerical electronic cameras are available to pick up and carry out the images directly. The visual appearance of the images is now comparable to, and often better than, the images attained through photochemical processes. However, the images picked up by the modern cameras are always corrupted by noise. Apart from affecting the image quality, such noise usually complicates the performance of computer vision appliances like tracking, object detection, object recognition, feature extraction and classification, etc. This leads to the notion of eliminating such noise which is the initial procedure in any image processing task. However, before this process is carried out, it is necessary to be familiar with the sources and characteristics of the noise corrupting the image.

Noise corrupting the image is introduced in several forms in different stages of the image formation method as illustrated in Fig. 1.1. Some of these noise sources arise from the camera characteristics. Initially, images are distorted due to inaccurate focusing of the lens assembly or light focusing system which projects the image on the camera sensor. The non-uniform response of the sensor elements produces the fixed
pattern noise, and the dark current noise is also produced due to the abnormal charges at the sensors even without any incident photons.

![Image Formation Model](image)

**Fig. 1.1. Image Formation Model**

In the image acquisition process, each pixel value of the digital image is attained by measuring the light intensity at each pixel location by the use of a Charge Coupled Device (CCD) matrix that acts as camera sensor and is coupled with a light focusing system [1]. Each captor of the CCD is approximately a square which is obtained by adding up the incoming photons during the abturation time. The sensors in CCD collect parasitic heat photons and endure electrostatic and photonic oscillations at the time of their loads and discharges, thereby causing disturbance in pixel values. In addition, each captor receives spurious heat photons due to inadequate cooling. Thus, the variations of the light intensity and the photo-electronic activity of the camera sensors produce the noise in the image. The efficiency of the camera sensors is also affected by the poor environmental conditions during image acquisition and by the quality of the sensing elements themselves. The analog-to-digital conversion of the image also produces the quantization noise in the image. The effect of the quantization noise can be lessened by using sufficient number of bits to store each pixel. One’s own perception also produces noise. It is observed when one perceives by opening eyes in darkness, or by simply closing the eyes. Even for good cameras, an image restoration is always required to extend their range of action.

In applications like satellite television, weather monitoring, etc. images are to be transmitted to distant places through the communication channel. During the transmission, the images are corrupted by various unavoidable intrinsic and extrinsic
conditions like transmitting channel imperfection, interference, lightning or other atmospheric disturbances.

1.2 IMAGE DENOISING PROBLEM

An image denoising algorithm restores the original image from the distorted or noisy image with preservation of image features, edges, textures and smooth regions in an image so as to achieve good visual quality. An efficient image denoising method is needed due to the massive production of digital images, often acquired in poor conditions [1]. It is the preliminary and essential step to increase the efficiency and accuracy of the high level image processing tasks like segmentation, feature extraction and classification, pattern recognition and more. There are several efficient approaches to estimate the original image from the noisy image by classically preserving the essential geometric details and edges. However, it is not possible to separate the noise significantly from the images. Also, the denoising methods depend upon specific problems. As an illustration, a method used for denoising satellite images may not be appropriate to denoise medical images. As a consequence, image denoising still continues as an elementary problem in image processing.

1.2.1 Image Degradation and Restoration

In practice, an image is affected by several types and forms of noise. However, the most common type of noise is the Additive White Gaussian Noise (AWGN) with zero-mean. As Fig. 1.2 shows, the image $x(n_1, n_2)$ is corrupted by the AWGN $W(n_1, n_2)$ resulting in change in pixel values of the image from its original value by a small amount. A histogram, a graphical sketch of the amount of variation of a pixel value against the frequency with which it appears, exhibits a Gaussian distribution [2] as given by

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

(1.1)

where $\mu$ is the mean value, and $\sigma$ is the standard deviation of the noise.

The resulting degraded image $d(n_1, n_2)$ is given by;

$$d(n_1, n_2) = x(n_1, n_2) + W(n_1, n_2)$$

(1.2)

Fig.1.3 shows the noisy Lena image obtained by adding AWGN of zero-mean to the original Lena image. To analyze the image efficiently, noise must be removed from the image by means of a suitable restoration process. The main goal of image restoration process is to generate an estimate of the original image prior to degradation. The restoration filter involves three steps as follows:
- Decomposition of the noisy image into subbands by forward transform to separate the edge related information.
- Estimate or filter the subbands to obtain the denoised coefficients
- Restore the denoised image \( \hat{x}(n_1, n_2) \) which is the best estimate of the original image. For a perfect restoration filter, \( \hat{x}(n_1, n_2) = x(n_1, n_2) \)

Additive White Gaussian Noise \( W(n_1, n_2) \)

Fig. 1.2 Image Denoising Model

Fig. 1.3 Original Lena Image and Its Noisy Version
(a) Lena Image  
(b) Additive White Gaussian Noise  
(c) Noisy Lena image

In order to find out a suitable transform and estimation methods for accurate restoration process, the different structural properties of natural images that describe the
image contents statistically have to be considered for statistical modeling of the image. The important properties of the natural images [3] are given as follows:

- **Self-Similarity**
  Natural images have statistically self-similar property. As a result, they have scale invariance property so that the statistical properties of the image does not alter with the scale of the image.

- **Spatial Adaptivity** - Natural images are comprised of different textures, small features, sharp edges and homogeneous areas. Due to their strong spatial adaptivity, any image denoising scheme must be spatially adaptable to achieve better denoising performance. In order to achieve this, a spatially variant model is also required due to the inefficiency of stationary approaches for modeling the images accurately. However, it is a difficult task to consider the space-varying characteristics of natural scenes since it necessitates to define a large number of additional parameters at least one per pixel, followed by the estimation. This surely leads to overfitting issues since the nonstationary parameters without any constraints adapt more to the noise than to the underlying information. For effective spatial adaptation, these parameters must be constrained by making use of a prior probability density function.

- **Interscale Persistence** - A multiresolution decomposition is appropriate to analyze the scale invariant data and obtain a sparser representation of the image. The underlying spatial structure of the image persists through the different scales, i.e. high/low value of the coefficient magnitudes often lead to high/low values at the next scale, due to the inability of the multiscale transform to perfectly decorrelate natural images. Such a transform exhibits some interscale redundancy.

- **Intrascale Dependencies** - While considering two different subbands of the same scale, but with different orientations, homogeneous areas and details are found approximately at the same spatial location in the different subbands. Isotropic details, such as smooth areas and round features, are naturally found at all orientations. This shows again that multiscale transforms do not perfectly decorrelate the information contained in natural images.

By taking into account the properties of natural images, an appropriate transform must be used to represent optimally the natural images by a set of orthogonal basis.
Also, a proper statistical estimation method based on the properties of natural images enables the efficient removal of noise from the noise corrupted image.

1.3 MOTIVATION FOR THE WORK

In the last few decades, there have been several efficient denoising approaches in both spatial and transform domain developed by researchers. The spatial domain approaches operate on the pixels of the image directly. The transform domain approaches modify the transform coefficients of the image. These denoising algorithms remove noise efficiently under the assumption that the images are mostly formed by the means of linear system and also the images are stationary. In fact, real images are nonstationary and they are formed through the nonlinear process. In such a case, the performance of the linear denoising algorithm is limited. This leads to the notion of developing a nonlinear denoising algorithm by taking into account the variation in local statistical characteristics. Till now, noise is not completely removed from images with distinguishable characteristics in nature. Sometimes, the visual quality of the denoised image is not satisfactory for images with high PSNR. But, better visual quality and high PSNR values are important criteria to be considered. Some denoising methods generate the denoised image with some of the following artifacts.

- Blur: The smoothing of edges results due to the elimination of high spatial frequencies in the image.
- Ringing/Gibbs oscillation: Shrinkage of high frequency transform coefficients may lead to oscillations along the edges or ringing distortions in the image.
- Blocking artifacts: Thresholding of transform coefficients results in block-like appearance in the denoised image.
- Staircase effect: Aliasing of high frequency components may lead to stair-like structures in the image.
- Checkerboard effect: Denoised images may sometimes have checkerboard structures.
- Occurrence of false edges in the denoised image and scratch phenomena in smooth regions.
- Wavelet outliers: These are distinct repeated wavelet-like structures that are visible in the denoised image in algorithms that work in the wavelet domain.
- The local signal spectrum changes drastically between different image regions. Basically, to reduce noise one would like to smooth a lot where the true signal
is uniform (low frequency), and smooth less where the true signal varies rapidly (near edges in particular) by adaptive methods. Obviously, such considerations are application-dependent. One can apply adaptive methods either pixel by pixel or block by block. The pixel by pixel methods generally require more computation. However, the block by block methods can cause abrupt changes in image intensity between blocks called the blocking effect. A common and effective method for reducing the blocking effect is to use overlapping blocks. This increases the computational complexity somewhat, but not as much as pixel by pixel methods.

These artifacts should not appear in the denoised image while using suitable denoising algorithm with reduced complexity since they affect the visual quality of the image. To achieve this, a suitable denoising method must be used to separate the edges from the noisy image as much as possible and reduce artifacts with image smoothing. The methods in both the spatial and transform domain have some problems that need to be overcome. In this work, such problems are identified and tried to provide an effective solution to these problems.

1.4 OBJECTIVES OF THE THESIS

Edge preserving image denoising techniques in transform domain are presented to remove AWGN. The vital goal is to obtain a denoised image with better edge-preservation for good visual interpretation. Main objectives of the work are:

- To introduce a new denoising algorithm in the transform domain which represents the directional information of an image efficiently by a set of orthogonal basis functions, eliminates staircase and ringing artifacts, and reduces the blurring effect.
- To estimate the denoised coefficients using the model-based estimation methods to remove blocking artifacts.
- To implement a multiscale, multidirectional transform to approximate directional information more effectively for better edge preservation.
- To integrate a locally adaptive, nonlinear, noniterative spatial filter with a multiscale, multidirectional transform to prevent the occurrence of false edges.
- To design and implement an analysis and synthesis filter bank for multiscale transform with good frequency selectivity and high stopband attenuation to reduce aliasing distortion.
To check the applicability of these algorithms in denoising the medical images.

1.5 THESIS CONTRIBUTION
In this research work, two transform-based image denoising algorithms are implemented to remove noise from the images corrupted by additive white Gaussian noise (AWGN) with zero mean for obtaining good visual quality and high PSNR.

The Hybrid Wavelet And Quincunx Diamond Filter Bank (HWQDFB)-based denoising scheme employs the HWQDFB structure which consists of the Wavelet Filter Bank (WFB) in conjunction with Quincunx Diamond Filter Bank (QDFB) to provide an efficient representation of images. The Bayes least squares (BLS) estimator is applied on the noisy image subbands modeled as the Gaussian Scale Mixture (GSM) to obtain the denoised detail coefficients. This denoising scheme is experimented with images of diversified characteristics like Lena, Barbara, boat, pepper, cameraman, circuit etc. It reveals that this denoising scheme reduces blocking, ringing and staircase artifacts and scratch phenomena in smooth regions with satisfactory visual quality measures, Structural Similarity Index Metrics (SSIM) and Figure of Merit (FOM) and high Peak Signal-to-Noise Ratio (PSNR). This algorithm is computationally more efficient. But at high noise densities, this algorithm fails to preserve edges, and fewer artifacts are present in the denoised image. To overcome this limitation, the Subsampled Pyramid and Nonsubsampled Directional Filter Bank (SPNSDFB)-based image denoising scheme is proposed.

This SPNSDFB-based denoising scheme incorporates a locally adaptive, nonlinear, noniterative bilateral filter with a multiscale, multidirectional SPNSDFB transform. This denoising scheme results in high peak signal-to-noise-ratio (PSNR) and improves the visual quality metrics, SSIM and FOM, even at high noise densities by reducing artifacts like blocking, ringing and staircase artifacts and the occurrence of false edges. The proposed algorithms are used to denoise Computed Tomography (CT) images.

1.6 THESIS ORGANIZATION
The chapters of this thesis are organized as follows:

Chapter II presents the review of various denoising algorithms in spatial domain and transform domain. It also presents the literatures available for thresholding and various estimation methods in the transform domain by statistically modeling the
transform coefficients. It also presents hybrid methods that incorporates spatial filter in transform domain.

Chapter III describes the proposed algorithm based on HWQDFB to remove AGWN with zero-mean. The HWQDFB is a translation invariant, directional and multiresolution expansion. Initially, the noisy image is decomposed into different subbands of frequency and orientation using HWQDFB. The Gaussian scale mixture (GSM) model is utilized to model the directional coefficients of the transform to recover the noise-free image using Bayes Least Square (BLS) estimator from the observation. The simple structure of the HWQBFB reduces the computational complexity. Selection of wavelet filters and diamond filters with sharp frequency selectivity and stopband attenuation in HWQDFB is also discussed. The denoising algorithm with various thresholding strategies is compared with other techniques in terms of PSNR and visual quality by the quantitative measures like SSIM and FOM.

Chapter IV describes a proposal to remove AWGN with zero-mean by applying bilateral filter in SPNSDFB transform domain to improve the visual quality at high noise densities. The SPNSDFB transform decomposes the noisy image into approximation subbands and detail subbands of different frequencies and orientations at each scale. Then, the nonlinear bilateral filter which does spatial averaging without smoothing edges is applied on detail subbands to remove noise. Its denoising performance is evaluated and compared with other techniques in terms of PSNR and visual interpretation by SSIM and FOM for the test images like Barbara, Lena, pepper, circuit and cameraman.

Chapter V concludes the thesis by presenting an overview of all the proposed denoising methods and future work.