1.1 INTRODUCTION

In this digital era, images are captured by a range of devices, such as still and video cameras, X-ray devices, microscopes, radar, ultrasound, etc., and are produced as digital images for various purposes, like medical, industrial, military, traffic, security, scientific, and entertainment. The ultimate goal of digital image processing is to extract useful information from the images. Image processing can be broadly categorized into two levels namely preprocessing and postprocessing. Preprocessing includes contrast enhancement, noise reduction, and image sharpening. Postprocessing includes segmentation, description, object recognition, and image analysis (Gonzalez & Woods 2002). Even though the postprocessing techniques look appealing in the user end, preprocessing is the backbone for all the postprocessing methods in order to mitigate fault diagnosis and achieve better performance.

1.2 IMAGE PREPROCESSING

Preprocessing is a set of operations with images at the lowest level of abstraction, for which the input and output are intensity images. Preprocessing improves the visual quality of the image by suppressing undesired distortions or by enhancing the important image features to facilitate further processing.
To correct the degradation in the image using preprocessing techniques, the nature of prior information such as nature of the degradation, properties of the image acquisition device, and various constraints applied for image acquisition are considered. The nature of noise (spectral characteristics) and knowledge about the objects that are searched for in the images are usually known as prior information. If this information is not known, it can be estimated during processing (Gonzalez & Woods 2002).

1.3 IMAGE DENOISING

In general, an image is contaminated by undesired noise during acquisition and transmission. A common cause of image degradation is the unwanted non-linearity in the sensor and display system. It can be significantly reduced by postprocessing correction of sensor signals and preprocessing correction of display system (Jain 1989). The noise present in the images may appear as additive or multiplicative components which have been modeled in different ways in the literature (Gonzalez & Woods 2002) (Jain 1989) such as Gaussian noise, speckle noise, etc. Due to the randomness of the occurrence of noisy pixels, their distributions are modeled using probabilistic methods (Vaseghi 2008) (Chan & Shen 2005). In most of the real-time applications such as medical imaging, satellite image data analysis, remote sensing applications, etc., the noisy components need to be removed in order to ensure faithful information retrieval from the images. Hence, preprocessing is an essential component in any information analysis and retrieval system.

Denoising is one of the preprocessing techniques that attracted researchers over a few decades. Yet, till date, significant part of image processing research is dedicated to image denoising and enhancement. Denoising plays an imperative role in image preprocessing as it handles the random variation of brightness or colour information in images produced by
the sensor and circuitry of a scanner or digital camera (Zhang et al 2009). Noise removal may be regarded as the process of estimating the content of interest \( f(.) \) from the noisy observation \( g(.) \) of the image. Noises having Gaussian-like distribution with zero mean property are very often encountered in acquired image data. Various methods of image denoising are described in the following section.

1.4 METHODS OF DENOISING

If \( f(x,y) \) be the uncorrupted image of size \( N \times N \), \( (x,y) \) be the spatial coordinates, and \( n(x,y) \) be the noise function, then the noisy image observation \( g(x,y) \) with additive noise and multiplicative noise, are given by Equation (1.1) and Equation (1.2) respectively.

\[
g(x,y) = f(x,y) + n(x,y) \quad \forall x, y \leq N \tag{1.1}
g(x,y) = f(x,y) \times n(x,y) \quad \forall x, y \leq N \tag{1.2}
\]

where

\[ f(x,y) \quad \text{– Uncorrupted image} \]
\[ g(x,y) \quad \text{– Noisy image} \]
\[ n(x,y) \quad \text{– Noise function} \]
\[ (x,y) \quad \text{– Spatial coordinates} \]
\[ N \quad \text{– Number of rows and columns in the image} \]

The process of denoising is regarded as the estimation of information from the noisy observation and may be described as in Equation (1.3).

\[
\hat{f}(x, y) = g(x, y) - \hat{n}(x, y) \quad \forall x, y \leq N \tag{1.3}
\]
where

\[
\hat{n}(x, y) \quad - \quad \text{Estimated noise}
\]

\[
\hat{f}(x, y) \quad - \quad \text{Estimate of uncorrupted image}
\]

The state-of-the-art image denoising methods can be categorized as follows:

1.4.1 Spatial Filtering Techniques

Spatial filtering is the method of choice in situations when only additive noise is present. This category consists of mean filter and the order statistic filters such as median filter, maximum and minimum filter, midpoint, and alpha trimmed median filter. Geometric and arithmetic mean filters are well suited for random noise like Gaussian or uniform noise. The contra-harmonic filter is well suited for impulse noise, but it requires the prior knowledge about the noise (light or dark). As found in the literature (Jain 1989) (Gonzalez & Woods 2002), median filter can perform well in removing substitutive noise such as impulse noise while the number of passes of the median filter has to be kept as low as possible, since larger number of passes may result in blurred images. The process of spatial filtering consists of moving the filter mask (Figure 1.1) from point to point in an image. At each point (x,y), the response of filter at that point is calculated. The mask can be at any size of interest such as 3×3, 5×5, 7×7, and etc. Also, it is noted that size of the filter mask (Loupas et al 1989) affects the performance of the filter.

Another class of filters which fall under spatial filters is known as adaptive filter. The behaviour of the adaptive filter changes and it depends on the statistical characteristics of the image inside the filter region, defined by rectangular window (kernel) of size \(m \times n\). These filters can offer superior denoising performance (Chan & Shen 2005) with the cost of increased computational complexity.
Adaptive median filter is the prime variant of adaptive filter. Size of the filter mask is altered according to the parameters calculated in the mask area considered originally. It performs better for the impulse noise with low spatial density and seeks to preserve details while smoothing non-impulse noise too. Researchers have shown interest to evolve adaptive iterative median filter and decision-based median filters that outperform even for high-density noises (Leavline & Singh 2013).

1.4.2 Frequency Domain Filtering

Frequency domain filtering is originally used for periodic noise reduction and removal. This category of filters includes bandstop filter, bandpass filter, and Notch (reject/pass) filters. The appropriate filter can be chosen with the prior knowledge of noise distribution. Fourier domain filtering techniques such as Wiener’s filter (Kazubek 2003), inverse filter (Jain 1989), and least square filter (Helstrom 1967) are found in image processing literature. A simple homomorphic filtering (Gonzalez & Woods 2002, Jain 1989) method is proposed to remove multiplicative noise such as speckle noise. Fourier transform has been found to be an important tool for image processing and analysis. The key merit of Fourier domain analysis is that, it can explore the geometric characteristics of a spatial domain image (Boggess & Narcowich 2009). It has been used for the removal of additive noise from the images. Unlike Fourier transform, wavelet transform shows localization in both time and frequency (Rao & Bopardikar 1997), and hence,
it has proved itself to be an efficient tool for a number of image processing applications including noise removal. Fourier transform-based methods are less useful, because they can capture only global features and they cannot work on non-stationary signals. But in the real scenario, the noise distributions are random in nature, the images are only piecewise smooth, and Fourier transform cannot perform well for the stochastic noise. But, wavelets can do this job in a better way (Donoho & Johnstone 1995). Hence wavelet-based noise removal has attracted much attention of the researchers for several years. A detailed study on wavelet-based denoising techniques is presented in Chapter 3.

1.5 PROBLEM FORMULATION

Wavelet transform is effectively used in several image processing applications including denoising. Yet, the denoised images that result from wavelet-based denoising suffer with blocking artefacts. This is due to the fact that the separable wavelet basis functions are non-local, signal independent, and fixed shape and they are not capable of capturing and preserving significant image features such as edges and fine details (Do & Vetterli 2005). Hence, multiscale and multiresolution schemes that are highly directional with flexible basis functions and that obey orthogonal, critical sampling properties need to be used to improve the denoising performance. Several multiscale representations such as Gabor wavelet (Nestares et al 1998), ridgelet (Do & Vetterli 2003), curvelet (Starck et al 2002), steerable pyramid (Rabbani 2009), shearlet (Easley et al 2008), contourlet (Do & Vetterli 2005), etc. have been proposed in the literature. The contourlet transform, alternatively known as pyramidal directional filter banks (PDFB) was found suitable and used in various image processing applications in spite of its redundancy and computational complexity. A modification to the PDFB, namely the multiscale directional filter bank (MDFB), is designed to have fine
high-frequency decomposition. The MDFB is redundant as it introduces an additional decomposition in the high-frequency band and thereby improves the radial frequency resolution at a cost of one set of extra-scale and directional decompositions on the full image size. This results in increased number of computations. In addition, MDFB has a higher redundancy than contourlet transforms.

A fast and reduced redundancy structure for this MDFB (FMDFB) was proposed by Cheng et al (2007a). The idea behind achieving reduced redundancy and computational complexity is that, directional decomposition on the first two scales is performed prior to the scale decomposition. This permits sharing of directional decomposition among the two scales, thus reducing the computational complexity significantly. The resultant scheme has the same redundancy as a contourlet transform and has a 33% reduction in the number of computations as compared to MDFB. Further, FMDFB exhibits a perfect reconstruction. The total number of directional subband coefficients is the same as the size of the original image because of the critically sampled DFB, and hence, no extra computations are introduced by the scale decomposition.

Because of these advantages, a novel image denoising scheme using FMDFB is proposed, which has not been addressed yet. The fast and reduced redundancy structure namely FMDFB is chosen as an image transformation scheme to aid multiscale representation of images for denoising. A mathematical model of the FMDFB subband coefficients is derived based on the chi-square goodness-of-fit (GoF) test. The statistical nature of the FMDFB subbands is also analysed to observe how the FMDFB subbands are different from wavelet subbands. Furthermore, an experimental study is performed on various wavelet-based thresholding methods for image denoising. Initially, the simple global threshold function namely VisuShrink
is applied on FMDFB coefficients for denoising images corrupted by additive white Gaussian noise. Then, an adaptive threshold technique is adopted to enhance the denoising performance. In order to calculate the threshold value, the noisy subband selection algorithm (NSSA) is proposed to identify the highly noisy subband, based on which the threshold is estimated. This algorithm is tested on natural images and real gallstone ultrasound images. Further, a new subband adaptive threshold (SAT) estimation method is proposed for thresholding FMDFB coefficients. The denoising performance of the proposed denoising algorithms is studied on standard grayscale and colour images.

1.6 ORGANIZATION OF THE THESIS

This thesis is organized as follows. Chapter 2 comprehends the related literature. Chapter 3 details the methodologies used in this thesis. In Chapter 4, the image denoising scheme using wavelet transform is described with the experimental results of image denoising with various wavelet shrinkage methods. Chapter 5 analyses the suitability of multiscale transforms for image denoising. In Chapter 6, the statistical nature of the FMDFB subbands is analysed and a mathematical model of FMDFB coefficients is derived. Further, the design of component filters of the FMDFB analysis and synthesis filter structure is addressed. In Chapter 7, the detailed description of the proposed image denoising method using FMDFB is presented. Also, the methods of Gaussian noise removal and speckle noise removal using the proposed algorithms are discussed with experimental results and the conclusion is drawn in Chapter 8. The statistical measures used to analyse the FMDFB subbands and the details of various test images used to evaluate the proposed algorithms are presented in Annexure 1 and Annexure 2, respectively.