CHAPTER 2

IMAGE DENOISING

In this chapter, different type of noises and various denoising techniques such as spatial domain filtering, transform domain filtering, directional lifting technique, adaptive directional lifting technique and proposed hybrid directional lifting technique are discussed.

2.1 INTRODUCTION

Image denoising is defined by Donoho (1995) and David et al (2006) as follows: It is procedure aimed at removing noise from images while retaining as many important signal features as possible. Many images suffer from the following degradations: poor contrast due to inadequate illumination or finite sensitivity of the imaging device, electronic sensor noise or atmospheric disturbances.

Noise present in a digital image has low 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 images have additive random noise, which can be modeled by Gaussian type noise and also by speckle noise.

This chapter discusses different noises commonly present in an image and the various denoising techniques. Amandeep Kaur et al (2011)
discussed the images are corrupted with noise modeled either as Gaussian or salt and pepper distribution of noises. Another one type of noise is a speckle noise, which is multiplicative in nature.

An additive noise is defined as in Equation (2.1) as follows

\[ N(x, y) = I(x, y) + \eta(x, y) \]  

(2.1)

and the Equation (2.2) defines the multiplicative noise.

\[ N(x, y) = I(x, y) \times \eta(x, y) \]  

(2.2)

where \( I(x, y) \) is the original signal, \( \eta(x, y) \) denotes the noise introduced into the signal to produce the corrupted image, \( N(x, y) \) is the noisy image and \( (x, y) \) represents the pixel location. In electronic image processing, at each step in the process there are fluctuations caused by natural phenomena, adding a random value to the exact brightness value for a given pixel. The following sections 2.1.1 to 2.1.3 will discuss on the various additive and multiplicative noises present in an image

2.1.1 Salt and Pepper Noise

Salt and pepper noise, often called as intensity spikes, are an impulse type of noise. This type of noise is generally caused due to errors in data transmission. It has only two possible values, either 0 or 1 i.e., minimum or maximum. The probability of each value is less than 0.1. The degraded pixels can take a minimum or maximum value, giving the image a “salt and pepper” appearance. The unaffected pixels are not changed. For an 8-bit image, the minimum value or pepper noise value is 0 and maximum or salt noise value is 255. The salt and pepper noise is caused by malfunctioning of pixel elements in the camera sensors, faulty memory locations or timing
errors in the digitization process. Salt and pepper noise with a variance of 0.02 is shown in Figure 2.1.

![Figure 2.1 Salt and pepper noise](image)

Salt and pepper noise can be eliminated in large part by using dark frame subtraction and by interpolating around dark/bright pixels. The following section 2.1.2 discusses on Gaussian noise which is evenly distributed over the frequency domain.

### 2.1.2 Gaussian Noise

In Gaussian noise model, each pixel in the image is the sum of the true pixel value and a random Gaussian distributed noise value. This model has a Gaussian distribution function defined as in Equation (2.3), which has a bell shaped probability distribution function given by

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$  \hspace{1cm} (2.3)

where $x$ represents the gray level of the pixels, $\mu$ is the mean or average value of the function, and $\sigma$ is the standard deviation of the noise. Graphical
representation of Gaussian noise model is shown in Figure 2.2. When introduced into an image, Gaussian noise with zero mean and variance as 0.02 would look as in Figure 2.3.

![Gaussian distribution](image1.png)

**Figure 2.2 Gaussian distribution**

![Gaussian noise image](image2.png)

**Figure 2.3 Gaussian noise image**

The following section 2.1.3 describes speckle noise which increases the mean gray level of a local area in an image.
2.1.3 Speckle Noise

Speckle noise, one of the multiplicative noises, is an unwanted effect caused by coherent restoration of the image. An image with speckle noise is considered as a poor quality image. This type of image can lead to inefficient interpretation of data during processing.

Generally the laser, acoustics and synthetic aperture radar imagery are caused by speckle noise. The origin of this noise is attributed to random interference between the coherent returns. Fully developed speckle noise is multiplicative in nature. This model has a gamma distribution function defined in Equation (2.4) and is given by

\[
f(x) = \frac{x^{\alpha-1} e^{-\frac{x}{a}}}{(\alpha - 1)! a^\alpha}
\]  

(2.4)

where \( x \) represents the gray level of the pixels and variance is \( a^2 \alpha \). Graphical representation of speckle noise model (gamma distribution) is shown in Figure 2.4. On an image, speckle noise with variance 0.05 as shown in Figure 2.5.

![Figure 2.4 Gamma distribution](image)

Figure 2.4 Gamma distribution
Thus, when an image is affected by speckle noise, image recognition and interpretation becomes difficult. The following section 2.2 discusses the various denoising techniques to remove the above mentioned noises for retaining the original information from the images.

2.2 IMAGE DENOISING TECHNIQUES

Image filtering can be adopted as a technique to perform denoising on images. This section discusses spatial, transform and wavelet image denoising techniques to retain the original information. Motwani et al (2004) discussed a filter is defined by a kernel, which is a small array applied to each pixel and its neighbours within an image. Different algorithms are subjected to the target image depending on the type of the noise that the image is suffering from. Imola and Chandrika (2001) discussed it can be done locally, as in the Gaussian smoothing model or in anisotropic filtering or in the frequency domain, such as wiener filters.
Generally image denoising is classified into two categories:

- Spatial domain filtering
- Transform domain filtering

2.2.1 Spatial Domain Filtering

Spatial domain filters are employed to remove the noise from the digital images. Spatial domain filtering is further classified into linear filters and non-linear filters.

2.2.1.1 Linear filters

One of the linear filters is a mean filter that is optimal for Gaussian noise in the sense of mean square error. Linear filters have a tendency to blur sharp edges, destroy lines and other fine details of image. Linear filter includes mean filter and wiener filter.

- Mean filter

Jappreet et al (2012) discussed mean filter reduces the intensity variations between the adjacent pixels. Mean filter is a simple sliding window spatial filter that replaces the centre value of the window with the average value of all its neighbouring pixel values including itself. It is implemented with the convolution mask, which provides weighted sum of values of a pixel and its neighbours. The mask or kernel is a square matrix, 3×3 kernel being the commonly used matrix. If the coefficient of the mask sum is one, then the average brightness of the image is not changed. If it is zero, average brightness is lost, and it returns a dark image.
**Wiener filter**

Wiener filtering requires the information about the spectra of noise and original signal. This works well only if the underlying signal is smooth. Jingdong Chen (2006) defined the denoised output of wiener filter, which is obtained by Equation (2.5) as follows

\[
D(i, j) = \frac{H(i, j)^*}{H(i, j)^2 + \left[\frac{S_n(i, j)}{S_f(i, j)}\right]} G(i, j) \tag{2.5}
\]

where \(H(i, j)\) is the degradation function, \(H(i, j)^*\) is its conjugate complex, \(G(i, j)\) is the degraded image, functions \(S_f(i, j)\) and \(S_n(i, j)\) are power spectra of original image and the noise and \(D(i, j)\) is the denoised image.

### 2.2.1.2 Non-linear filters

The noise removal of non-linear filter attempts to eliminate noise without explicitly identifying it. Spatial filters employ a low pass filtering with the assumption that noise occupies the higher region of the frequency spectrum. Generally spatial filters remove the noise to some reasonable extent but at the cost of blurring the images which in turn makes the edges invisible. Median filter is the non-linear filter that follows the moving window principle. It uses square window kernels like 3×3, 5×5 or 7×7 kernel window. The median of window is calculated and the center pixel value of the window is replaced with that value.

### 2.2.2 Transform Domain Filtering

Transform domain filtering mainly includes wavelet based filtering techniques.
2.2.2.1 Wavelet transform

Mallat and Hwang (1992) reported wavelet transform is a mathematical function or tool that analyzes the data according to requirement. Noise reduction using wavelets is performed by first decomposing the noisy image into wavelet coefficients. The proper selection of thresholding value modifies the wavelet coefficients based on the thresholding function. Finally, the denoised image is obtained by applying the inverse wavelet transform on modified coefficients.

2.3 DIRECTIONAL LIFTING TECHNIQUE

The two dimensional wavelet transform has a legacy from two dimensional discrete cosine transform for that it was implemented by one dimensional filtering in horizontal and vertical directions. The drawback of two dimensional wavelet transform is that they are ill suited to approximate image features with arbitrary orientation that are neither vertical nor horizontal. In these cases, the wavelet transform, results in large-magnitude and high-frequency coefficients.

Piella et al (2002) discussed the basic idea of the directional transform is to reorganize pixels along a certain direction for every one directional transform. The lifting stage consists of three steps: split, predict, and update as shown in Figure 2.6. The input signal \( x \) is first split into its even and odd polyphase components, respectively called the approximation signal \( x_o \) and the detail signal \( x_e \). These are obtained using Equation (2.6) as follows

\[
\begin{align*}
  x_e(i, j) &= x(2i, j) \\
  x_o(i, j) &= x(2i + 1, j)
\end{align*}
\]  

(2.6)
Figure 2.6 General lifting technique

Second, the even numbered samples are used to predict the odd numbered ones. This prediction is the high-pass coefficients, $h(i, j)$ is defined in Equation (2.7) as follows

$$h(i, j) = x_o(i, j) - p(i, j)$$  \hspace{1cm} (2.7)

where $p(i, j)$ is the predicting value.

Then, the high-pass coefficients are updated to the odd numbered signals to generate the low-pass coefficients $l(i, j)$ obtained using Equation (2.8).

$$l(i, j) = x_e(i, j) + u(i, j)$$  \hspace{1cm} (2.8)

The new obtained signal $x'_e = x_e - P(x_o)$ is then smaller than $x_e$. Finally, the even samples of $x$ are transformed into a low-pass filtered and
subsampled version $x'_o$ of the original signal $x$. This is performed by using an updating operator $U$ which is a linear combination of the elements of $x'_e$. The approximation signal $x'_o = x_o + U(x'_e)$ is then obtained. The principal disadvantage of the LS described above, is that the linear filtering structure is fixed and thus, cannot match well the sharp transitions in the signal.

2.4 ADAPTIVE DIRECTIONAL LIFTING TECHNIQUE

ADL assimilates orientation transform into the lifting scheme and incorporates local spatial direction prediction into each lifting stage was discussed by Wang et al (2011). Instead of applying horizontal and vertical lifting steps, it performs the lifting in local window in the direction of the highest pixel correlation.
Every ADL lifting stage, the prediction step can be done in the direction of the pixel correlation rather than fixed in the horizontal or vertical direction. Although ADL predict and update operations are based on fractional pixels, its transform can assure perfect restoration, without imposing any restriction on the interpolation method. However, there are still several open issues to be investigated in the ADL lifting schemes. It may blur the orientation property existing in raw images; image blocks with different directions are continuously processed and may cause boundary effects.

Two dimensional conventional lifting techniques apply horizontal and vertical lifting steps alternately. However, most of the natural images especially satellite images usually contain great amount of directional attributes that can be considered as linear edges in a local window. In order to further remove the spatial redundancy of these directional attributes, researchers developed the adaptive directional lifting technique. In ADL, directional prediction is incorporated into the lifting scheme to give an efficient representation. In the prediction step, the pixels of the odd numbered subset are predicted from the neighbouring even numbered subsets with an optimal direction. Figure 2.7 shows the directions used in directional lifting transform. In principle, the prediction angle $\theta$, which demonstrates local direction information; however, in practice, nine different directions of correlation are predefined as $-4, -3, -2, -1, 0, +1, +2, +3, +4$. Suppose that there is strong texture feature in the direct towards angle $\theta$, the prediction in ADL would come from the quarter pixels of the even indexed samples, and the direction should be $dir = 3$. Therefore the predict $P$ and update $U$ can be represented in Equation (2.9) as

$$
\begin{align*}
P(x_r, dir) &= \sum_i P_x \ast \left[ m + i, n + \text{sign}(i - 1) \times dir \right] \\
U(h, dir) &= \sum_i U_h \left[ m + i, n + \text{sign}(i - 1) \times dir \right]
\end{align*}
$$

(2.9)
where \( x_e^{*}(i, j) \) is the interpolated version even numbered subsets and \( h(i, j) \) is the interpolated version of prediction residual.

### 2.5 PROPOSED SYSTEM FOR IMAGE DENOISING

The proposed work uses hybrid directional lifting technique to overcome the difficulties of ADL. Figure 2.8 shows a schematic of various steps involved in removing noise from a satellite image.

First, the input image \( I(i, j) \), which is any noisy image like salt and pepper or Gaussian noisy image is obtained. Then, the standard deviation of the image is calculated. Selection of threshold is very important to denoise an image. After determining the threshold value, it is subjected to HDL to remove the noise from the image.
The hybrid directional lifting technique varies from traditional technique in pixel classification and orientation estimation. HDL involves three important steps for satellite image denoising such as pixel classification, orientation estimation and hybrid transform as shown in Figure 2.9. Image pixel classification results into the pixels belonging to two categories namely texture regions and smooth regions. Orientation estimation based on pixel classification and correlation provides more accurate directional estimation. Hybrid transform strategy performs the transform on pixel level instead of block based transform to avoid artifacts in the smooth regions.

Figure 2.9 Hybrid directional lifting technique
2.6.1 Image Pixel Classification

Generally the image containing noise has two regions: smooth region and texture region. The texture and smooth regions are set by the threshold and flag values. A $\text{flag}_{(i,j)}$ value of 1 indicates a texture region and that of 0 indicates a smooth region. Thus a $\text{flag}_{(i,j)}$ represents the local activity of each pixel in the image. In HDL, two classification steps are required to complete the pixel classification. First, the image is divided into sub-blocks. The size of each sub-block is $25 \times 25$ and these sub-blocks are classified into ‘Region of Interest’ (ROI) and ‘Region of Non-Interest’ (RONI).

ROI comes under the texture region where the direction estimation is performed and RONI belongs to the smooth region where no orientation information exists. Second, the pixel classification procedure is performed in each pixel of the ROI instead of sub-blocks. A pixel value of any image component should be lying in the interval of two thresholds (lower and upper thresholds). The following procedure classifies an image into texture and smooth regions.

Let $I$ be a matrix that represents the noisy image. Hence, $I_{(i,j)}$ represents the $(i,j)^{th}$ pixel of the image $I$. The set of all pixels of the image $I$ is defined as in Equation (2.10).

$$S := \{(x, y) : 1 \leq x \leq m_{\text{row}}, 1 \leq y \leq m_{\text{col}}\} \quad (2.10)$$

where $m_{\text{row}}$ and $m_{\text{col}}$ represent the number of rows and number of columns of the image $I$ and $x$, $y$ denote the pixel in an image $I$.

Let $N$ represents the cardinality of $S$, i.e., the number of pixels. For each pixel $(i, j), \sigma^2_{I(i,j)}$, the variance of the local window of size $3 \times 3$ centered
at the pixel is calculated as in Equation (2.11). A $3 \times 3$ window is used for identifying the noise pixels in the image to slide over the image starting from the first pixel to the last was discussed by Wang et al. (2011). The corrupted pixel is easily found by using a $3 \times 3$ window to slide over the image. This can also be experimented using $4 \times 4$, $8 \times 8$, etc.,

$$\sigma^2 l(i,j) = \frac{1}{9} \sum_{x=i-1}^{i+1} \sum_{y=j-1}^{j+1} (l(x,y) - \mu_{l(i,j)})^2$$  \hspace{1cm} (2.11)

where $\mu_{l(i,j)}$ is the mean value of the local window centered at the pixel, and it is defined as Equation (2.12) as follows

$$\mu_{l(i,j)} = \frac{1}{9} \sum_{x=i-1}^{i+1} \sum_{y=j-1}^{j+1} l(x,y)$$  \hspace{1cm} (2.12)

The variance of the noisy image is calculated as Equation (2.13)

$$\sigma^2 I = \frac{1}{N} \sum_{(x,y) \in S} (I(x,y) - \mu_I)^2$$  \hspace{1cm} (2.13)

where $\mu_I$ is the mean value of the noisy image, which is defined as in Equation (2.14)

$$\mu_I = \frac{1}{N} \sum_{(x,y) \in S} I(x,y)$$  \hspace{1cm} (2.14)

The smooth and the texture regions are now defined as follows. The smooth region is defined as in Equation (2.15)
\[ A = \left\{ (i, j) \in S : \frac{\sigma^2 I(i,j)}{\sigma^2 I} \leq T \right\} \] (2.15)

where threshold \( T \) (ranging from 0.1 – 0.6) is assigned from trial experiments with various values and the texture region is defined as in Equation (2.16)

\[ B = \left\{ (i, j) \in S : (i, j) \notin A \right\} \] (2.16)

The notation \( \sigma^2 I(i,j) \) is used to separate the noisy image into texture and smooth regions based on the threshold \( T \).

2.6.2 Direction Estimation

The accuracy of direction estimation is the key to obtain good performance. First the gradient factors \( D_x \) and \( D_y \) are assigned.

\[
D_x = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \quad \quad D_y = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}
\]

For each \((i, j)\) pixel of the image \( I \), the convolution of the image along with the gradient factor is computed using Equation (2.17) and Equation (2.18) in order to estimate the orientation.

\[
I^x_{\text{new}(i,j)} = \sum_{k=-1}^{1} \sum_{l=-1}^{1} D_x(k,l) I(i-k, j-l)
\] (2.17)

\[
I^y_{\text{new}(i,j)} = \sum_{k=-1}^{1} \sum_{l=-1}^{1} D_y(k,l) I(i-k, j-l)
\] (2.18)
where $I'_{\text{new}(i,j)}$ and $I''_{\text{new}(i,j)}$ represent the new convolution matrices. Finally, the direction information for each pixel is calculated by the following Equation (2.19).

$$
\text{dir}(i, j) = \tan^{-1}\left( \frac{I''_{\text{new}(i,j)}}{I'_{\text{new}(i,j)}} \right)
$$

(2.19)

where $\text{dir}(i, j)$ is the directional information of each pixel and $I'_{\text{new}(i,j)}$, $I''_{\text{new}(i,j)}$ are obtained by convolution. This work concerns with the directions from $45^\circ - 135^\circ$ for image denoising.

The PSNR values obtained for different directions like $45^\circ$, $90^\circ$, and $135^\circ$ as shown in figure 2.10.

![Figure 2.10 PSNR value of different directions](image)

2.6.3 Direction Modification

In the blocks of ROI, the image pixel can be further classified into pixels belonging to edges and pixels belonging to smooth regions beside the edges, for modifying the direction of each pixel. Equation (2.20) shows the direction modification of each pixel in an image.

$$
\text{dir}_{\text{new}}(i, j) = \text{dir}(i, j) \times \text{flag}(i, j)
$$

(2.20)
However, it is very difficult to perform directional transform to the pixels in the smooth regions.

### 2.6.4 Hybrid Transform

The new HDL uses the pixel classified image, $X_{(i,j)}$. It can be computed by a well established statistical classification technique called Bayesian classifier. Using this, Equation (2.21) defines a pixel $x$ is considered as a ROI pixel if

$$\frac{p(x/ROI)}{p(x/RONI)} \geq T$$

(2.21)

where $p(x/ROI)$ and $p(x/RONI)$ are the class conditional probability distribution functions and $T$ is a threshold value. The theoretical value of $T$ that minimizes the classification depends on the priori probabilities of ROI and RONI classifications; however, $T$ is often determined empirically. Then the minimum direction estimation $dir_{\text{min}(i,j)}$ is obtained by using the directional information of the image, $dir_{\text{new}(i,j)}$ and $X_{(i,j)}$ as defined in Equation (2.22)

$$dir_{\text{min}(i,j)} = I(i,j) - \left[X(i,j) - dir_{\text{new}(i,j)}\right]$$

(2.22)

where $I_{(i,j)}$ is the noisy image.

The main aim of hybrid transform is to reduce the noise in the smooth region also. The denoising operation performed in the smooth region has assigned the original pixel value to the smooth region of the image as defined in Equation (2.23)

$$flag_{(i,j)} = I_{(i,j)}$$

(2.23)
Then the estimated minimum direction, \( \text{dir}_{\min(i, j)} \) can be added with the smooth region of the image to obtain the hybrid transform, \( H(i, j) \) obtained using Equation (2.24) as follows

\[
H(i, j) = \text{dir}_{\min(i, j)} + \text{flag}(i, j)
\]  

(2.24)

The hybrid value computed from the above equation can be subtracted from \( R(i, j) \), represents independent and identically distributed Gaussian random variables having mean 0 and variance 1. Hence, the denoised image \( D(i, j) \) can be obtained by Equation (2.25)

\[
D(i, j) = H(i, j) - R(i, j)
\]  

(2.25)

### 2.6.5 Performance Evaluation

The quantitative performance of the denoised image as well as visual quality of the images is evaluated by peak signal to noise ratio. PSNR is defined as the ratio of the variance of the noise-free signal to the mean-squared error between the noise-free signal and the denoising signal. PSNR is computed using Equation (2.26) as follows

\[
\text{PSNR} = 10 \log_{10} \frac{\sum_{i=1}^{\text{row}} \sum_{j=1}^{\text{col}} 255^2}{\sum_{i=1}^{\text{row}} \sum_{j=1}^{\text{col}} [I(i, j) - D(i, j)]^2}
\]  

(2.26)

where \( I(i, j) \) be the noisy image and \( D(i, j) \) be the denoised image.

### 2.7 EXPERIMENTAL RESULTS AND DISCUSSIONS

This work deals with the Land Remote-Sensing Satellite (LANDSAT) images taken from different time frames of Kochi, Kanyakumari, Kolkata, Visakhapatnam and Sydney regions.
Figure 2.11 to Figure 2.15 show the experimental results of (a) noisy image, (b) direction estimated image and (c) proposed HDL denoised images of Kochi, Kanyakumari, Kolkata, Visakhapatnam and Sydney regions.

The performance of the HDL technique is compared with the conventional directional lifting and adaptive directional lifting technique for evaluating the performance by PSNR. The comparison results are shown in Table 2.1.

**Table 2.1 Performance comparison between conventional directional lifting, adaptive directional lifting and hybrid directional lifting**

<table>
<thead>
<tr>
<th>Sl. No</th>
<th>Region Title</th>
<th>Denoising Techniques</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Directional Lifting Technique - PSNR (dB)</td>
</tr>
<tr>
<td>1</td>
<td>Kochi</td>
<td>27.56</td>
</tr>
<tr>
<td>2</td>
<td>Kanyakumari</td>
<td>27.69</td>
</tr>
<tr>
<td>3</td>
<td>Kolkata</td>
<td>27.47</td>
</tr>
<tr>
<td>4</td>
<td>Visakhapatnam</td>
<td>27.55</td>
</tr>
<tr>
<td>5</td>
<td>Sydney</td>
<td>27.75</td>
</tr>
</tbody>
</table>
Figure 2.11 Experimental results of (a) noisy, (b) direction estimated and (c) HDL denoised images of Kochi region
Figure 2.12 Experimental results of (a) noisy, (b) direction estimated and (c) HDL denoised images of Kanyakumari region
Figure 2.13 Experimental results of (a) noisy, (b) direction estimated and (c) HDL denoised images of Kolkata region
Figure 2.14 Experimental results of (a) noisy, (b) direction estimated and (c) HDL denoised images of Visakhapatnam region
Figure 2.15 Experimental results of (a) noisy, (b) direction estimated and (c) HDL denoised images of Sydney region
Figure 2.16 Graphical representation of performance of directional lifting, adaptive directional lifting and hybrid directional lifting techniques

Figure 2.16 shows the graphical representation of the quantitative performance measure of conventional directional lifting, adaptive directional lifting and HDL technique.

In order to evaluate the quantitative performance of the HDL technique, the well known Barbara image is taken into account to determine the performance of the proposed technique. Table 2.2 shows the performance of Barbara denoised image. While performing the HDL denoising technique the PSNR value of the Barbara image is improved from 28.34dB to 29.17dB. Figure 2.17 shows (a) noisy image, (b) direction estimated image and (c) proposed HDL denoised Barbara image.
Figure 2.17 Experimental results of (a) noisy, (b) direction estimated and (c) HDL denoised images of Barbara
Table 2.2 Performance comparison of Barbara image

<table>
<thead>
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<th>Image Title</th>
<th>Denoising Techniques</th>
<th></th>
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<tbody>
<tr>
<td></td>
<td>Directional Lifting Technique- PSNR (dB)</td>
<td>Adaptive Directional Lifting - PSNR (dB)</td>
</tr>
<tr>
<td>Barbara</td>
<td>27.55</td>
<td>28.34</td>
</tr>
</tbody>
</table>

In the proposed HDL technique, pixel classification and inter-scale correlation are taken into account to strengthen the robustness of the orientation estimation algorithm. Moreover, the transform is performed at pixel level by only carrying out directional transform on pixels belonging to texture regions. The proposed technique outperforms the traditional wavelet and lifting scheme in both peak signal to noise ratio and visual quality, especially for images with rich texture features such as remote sensing images. Comparison results explicitly show the efficiency of HDL technique over conventional directional lifting technique in image denoising. Thus image denoising is the primary step for image analysis.

2.8 SUMMARY

In this chapter, HDL technique is proposed for satellite image denoising. In HDL, the direction information is incorporated into texture region and smooth region of the image to remove the noise from an image. The pixel classification, orientation estimation and hybrid transform are taken into account to strengthen the technique to retain the useful information in denoising. The comparative results are made to prove the efficiency of HDL when compared to the conventional lifting technique. This work can be utilized in image enhancement to improve the visual quality of the image. The Chapter 3 provides various resolution enhancement techniques to improve the visual quality.