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ORIGINAL PAPER

Impact of applying pre-processing techniques for improving classification accuracy

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Abstract Image denoising is a procedure aimed at removing noise from images while retaining as many important signal features as possible. Many images suffer from poor contrast due to inadequate illumination or finite sensitivity of the imaging device, electronic sensor noise or atmospheric disturbances. This paper proposes a hybrid directional lifting technique for image denoising to retain the original information present in the images. The primary objective of this paper is to show the impact of applying preprocessing techniques for improving classification accuracy. In order to classify the image accurately, effective preservation of edges and contour details of an image is essential. The discrete wavelet transform-based interpolation technique is developed for resolution enhancement. The image is then classified using support vector machine classifier, which is well suitable for image classification. The efficiency of the classifier is analyzed based on receiver operating characteristic (ROC) curves. The quantitative performance measures peak signal to noise ratio and ROC analysis show the significance of the proposed techniques.

Keywords Accuracy · Classification · Denoising · Enhancement · PSNR · ROC

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1 Introduction

Synthetic aperture radar (SAR) imaging is widely used for acquiring high-resolution images of the earth. These images are used in the fields of remote sensing, oceanography, geology, ecology and interferometry. Most of the images are greatly affected by unwarranted noise likely to be contributed by capturing devices, transmission media, discrete sources of radiation and other environmental aspects. Moreover, noise can be introduced by transmission errors and compression.

The removal of noise from these images is a challenging problem for researchers because this introduces artifacts and causes blurring of the images. In order to remove the presence of noise in the images, many complex denoising techniques have been proposed. In spite of the complexity of the existing methods, these techniques have not yet achieved a desirable level of applicability. All show a good performance when the images are corresponding to the assumption of an algorithm but remove image fine structures. Thus, efficient denoising is the first and crucial step to be taken before the images are analyzed.

One of the important objectives of this research is to first define a mathematical and experimental methodology called hybrid directional lifting (HDL) for image denoising. The primary aim of this work is to improve the accuracy of classifying an image into area of interest like water body and non-water body regions. The improvement of classification accuracy results in better realization of edge and contour information in an image.

The image classification is broadly divided into unsupervised and supervised learning techniques. Clustering algorithms used for unsupervised classification of data vary according to the efficiency with which clustering takes place. The unsupervised clustering provides the cluster information about the area of interest in a relatively quick manner.

This lacks complete information about the region of interest (ROI) and particularly subtle variations therein. To avoid these variations, supervised classification is recommended. The mapping of classes is much more accurate in supervised classification but is heavily dependent on the input given. The classes and the learning rate are determined to optimize the classification accuracy of the images. The performance of the classification shows the requirement of denoising and resolution enhancement techniques.

2 Analysis of image denoising techniques

Noise present in a digital image has low and 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 noise. The desire is to improve the accuracy of images in order to facilitate different applications prevalent in image processing.

Some state-of-the-art image denoising techniques like BM3D, K-SVD, SKR and K-LLD have been discussed by the researchers, and it has been proved that "image denoising is not dead—yet" [1]. The sparsity and multi-resolution structure properties of wavelets give a high performance in image denoising [2]. In the past two decades, the researchers introduced various algorithms for image denoising in wavelet transform domain. The focus was shifted to the wavelet transform domain from the spatial and Fourier domain. Donoho developed a wavelet-based thresholding approach [3]. There was a renewed attention in wavelet-based denoising technique since it demonstrated a simple approach to a difficult problem. The different ways of computing the thresholding parameters of wavelet coefficients were also explained.

The significant improvements in the quality of an image could be obtained by translating invariant methods based on thresholding of an undecimated wavelet transform. Later, these methodologies were used to obtain the non-orthogonal wavelet coefficients to reduce artifacts. The lifting scheme (LS) is an alternative to wavelet transform, leading to the second generation wavelet [4]. It is very famous because it has the capacity to adjust the wavelet transform to complex geometries and offers a simple and efficient implementation of traditional, first generation wavelet transform.

In the recent years, a large amount of research has been performed on wavelet thresholding and threshold selection for denoising since wavelet provides an appropriate basis for separating noisy image from the original image. Next, data adaptive thresholding method was introduced to achieve optimum value of threshold [5]. Following the thresholding algorithm, a wavelet-domain hidden Markov model for image denoising called local contextual HMM (LCHMM) was developed [6]. A mixture field was introduced to locally follow the Gaussian mixture distributions determined by their neighborhoods. The LCHMM can exploit both the local statistics and the intrascale dependencies of wavelet coefficients at a low computational complexity.

The adaptive lifting scheme (ALS) was designed to adapt itself to data [7]. The perception behind the ALS through thresholding is that this scheme perfectly allows to preserve the original characteristics of the input signal. This offers a sparse representation, which makes the thresholding rules more effective than in the case of the traditional non-adaptive LS. However, LS is just a simplified approach to perform DWT, which does nothing to increase the direction flexibility. Therefore, researchers have also suggested to present LS with finer directionality, while retaining its structure and important features by using adaptive directional lifting (ADL) based wavelet transform.

Next, much effort has been devoted to Bayesian denoising in wavelet domain. Alin et al. [8] proposed a Bayesian-based algorithm within the framework of wavelet analysis, which reduces speckle noise in SAR images while preserving the structural features and textural information of the scene. The applications of discrete wavelet transform have been extensively studied and have offered plenty of processing algorithms and realizing structures [9]. An important step in wavelet thresholding is the selection of threshold values. An improperly selected threshold value affects not only the denoised image, but also creates visually annoying artifacts.

Adaptive directional lifting (ADL) integrates the directional transform into the structure of conventional LS and incorporates local spatial direction prediction into each lifting stage [10,11]. So far, ADL transform has achieved a very good success in image compression [12], whereas a very little interest has been given to the probable use for image denoising. Thus, this research is also giving importance to wavelet-based image denoising technique, called as HDL.

2.1 Hybrid directional lifting

The input image $I(i, j)$, which is the Gaussian noisy image with variance 0.02, is obtained. 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 Eq. (1), which has a bell-shaped probability distribution function given by

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x-\mu)^2/2\sigma^2} \tag{1}$$

where x represents the gray level of the pixels, μ is the mean or average value of the function, and σ is the standard deviation of the noise.

The standard deviation of the image is also calculated. Selection of threshold is very important to denoise an image [18]. After determining the threshold value, it is subjected to HDL to remove the noise from the image. Generally, the image containing noise has two regions: smooth region and texture region [12]. The texture and smooth regions are set by the threshold and flag values. A flag value of 1 indicates a texture region and that of 0 indicates a smooth region. Thus, a flag 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 25×25, and these sub-blocks are classified into 'region of interest' (ROI) and 'region of non-interest' (RONI) [13].

Region of interest (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 [12]. 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.

$$\begin{aligned} &V_{\text{var}}(i, j)/V_n <= T,\ I(i, j),\ \text{smooth region} \\ &V_{\text{var}}(i, j)/V_n > T,\ I(i, j),\ \text{texture region} \end{aligned} \tag{2}$$

$$\begin{aligned} &\text{flag}(i, j) = 0,\ \text{smooth region} \\ &\text{flag}(i, j) = 1,\ \text{texture region} \end{aligned} \tag{3}$$

For each pixel of $I(i, j)$, a flag value based on the threshold T (ranging from 0.1–0.6) is assigned, computed by calculating $V_{\text{var}}(i, j)$, variance of the local window centered by the pixel; the size of local window is 3×3 and V_n, variance of the noisy image. The notation $V_{\text{var}}(i, j)$ is used to separate the noisy image into texture and smooth regions based on the threshold T.

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

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

The convolution of the image along with the gradient factor is computed in order to estimate the orientation.

$$D_{\text{xnew}} = \sum_{i=1}^{\text{row}} \sum_{j=1}^{\text{col}} I(i, j) D_x \tag{4}$$

$$D_{\text{ynew}} = \sum_{i=1}^{\text{row}} \sum_{j=1}^{\text{col}} I(i, j) D_y \tag{5}$$

where row and col denote the size of an image and D_{xnew} and D_{ynew} represent the new convolution matrices. Finally, the direction information for each pixel is calculated by the following equation.

$$\text{dir}(i, j) = \tan^{-1}(D_{\text{ynew}}/D_{\text{xnew}}) \tag{6}$$

where $\text{dir}(i, j)$ is the directional information of each pixel and D_{xnew}, D_{ynew} are obtained by convolution. 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.

$$\text{dir}_{\text{new}}(i, j) = \text{dir}(i, j) \times \text{flag}(i, j) \tag{7}$$

However, it is very difficult to perform directional transform to the pixels in the smooth regions. 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 [23]. Using this, a pixel x is considered as a ROI pixel if

$$\frac{p(x/\text{ROI})}{p(x/\text{RONI})} \geq T \tag{8}$$

where $p(x/\text{ROI})$ and $p(x/\text{RONI})$ are the respective class conditional probability distribution functions and T is a threshold value [24]. 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 $\text{dir}_{\text{min}}(i, j)$ is obtained by using the directional information of the image,$\text{dir}_{\text{new}}(i, j)$ and $X(i, j)$.

$$\text{dir}_{\text{min}}(i, j) = I(i, j) - [X(i, j) - \text{dir}_{\text{new}}(i, j)] \tag{9}$$

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.

$$\text{flag}(i, j) = I(i, j) \tag{10}$$

Then, the estimated minimum direction, $\text{dir}_{\text{min}}(i, j)$, can be added with the smooth region of the image to obtain the hybrid transform, $H(i, j)$.

$$H(i, j) = \text{dir}_{\text{min}}(i, j) + \text{flag}(i, j) \tag{11}$$

The hybrid value computed from the above equation can be subtracted from small random value matrix, $R(i, j)$ represents independent and identically distributed Gaussian random variables having mean 0 and variance 1, in order to obtain a better PSNR value of an image. Hence, the denoised image $D(i, j)$ can be obtained by

$$D(i, j) = H(i, j) - R(i, j) \tag{12}$$

2.1.1 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). 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 [10]. PSNR is computed as follows:

$$\mathrm{PSNR} = 10\log_{10}\frac{\sum_{i=1}^{\mathrm{row}}\sum_{j=i}^{\mathrm{col}} 255^2}{\sum_{i=1}^{\mathrm{row}}\sum_{j=i}^{\mathrm{col}}\left[I(i,j)-D(i,j)\right]^2} \tag{13}$$

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

3 Analysis of resolution enhancement techniques

Image resolution enhancement focuses on modifying the resolution of an image so that the result is similar to the original image. Images can have geometric distortions due to different satellite view angles, variable ground resolution cell sizes, environmental conditions and directional reflectance effects from surface materials. For overcoming these geometric distortions, satellite image resolution enhancement is very important in image processing applications. Here, a DWT-based interpolation technique is proposed to improve the resolution of the satellite image.

Interpolation technique is a method to increase the number of pixels in a digital image. Interpolation has been widely used in many image processing applications, such as facial reconstruction [14], multiple description coding [15] and image resolution enhancement. The interpolation-based image resolution enhancement has been used for applications to increase the quality of this task. The nearest neighbor, bilinear and bicubic are the three well-known interpolation techniques.

The interpolation of an image aims at estimating intermediate pixels between the known pixel values in the available low-resolution image [15]. The image interpolation process is nothing but the image synthesis operation. This process is performed row by row and then column by column. The discrete sequence $f(x_k)$ of length N as shown in Fig. 1a and this sequence is filtered and down sampled by 2, thereby getting another sequence $g(x_n)$ of length $N/2$ as shown in Fig. 1b. The interpolation process aims at estimating a sequence $l(x_k)$ of length N as shown in Fig. 1c, which is as close as possible to the original discrete sequence $f(x_k)$.

3.1 Discrete wavelet transform-based interpolation

The 1-D discrete wavelet transform is applied along the rows of the image first and then along the columns to produce 2-D decomposition of an image [16,17]. Discrete wavelet transform decomposes an image into four sub-bands namely low–low, low–high, high–low and high–high. These four sub-bands can also be used to generate the original image [18–20]. The LL sub-band consists of illumination information, where as the remaining sub-bands contain the information of edges. The manipulation of these sub-bands gives the improved image, i.e., the enhancement in resolution.

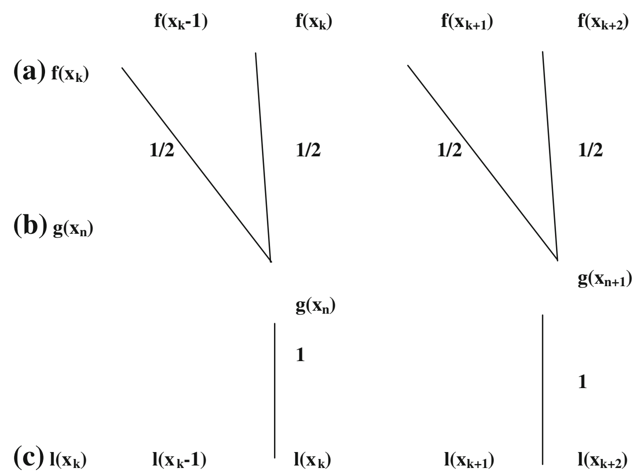


Fig. 1 Interpolation of signal **(a)** original data sequence **(b)** down sampled version of original data sequence and **(c)** interpolated data sequence

This work proposes DWT-based interpolation technique for satellite image resolution enhancement in high-frequency sub-band images and the denoised image. The final resolution -enhanced image has been obtained by inverse discrete wavelet transform. In order to obtain a sharper image that preserves the edge information, interpolation technique is used. This technique approximates the high-frequency sub-band by subtracting the interpolated LL sub-band from the denoised image. The LL sub-band without quantization is used as input for this proposed technique. The interpolation technique uses this low-frequency sub-band image, which contains little information than the denoised image. Therefore, the low-resolution image is interpolated with the half of the interpolation factor, to interpolate the high-frequency sub-band as shown in Fig. 2.

The difference between the low-resolution denoised image and the interpolated LL sub-band image is a high-frequency component. This estimation is calculated by interpolating the high-frequency sub-band by two and performing IDWT using half of the interpolation factor. The additional step proposed, that is, adding the difference image with the high-frequency components, generates sharper resolution-enhanced image.

4 Supervised classification

Supervised classification identifies the specific area of interest, i.e., different class details in the image. The supervised classification is much more accurate for mapping classes,

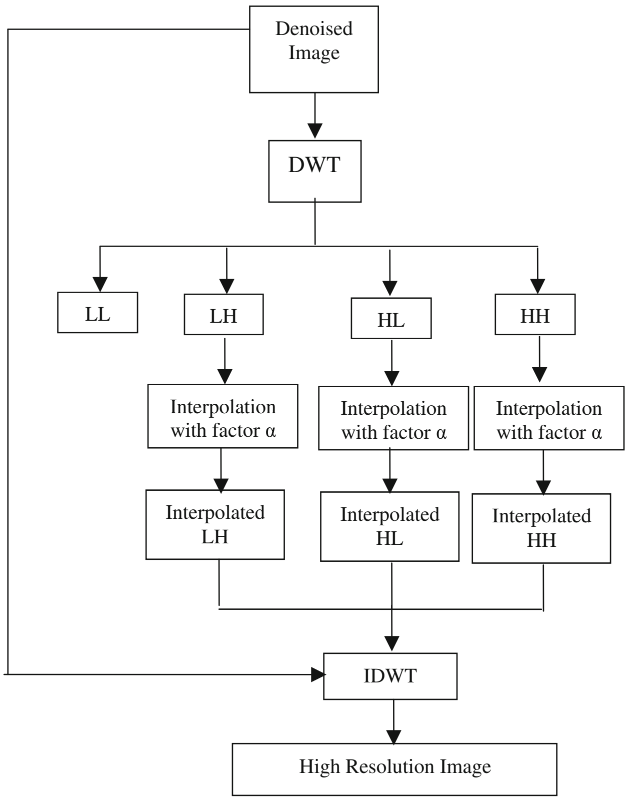


Fig. 2 DWT-based interpolation technique

but depends heavily on the cognition and skills of the image specialist [21]. The strategy is simple: The specialist must recognize conventional classes or meaningful classes in a scene from prior knowledge, such as personal experience with what's present in the scene, or more generally, the region it is located in, by experience with thematic maps, or by on-site visits. This familiarity allows the individual making the classification to choose and set up discrete classes and then, assign them category names [22].

As a rule, the classifying person also locates specific training sites on the image to identify the classes. The resulting training sites are areas representing each known land cover category that appear fairly homogeneous on the image [23]. Many of the classes for the satellite images are almost self-evident in portraying ocean water, waves, beach, marsh and shadows. For example, difference between ocean and bay waters, but their gross similarities in spectral properties would probably make separation difficult. Some classes are broad-based, representing two or more related surface materials that might be separable at high resolution but are inexactly expressed in the image [24]. Thus, the supervised classification has an edge over the unsupervised methodology.

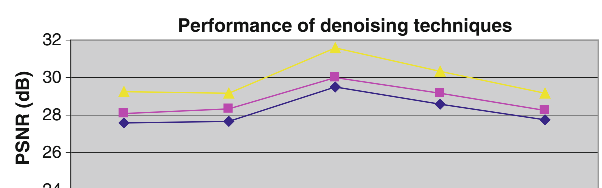
Selection of suitable training samples is a critical step for successful implementation of an image classification. So, it is very important to select the training samples that are most useful for separating water body and non-water body regions. The retrieval of these training samples is called as image feature extraction [25].

4.1 Statistical texture feature extraction

Statistical methods characterize the texture indirectly according to the non-deterministic properties that manage the relationships between the gray levels of an image. Statistical methods are used to analyze the spatial distribution of gray values by computing local features at each point in the image and deriving a set of statistics from the distributions of the local features [26–28]. The statistical methods can be classified into first-order (one pixel), second-order (pair of pixels) and higher-order (three or more pixels) statistics. The first-order statistics estimate properties (e.g., average and variance) of individual pixel values by waiving the spatial interaction between image pixels. The second-order and higher-order statistics estimate properties of two or more pixel values occurring at specific locations relative to each other. The most popular second-order statistical features for texture analysis are derived from the co-occurrence matrix.

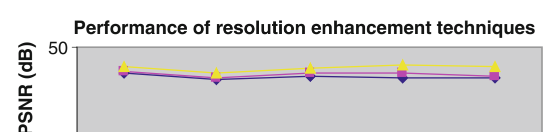
4.1.1 Second-order gray-level co-occurrence matrix features

The GLCM is a well-established statistical device for extracting second-order texture information from images. GLCM is



	Chennai region	Kolkata region	Brain image	Knee image	Lena image
DL	27.56	27.69	29.47	28.55	27.75
ADL	28.12	28.35	29.96	29.17	28.23
HDL	29.21	29.16	31.58	30.3	29.2

Fig. 3 Performance comparison of various denoising techniques



	Chennai	Kolkata	Brain	Knee	Lena
DWT	35.32	31.91	33.78	33.19	32.8
SWT	36.25	32.91	35.27	35.32	33.78
DWT based	39.19	35.39	38.58	40.14	39.6

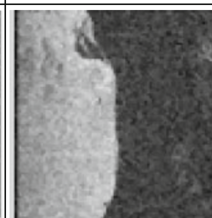
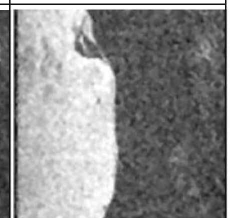
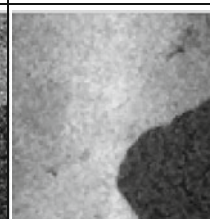
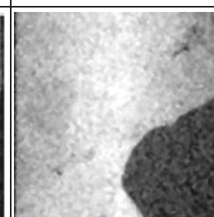
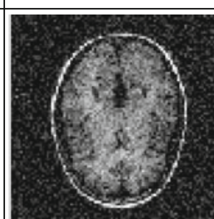
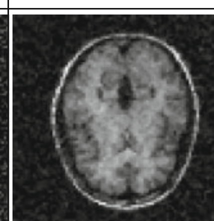
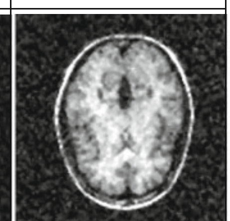
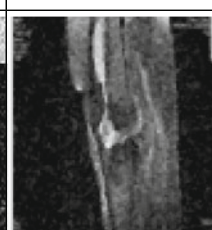
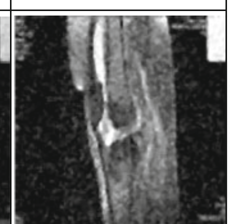
Image Titles

Fig. 4 Performance comparison of resolution enhancement techniques a matrix that describes the frequency of one gray level appearing in a specified spatial linear relationship with another gray level within the area of investigation [29]. Given an image, each with an intensity, the GLCM is a tabulation of how often different combinations of gray levels co-occur in an image or image section.

Texture feature calculations use the contents of the GLCM to give a measure of the variation in intensity at the pixel of interest. Typically, the co-occurrence matrix is computed based on two parameters, which are the relative distance between the pixel pair d measured in pixel number and their relative orientation θ. Normally, θ is quantized in four directions (e.g., 0°, 45°, 90° and 135°), even though various other combinations could be possible.

GLCM has thirteen features, but between them, most useful features are: angular second moment (ASM), contrast, correlation, inverse difference moment, sum entropy and information measures of correlation [30].

Fig. 5 Denoised and resolution-enhanced output image

Sl. No	Image Title	Noisy Image	HDL Denoised Image	Resolution Enhanced Image
1	Chennai region			
2	Kolkata region			
3	Brain image			
4	Knee Image			
5	Lena Image			

4.2 Support vector machine classifier

A support vector machine (SVM) is a concept for a set of related supervised learning methods that analyze data, recognize patterns and then used for classification and regression analysis [31]. The classification problem can be restricted to consideration of the two-class problem without loss of generality. The goal is to separate the two classes by a function which is induced from available training data sets.

For each given input, the SVM determines whether the input is a member of water body or non-water body class. This makes SVM as a linear classifier. The goal is to separate the two classes without loss of generality by a function which is induced from available training data sets. The task is to produce a classifier that will work in a generalized manner. The application of SVM for the desired problem is minimizing the error through maximizing the margin which means that it maximizes the distance between it and the nearest data point of each class [32–34]. Since SVMs are known to generalize well even in high-dimensional spaces under small training samples, this linear classifier is termed as the optimal separating hyper plane. SVM is used to construct a decision plane called the hyper plane which separates the water body class from non-water body class.

The accuracy assessment of the classification technique enlightens the algorithm to classify the images into ROI. Before implementing a classification accuracy assessment, it is very important to know the sources of errors [35]. The factors for generating error matrix such as collection of reference data, classification algorithm, feature extraction technique, spatial autocorrelation and sample size should be considered [36].

5 Results and discussions

The experimental results deal with the Land Remote Sensing Satellite (LANDSAT) images taken from different time frames of Chennai and Kolkata regions, brain and knee medical images and Lena image. The performance of the HDL technique is compared with the conventional directional lifting and ADL technique for evaluating the performance by PSNR. The comparison results are shown in Fig. 3.

The proposed technique outperforms the traditional wavelet and LS in both PSNR and visual quality, especially for images with rich texture features such as remote sensing images and medical 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.

This work also uses the DWT-based interpolation technique to enhance the resolution of the denoised image. The performance of this proposed technique is compared with discrete and stationary wavelet transform. The quantitative performance is measured using PSNR and it can be improved in the resolution-enhanced image compared to the denoised image. The comparison results of DWT, SWT and DWT-based interpolation technique are shown in Fig. 4. While comparing the performance of SWT with DWT-based interpolation technique the PSNR value of the Lena image is improved from 33.78 to 39.6 dB. The visual quality of proposed denoised and resolution-enhanced images are shown in Fig. 5.

The SVM classifies the images into the area of interest that is the water body and non-water body as shown in Fig. 6 and this shows that the resolution-enhanced image gives better accuracy than the denoised image.

The classification accuracy of denoised images and resolution-enhanced images is described using area under receiver operating characteristic (ROC) curves. ROC analysis is a technique for visualizing, organizing and selecting classifiers based on their performance. The Figs. 7 and 8 illustrate how the denoising and resolution enhancement techniques are influenced for improving classification accuracy through ROC analysis. For the denoised image, the classifier gives 85 % accuracy in the Chennai region and 70 % accuracy in the Kolkata region. It also gives 90 % accuracy for the resolution-enhanced input image of Chennai region. The accuracy of the Chennai region is improved by 5 after applying the resolution enhancement technique. The ROC analysis also shows that Chennai region has a sensitivity of 83.3 % and specificity of 92.9 %.

6 Conclusions and future work

In this research work, it has been proposed to apply HDL technique and DWT-based interpolation technique for image denoising and resolution enhancement for improving classification accuracy. In HDL, the direction information is incorporated into texture and smooth regions to remove the noise

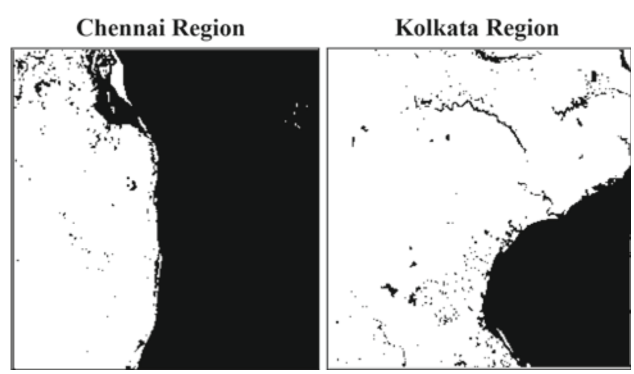


Fig. 6 Classified results

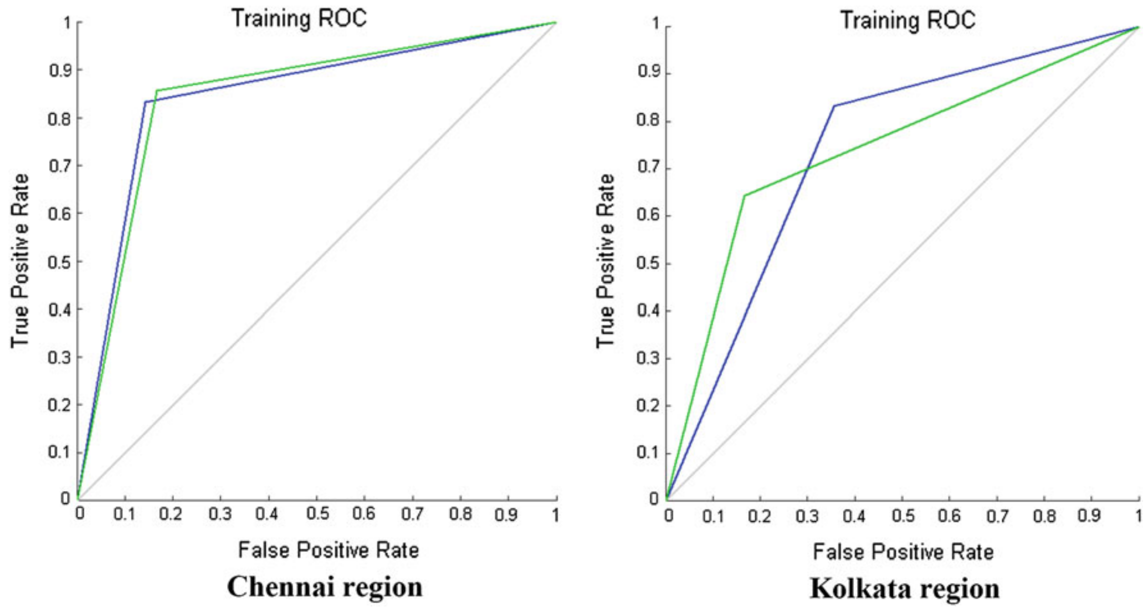


Fig. 7 ROC analysis of classified images—input as the denoised image

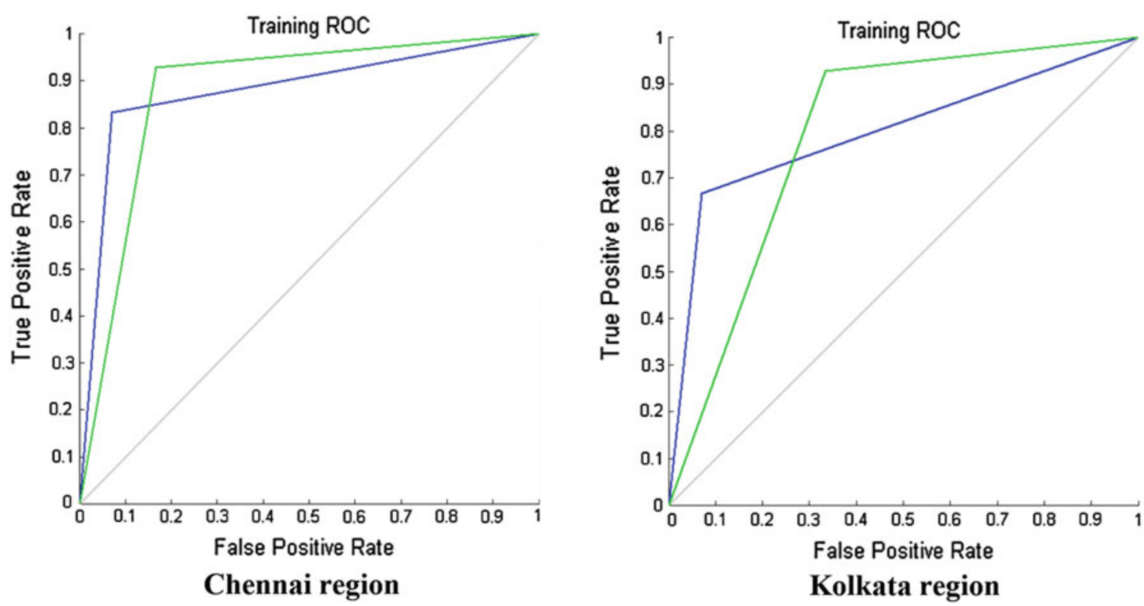


Fig. 8 ROC analysis of classified images—input as the resolution-enhanced image

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 efficacy of HDL when compared to directional lifting and ADL technique. The resolution enhancement technique using the high-frequency sub-band images and the denoised image is also elaborated in this research. The HDL denoising and DWT-based interpolation are taken into account to improve the performance of image classification.

It is also illustrated how the proposed techniques positively impact the classification accuracy of the task of classifying the image into area of interest by using SVM classifier. These proposed techniques have been tested on Landsat remote sensing satellite images, medical images and a standard Lena image where their PSNR and visual results show the efficacy of the proposed techniques over the conventional denoising and resolution enhancement techniques. The future work lies in devising optimal techniques in order to enhance the correctness in classification rate, thereby improving the quality of the denoised image. This research also leads toward defining a mechanism to aid long-term planning by predicting preventable losses and to generalize this work for supporting crisis management due to global warming.

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