Curvelet Transform based Denoising of Multispectral Remote Sensing Images

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Abstract. With the advent of sensor technology, the exertion of multispectral image (MSI) is comely omnipresent. Denoising is an essential quest in multispectral image processing which further improves recital of unmixing, classification and supplementary ensuing praxis. Explication and ocular analysis are essential to extricate data from remote sensing images for broad realm of supplications. This paper describes curvelet transform based denoising of multispectral remote sensing images. The implementation of curvelet transform is done by using both wrapping function and unequally spaced fast Fourier transform (USFFT) and they diverge in selection of spatial grid which is used to construe curvelets at every orientation and scale. The coefficients of curvelets are docket by a scaling factor, angle and spatial location criterion. This paper crisps on denoising of Linear Imaging Self Scanning Sensor (LISS) III images. The proposed denoising approach has also been collated with some existing schemes for assessment. The efficacy of proposed approach is analyzed with calculation of facet matrices such as Peak signal to noise ratio and Structural similarity at distinct variance of noise.

Index Terms—Curvelet Transform, Fourier Transform, LISS III, Multispectral image, Remote Sensing, Wavelet Transform

1. Introduction
The advancement in sensor technological decorum is a asset for multispectral remote sensing, which provides utilization of various bands in electromagnetic spectrum and plays a prominent role in various research streams like planet surface exploration, remote sensing, land cover analysis, surveillance, forensics and security. Digital image processing is a broad research domain which entails more efficacies in the processing fields of satellite [4], medical, and natural images and so on. Direct application of denoising [1] schemes on images may leads to removal of fine features of original image, which is not at all desirable for above said applications. Even though multispectral images are abducted using ingenious sensors, they suffer with certain issues like frequency mixing, noise and dimensionality of data in high volumes which affects the quality of image which is captured. The process involving detection, classification and analysis of earth’s surface features by using electromagnetic radiations without any contact specifies Remote Sensing (RS). In various remote
sensing pleas, the key in data is often ruined by noise leading to degradation in quality. Generally the noise gets added up with original content during acquisition or transmission and compression. In case of remote sensing blur is introduced due to atmospheric instability, photon system digression and calibration errors. Some intrinsic and extrinsic noise sources cannot be dodged, so denoising is prior challenge in case of satellite imagery supplications. The basic theme of denoising is not only elimination of noise but also preserve the texture and edge information’s perfectly. Filtering and interpretation serves as key steps in image denoising schemes. Filtering is the primary step for remote machine audits like segmentation and identification of objects. The reconstructed informative image data is facile to untangle by humans in various errands of classification. There are various methods of filtering schema like frequency domain filters, spatial filters, smoothening filters and sharpening filters. The process of reducing noise using transformation schemes are referred as transform domain filtering which includes wiener filter \[3\], shift invariant wavelet packet decomposition and Gaussian scale mixture denoising. The process of reducing noise using spatial data redundancy is referred as spatial domain filtering which includes mean filter, median filter \[2\] and bilateral filter. Denoising acts as magnificent setup for modeling, segmentation, identification, estimation and tracking theories. Thus various denoising methods have been introduced to redeem noise free image from corrupted once.

\[\text{Fig.1. Image Denoising Process}\]

2. Related Work

The various existing approaches related to denoising of multispectral images is specified in this section. The various schemes that are widely used for MSI denoising includes filtering methods based on specification of captured signal and rife arguments, utilization of statistics of the image both locally and globally, patch based approaches, tensor based approaches, deep learning based approaches. The common schema for any transform based denoising involves the following steps:

- Computing the transformation coefficients
- Removing the noise from coefficients
- Reconstructing the image.

The basic transformation that is normally used in processing of images is wavelet transform by virtue of its special features like multi scute decomposition and non redundant orthonormal bases. D.Donoho in \[5\] evoked soft thresholding based wavelet approach. Othman and Qian in \[6\] expressed hybrid combo of spatial and spectral derivative domain wavelet shrinkage approach. Chen and Qian proposed a quantized approach which performs both denoising and classification uses wavelet shrinkage & principal component analysis which works very effectively for multispectral images \[12\]. Mallat
suggested pyramidal filter bank method for evaluating wavelet coefficients, which generally corresponds to WT, which has a drawback that it is variant under translation [8].

Kingsbury suggested a more feasible approach for decomposition of image into a set of wavelet coefficients called DTWT which makes use of Hilbert pairs. The shift invariance, perfect reconstruction and less complexity in computation are the biggest asset of this scheme [9]. Even though wavelet transform is widely used for denoising, but various studies ceased that it does not preserve edges or curves in images. The soft thresholding curvelet coefficients achieve better reduction of noise compared to wavelet coefficients and provide a better separation of background noise and geometric details. The representation of uncorrupted signals in curvelet pro forma can be estimated using multiple linear regressions, which is used for analysis of noise [10-11]. Suresh et al. [7] suggested wiener filter to remove Gaussian noise from satellite images which makes use of two dimensional finite impulse response to estimate original image and weights of window are adjusted in such a way that the Mean Square Error (MSE) is greatly minimized.

3. Proposed Methodology

The proposed methodology specifies the denoising of images using curvelet transform. Wavelets fail to represent edges and singularities of curves perfectly because of finite number of directional elements. To overcome this ridge lets and curve lets have been developed. The extension of ridge let transform is the proposed approach which grips singularities along smooth curves. Many imaging supplications needs high resolution images for further processing and analysis, which are prior requirements in human elucidation and automatic machine related areas for effective information. The different image resolution can be represented as spatial, radiometric, temporal, spectral and pixel. In satellite imagery, resolution in terms of spatial quantity is the key and depends on the type of sensors used [13-14]. The various super resolution methods are based on reconstruction approach, learning approach and interpolation approach. These posses the characteristics of fast processing and lacks in producing fine details of image. The first and second generations of curvelet transform has drawbacks of high redundancy and are not optimal beyond $C^2$ singularities for sparse estimation of curve features. Later ridge let analysis and transform is discarded resulting in fast and less redundant curvelet transform which can be implemented in two ways.

In general, noise can be approximated as white noise with Gaussian distribution which is caused by Johnson noise or Thermal noise or reset noise of capacitors. In RGB images, the blue color channel suffers with more noise as it has low intensity compared to red and green channels & it requires more amplification, whose probability density function is given by:

$$P(y) = \frac{1}{\sqrt{2\pi} \sigma^2} e^{-\frac{(y-a)^2}{2\sigma^2}}$$  \hspace{1cm} (1)

![Fig.2. Block diagram of curvelet transform based denoising](image-url)
The main difference between the two approaches of curvelet transform i.e., fast Fourier transform approach which is unequally spaced approach and wrapping ideology approach is the exertion of timed domain grid to construe curvelets at each orientation and scute. The curvelets have the following characteristics:

- Time frequency locality
- High directionality
- Highly anisotropic
- High sensitivity
- Translation invariant
- Ease of implementation
- Low computational complexity
- Stability against perturbations
- Robust to noise
- Less distortion of spectral characteristics
- Well suitable to denoise singular areas
- Well suitable to denoise smooth areas
- Easy to compute

The representation of coefficients of curvelets is specified by:

\[ C(r, \theta, s) = \sum_{a,b}^{\theta, r, s} F(a, b) \varphi_{r, \theta, a, b} \quad (2) \]

Where:
- \( r \rightarrow \) Scale value or decomposition levels value
- \( \theta \rightarrow \) Angle
- \( s = (s_1, s_2) \rightarrow \) Parameter of translation
- \( C \rightarrow \) Coefficients of curvelets
- \( \varphi(a, b) \rightarrow \) Function of curvelet
- \( F(a, b) \rightarrow \) Original image of size MxN

To evaluate curvelet transform the following steps are to be followed:

i) Evaluate the Fast Fourier Transform of the curvelet

ii) Evaluate the Fast Fourier Transform of the image

iii) Evaluate Inverse Fast Fourier Transform of the product of FFT (Curvelet) and FFT (Image)

Let us consider radial window \( W(p) \) on \( p \in \left( \frac{1}{2}, 2 \right) \) and angular window \( V(q) \) on \( q \in [-1, 1] \) which satisfies the conditions:

\[ \sum_{p=-\infty}^{\infty} W^2(2^r p) = 1, \quad p \in \left[ \frac{3}{4}, \frac{3}{2} \right] \quad (3) \]

\[ \sum_{q=-\infty}^{\infty} V^2(q - l) = 1, \quad q \in \left[ -\frac{1}{2}, \frac{1}{2} \right] \quad (4) \]

The frequency domain representation of window \( U_j \) is specified as follows:

\[ U_j(p, \theta) = 2^{\frac{3j}{2}} W(2^{-j} p) V \left( \frac{\theta}{2\pi} \right) \quad (5) \]

Curvelet provide solutions to the isotropic scaling and orientation problems suffered in wavelets. Denoising using curvelets results in preserving of features of image, irrespective of its frequency content.

Generally, the threshold can be calculated using the formula:
\[ \delta = \sigma \cdot \sqrt{\frac{2 \ln(n)}{\pi}} \]  \quad \text{(6)}

Where:  
\( \sigma \rightarrow \text{Standard deviation of noise;} \)
\( n \rightarrow \text{Length of the sampling signal.} \)

The curvelet thresholding or shrinkage function is given by:

\[ C_T(r, \theta, s) = \begin{cases} \text{sgn}(C(r, \theta, s)) & \text{if } |C(r, \theta, s)| \geq T \\ 0 & \text{if } |C(r, \theta, s)| < T \end{cases} \]  \quad \text{(7)}

Where:  
\( T = b \sigma \) \( \Delta \) \( \sigma \rightarrow \text{standard deviation of noise and} \ \sigma \rightarrow \text{approximated standard deviation of curvelet coefficients,} \)  
\( b \) is a constant which depends on orientation and scale, \( \text{sgn}(.) \) represents signum function. The thresholding function should be chosen in such a way that the curves of both input and output must be continuous and it should be smooth to reduce various effects and evaluated coefficients must remain unchanged so that fine features of image like edges, texture etc., are preserved.

![Flowchart of Proposed Methodology](image)

4. Results & Discussion
MATLAB 2019b software platform is used to perform simulation of proposed methodology. The efficacy of the proposed approach is evaluated both subjectively and objectively which specifies visual interpretation and evaluation of picture quality metrics such as Peak Signal to Noise Ratio (PSNR), which is the ratio of signal strength to noise strength and Structural Similarity (SSIM) which deals with contrast and luminance contents. The comparison of proposed schema is compared with that of existing approaches like wavelet transform [15], dual tree wavelet transform. The LISS III image data set is considered for processing the proposed novel methodology which has 4 bands with a spatial resolution of 23.5 meters. The middle infrared spectral area band is considered for Indore region,
Madhya Pradesh, India (Latitude/Longitude: 22.7196°N/75.8577°E) dated 16th February 2019 which is collected by Indian Remote sensing Satellite of LISS III sensor.

For a good denoising schema, the value of signal strength to noise strength must be high and it is measured by:

$$\text{PSNR} = 10 \cdot \log \left( \frac{S^2}{\text{MSE}} \right)$$  \hspace{1cm} (8)

Where:

- $S$ → Higher or Maximum gray level value
- MSE → Power of noise

$$\text{MSE} = \frac{1}{MN} \sum (f(a,b) - g(a,b))^2$$  \hspace{1cm} (9)

Where:

- $f(a,b)$ → Original or True image
- $g(a,b)$ → Reconstructed or Restored image

The specification of Structural Similarity is given by:

$$\text{SSIM} = \frac{2m m + C_1 \left( 2\sigma_x \sigma_y + C_2 \right)}{m_x^2 + m_y^2 + C_1 \left( \sigma_x^2 + \sigma_y^2 + C_2 \right)}$$  \hspace{1cm} (10)

Where:

- $m$ → Mean value
- $\sigma$ → Standard deviation
- $\sigma^2$ → Variance
- $C_1$ & $C_2$ → arbitrary constants

**Fig.4.** Simulation results of the proposed denoising approach for LISS III images of Indore region, Madhya Pradesh, India (a) True LISS III Image; (b) Noisy LISS III image with Gaussian noise variance of value 0.01; (c) Wavelet Transform (WT) output; (d) Dual Tree Wavelet Transform (DTWT) output; (e) Unequally Spaced Fast Fourier Transform based Curvelet Transform (USFFT_CT) output; (f) Wrapping function based Curvelet Transform (WRAP_CT) output.

The obtained PSNR and SSIM values of existing and proposed scheme for various Gaussian noise variance values are shown in Table 1 and Table 2 respectively.
The above quantitative results specify that the proposed schema of denoising using Curvelet transform based wrapping approach performs very effectively.

5. Conclusion
In this paper, the proposed curvelet transform based on wrapping function showed finer results compared to other existing denoising methods quantitatively. The simulation results shows that the formulated approach is very effective in preserving the fine details of image while smoothing noise and provides better visual quality. Patch wise denoising using effective mixture models and usage of effective thresholding approach which isolates the inherent deviation property, ringing and pseudo Gibbs effect can be stated as future work. However, it is an inceptive attempt. There are enormous
opportunities for further enhancement. There is also a need to develop effective classification approaches for image analysis.

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