Denoising of Remotely Sensed Images via Curvelet Transform and its Relative Assessment

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Abstract

To extract information from remotely sensed images for wide range of applications, visual analysis and interpretation are required. In this paper, the denoising of remotely sensed images based on Fast Discrete Curvelet Transform (FDCT) has been proposed. The Fast Discrete Curvelet Transform via Wrapping (WRAP) and Unequally-Spaced Fast Fourier Transform (USFFT) has been discussed. With its optimal image reconstruction capabilities, the curvelet outperforms the wavelet technique in terms of both visual quality and Peak Signal to Noise Ratio (PSNR). This paper focuses on the analysis of denoising the Linear Imaging Self Scanning Sensor III (LISS III) images, Advanced Very High Resolution Radiometer (AVHRR) images from National Oceanic and Atmospheric Administration 19 (NOAA 19), METOP satellites for the Tirupati region, Andhra Pradesh, India. Numerical illustrations demonstrated that this method is highly effective for denoising the satellite images.

1. Introduction

The sensing of the earth’s surface without physical contact from space by making use of the emitted electromagnetic (EM) wave properties implies the Remote Sensing (RS). The interaction of the EM wave with the object of interest for improving natural resource management, land use and environment protection. In many RS applications, the input data is often tainted by noise during acquisition and transmission. For RS purposes, atmospheric instability introduces blurs, optical system aberration and relative motion between camera and the ground when aerial photographs are in use. Image denoising is an essential challenge in satellite image processing, since many of the intrinsic and extrinsic image noise sources cannot be avoided.

The aim of noise filtering or image denoising, is to exploit the available data in the observed image to find an approximate of the noise-free signal. This estimate serves two purposes. First, the noise filtering can be performed as a preliminary step for further machine analysis, such as image segmentation, object identification, or visual tracking. Secondly, the denoised images are easier to interpret by human observers, aiding in tasks such as classifying crop types, ice types in Synthetic Aperture Radar (SAR) images, or assessing arterial disease in ultrasound images. Numerous methods have been projected, ranging from spatial filters, frequency-domain filters to multiscale wavelet filters. The

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transform domain methods perform noise reduction based on the transform domain coefficients. Methods in this class include Wiener filtering, collaborative Wiener filtering Gaussian scale mixture denoising and wavelet shrinkage. The second class spatial domain methods utilize spatial information redundancy. Methods in this class include Gaussian filtering, anisotropic filtering, bilateral filtering and nonlocal means. Thus, many denoising algorithms have been developed to recuperate the noise-free image from a corrupted input. Usually, image denoising enforces a tradeoff linking noise reduction and conserving noteworthy image particulars like edges.

2. Related Work

The mathematical tool which is extensively used in image processing is wavelet transform. A few purposes of the transform to RS images were explored in the review. For different applications like analyzing texture, compressing image and reducing noise, wavelet is the functional tool. A signal can be represented onto an orthonormal basis using it. The advantages of wavelets are non-redundant orthonormal bases, perfect reconstruction, multiresolution decomposition, attractive for object matching, fast algorithms with short filters.

According to Mallat, computing the coefficients of orthogonal wavelet representation can be done by fast pyramidal filter bank algorithm. This algorithm is in general known as the Discrete Wavelet Transform (DWT). A disadvantage of the DWT is that, in contrast to the Continuous Wavelet Transform (CWT), this representation is variant under translation. Due to the shift variance property it is not appropriate for pattern recognition and degrades the performance in denoising.

One of the main feasible decompositions is the Dual-Tree Discrete Wavelet Transform (DTDWT) as per N. Kingsbury. In this method two classical wavelet trees with filters forming Hilbert Pairs (HP) were developed simultaneously. HP advantages were also conferred by some authors. The main features of DTDWT are invariance of shift, selectivity in direction, accurate reconstruction, limitation in redundancy and less computational complexity. The general procedure for wavelet based image denoising includes – computing of the wavelet transform, removing the noise from coefficients and then reconstructing the denoised images.

In remote sensing applications of image denoising, the noise variance is very important, in some cases it is known, otherwise it can be measured from the information other than the corrupted data. A better estimate \( \hat{\sigma} \) can be attained with a median measurement which is highly insensitive.

The popular approach for wavelet denoising is Wavelet Thresholding. Here a threshold is applied for each coefficient. Each coefficient is put to zero when threshold exceeds it value, if not it can be modified or left unchanged. This was described by Weaver. The relevant literature was developed by Donoho.

Thresholding can be performed in two ways, namely Soft Thresholding and Hard Thresholding.

2.1 Hard Thresholding (HT):

The coefficients were not changed if the value is greater than the applied threshold value. The thresholding equation is defined as

\[
T_{\text{hard}}(w) = \begin{cases} 
    w & \text{if } |w| > T \\
    0 & \text{if } |w| \leq T 
\end{cases}
\]

where \( w \) is the value of the wavelet coefficient and \( T \) is the value of threshold.

2.2 Soft Thresholding (ST):

The threshold value is reduced from the coefficients which are greater than its value. The equation is given as

\[
T_{\text{soft}}(w) = \begin{cases} 
    \text{sgn}(w)(|w| - T) & \text{if } |w| > T \\
    0 & \text{if } |w| \leq T 
\end{cases}
\]

where \( \text{sgn}(.) \) is signum function.
Mostly ST is preferred to HT because the later produces the artifacts in the reproduced image if the level of noise is high. The problem with ST is that reconstructed image is smoothed.

Almost all the methods for estimating the threshold, assume Additive White Gaussian Noise (AWGN). The Universal Threshold is given by Donoho and Johnstone

$$T_{univ} = \hat{\sigma}_n \sqrt{2 \log(n)}$$

where $\hat{\sigma}_n$ is standard deviation estimate of additive white noise and $n$ is the total no. of wavelet coefficients of detailed image.

3. Proposed Method

Wavelets have a limited number of directional elements, which make them failing to present objects with anisotropic elements like edges, curves. Ridgelets and Curvelets have been evolved to overcome the weakness of wavelets.

The curvelet transform is the extension of ridgelet transform by Candes and Donoho which handles singularities along smooth curves. Representation of images at various angles and scales has been made easier by the curvelet transform because of its higher dimensionality. A unique part of the multi scale geometric transforms is the curvelet. This transform has a multi scale pyramid with multidirection at each length scale.

The simpler and faster, Fast Discrete Curvelet Transforms (FDCT) have been developed namely,

- USFFT based curvelets and
- WRAP based curvelets.

The first step in curvelet transform is the decomposition of the signal into subbands. The DCT takes Cartesian grid of the form $X(k_1, k_2), 0 < k_1, k_2 < k$ as an input and outputs a collection of coefficients $C^D(p, q, r)$ defined by

$$C^D(p, q, r) = \sum_{0 \leq k_1, k_2 < k} X(k_1, k_2) \Psi^D_{p,q,r}(k_1, k_2)$$

where $\Psi^D_{p,q,r}$ is a digital curvelet waveform, the superscript D represents “Digital”.

As said by Candes, the FDCT is the method depending on Unequally-Spaced Fast Fourier transform (USFFT) and on Wrapping of Fourier samples which are particularly chosen. The key difference between the above two is the usage of spatial grid to translate curvelets at every scale and angle.

3.1 FDCT via USFFT (FDCT-USFFT)

The implementation of the FDCT-USFFT considers a two dimensional image as the input in a Cartesian array form $X(k_1, k_2), 0 < k_1, k_2 < k$. The steps for applying FDCT via USFFT are given below:

3.1.1 Algorithm

Step 1: Obtain Fourier coefficients $\hat{X}(k_1, k_2)$ by applying the FFT.
Step 2: for each scale $j$ and orientation $l$ do

1. Attain sample values $\hat{X}(k_1, k_2 - k_1 \tan \phi_q)$ for $(k_1, k_2)$ by resampling or Interpolating $X(k_1, k_2)$
2. Obtain $\hat{X}_{p,q}(k_1, k_2) = \hat{X}(k_1, k_2 - k_1 \tan \phi_q) \hat{V}_p(k_1, k_2)$ by simply multiplying the interpolated object $\hat{X}$ with the Parabolic window $\hat{V}_p$ efficiently confining $\hat{X}$ near the parallelogram with orientation $\phi_q$.
3. Get the discrete coefficients by applying the IFFT to the wrapped data

Step 3: The discrete coefficients $C^D(p, q, r)$ are collected.

3.2 FDCT via Wrapping(FDCT-WRAP)

The execution of the FDCT via wrapping considers a two dimensional image as the input in a Cartesian array form $X(k_1, k_2), 0 < k_1, k_2 < k$. The steps for applying FDCT via WRAP are given below:
3.2.1 Algorithm

Step 1: Obtain Fourier coefficients \( \hat{X}(k_1, k_2) \) by applying the FFT and

Step 2: for each scale \( j \) and orientation \( l \)

1. Obtain the product \( \hat{V}_p(k_1, k_2) \hat{X}(k_1, k_2) \), where \( \hat{V}_p \) is the parabolic window.
2. Obtain \( \hat{X}_{p,q}(k_1, k_2) = W(\hat{V}_{p,q} \hat{X})(k_1, k_2) \), where the choice for \( k_1 \) is \( 0 \leq k_1 < L_{1,p} \) and \( k_2 \) is \( 0 \leq k_2 < L_{2,p} \)
   where \( L_{1,p} \sim 2^p \) and \( L_{2,p} \sim 2^{p/2} \) respectively.
3. Get the discrete coefficients by applying the IFFT to the wrapped data

Step 3: The discrete coefficients \( C^D(p, q, r) \) are collected.

3.3 Curvelet Shrinkage/Thresholding

In curvelet application, Shrinkage/Thresholding plays a prominent role. For observing the images, numerous techniques have been used on the curvelet coefficients. The signal information is carried by the large coefficients rather than small coefficients which are subjugated by noise. So, noisy coefficients will be replaced by zero.

The curvelet shrinkage function is given by

\[
\tilde{C}(p, q, r) = \begin{cases} 
\text{sgn}(C(p, q, r))(|C(p, q, r)| - T); & |C(p, q, r)| \geq T \\
0; & |C(p, q, r)| < T
\end{cases}
\]
where $T = a\hat{\sigma}\lambda\sigma$, ‘$\sigma$’ is the noise standard deviation estimate, ‘$\hat{\sigma}\lambda$’ is the standard deviation approximation for curvelet coefficients, ‘$a$’ is a dependent constant in direction and scale, $\text{sgn}(.)$ is signum function.

4. Results and Discussion

The data sets collected from IRS-R2 (Indian Remote Sensing Satellite – Resources at 2) of LISS III sensor, for Tirupati region, Andhra Pradesh, India (Lat/Lon: 13.6500°N/79.4200°E) dated 24th Oct 2015 has been used. The spatial resolution of LISS III sensor is 23.5 meter and it has 4 bands in which only one band (middle infra-red) is considered. The images of onboard AVHRR sensor from NOAA 19 dated 18th Mar 2016 and METOP satellite dated 19th Mar 2016 were also taken. The images of AVHRR sensor are not shown in this paper. The zero mean and standard deviation ($\sigma$) white Gaussian noise values ranging from 10–50 has been considered, added to images of size 512 $\times$ 512 pixels and subjected to denoising. The performance was tested using PSNR measure for Lena images and LISS III satellite images. Let $f(x, y)$ and $g(x, y)$ represent the original and the denoised image.

The root mean square error is defined as

$$
\epsilon = \sqrt{\frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} \| f(x, y) - g(x, y) \|^2}
$$

The Peak Signal to Noise Ratio in decibels is below

$$
\text{PSNR} = 20 \log_{10} \left( \frac{256}{\epsilon} \right)
$$

The proposed method was validated by comparing the values of Peak Signal to Noise Ratio (PSNR) obtained with that of existing methods. The Wavelet methods used for the assessment were Discrete Wavelet Transform (DWT) and Dual Tree Discrete Wavelet Transform (DTDWT). Besides, the proposed transform output images are visually more pleasant. The Fig. 2 and 3 illustrates this point.

The PSNR values obtained from existing and proposed methods were given in Table 1. The LISS III denoising image results indicated that the FDCT - WRAP showed higher values for standard deviation values ranging from 10–50 out of all other methods. Currently, in this paper, the effects of thresholding on the mean square error value have not been discussed. Even the image is completely buried in the noise (with high values of $\sigma$) the proposed method is able to retrieve the signal with acceptable PSNR value than the other methods.

Fig. 2. Denoising of Images (a) Original Lena Image; (b) Noisy Image with $\sigma = 20$; (c) DWT; (d) DTDWT; (e) FDCT–USFFT; (f) FDCT–WRAP.

Fig. 3. Denoising of LISS III Images of Tirupati Region (a) Original LISS III Image; (b) Noisy Image with $\sigma = 20$; (c) DWT; (d) DTDWT; (e) FDCT–USFFT; (f) FDCT–WRAP.
Table 1. PSNR Values for LISS III Image with Different $\sigma$ Values using Different Techniques.

<table>
<thead>
<tr>
<th>$\sigma$</th>
<th>DWT</th>
<th>DTDWT</th>
<th>FDCT-USFFT</th>
<th>FDCT_WRAP</th>
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<tbody>
<tr>
<td>10</td>
<td>28.75</td>
<td>28.95</td>
<td>29.24</td>
<td>29.56</td>
</tr>
<tr>
<td>20</td>
<td>24.47</td>
<td>25.02</td>
<td>25.12</td>
<td>25.68</td>
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<td>30</td>
<td>22.69</td>
<td>23.19</td>
<td>23.76</td>
<td>24.27</td>
</tr>
<tr>
<td>40</td>
<td>21.36</td>
<td>21.99</td>
<td>22.21</td>
<td>22.69</td>
</tr>
<tr>
<td>50</td>
<td>20.51</td>
<td>21.12</td>
<td>21.56</td>
<td>21.82</td>
</tr>
</tbody>
</table>

Table 2. PSNR Value for Different Images with Fixed $\sigma$.

<table>
<thead>
<tr>
<th>Method</th>
<th>LENA</th>
<th>METOP</th>
<th>NOAA</th>
<th>LISS III</th>
</tr>
</thead>
<tbody>
<tr>
<td>DWT</td>
<td>31.18</td>
<td>33.15</td>
<td>28.95</td>
<td>24.47</td>
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<tr>
<td>DTDWT</td>
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<td>33.86</td>
<td>29.14</td>
<td>25.02</td>
</tr>
<tr>
<td>FDCT-USFFT</td>
<td>31.78</td>
<td>33.91</td>
<td>29.53</td>
<td>25.12</td>
</tr>
<tr>
<td>FDCT_WRAP</td>
<td>32.15</td>
<td>34.26</td>
<td>29.89</td>
<td>25.68</td>
</tr>
</tbody>
</table>

From the above table, it can be summarized that FDCT_WRAP method is more reliable compared to the other existing wavelet transform even if other data sets were considered (NOAA and METOP Images).

5. Conclusions

The proposed Fast Discrete Curvelet Transform based on Wrapping showed better output than the existing wavelet transforms. The curvelet denoised images were also visually enhanced when compared to others. For denoising the color images, they are first mapped from RGB to YUV and then they are filtered independently. Through this study, it has been indicated that while comparing the two curvelet transforms, Wrapping based curvelet transform specified improved outcome than the Unequispaced FFT method. Henceforth, the performance of satellite image denoising using wrapping based FDCT outperforms than that of existing wavelet transforms.

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