Enhancing Satellite Imagesusing DT-CWT in Discrete and Redundant Wavelet Domain

Dr. G. Dhanalakshmi[1], Dr. Gopala Krishnan[2]
[1,2]Professor, [1,2]Department of ECE
[1,2]Siddhartha Institute of Technology and Sciences, Narapally, Hyderabad, Telangana

Abstract
In general, satellite images suffer fromlow resolution (LR)due to the environmental disturbances such as fog and haze, which will degrade the visual quality of the images. In order to find the location or the persons, someone needs to enhance these satellite images to improve the perceptual quality of images. In this a novel resolution enhancement (RE) approach for satellite images is proposed. The proposed approach employeda dual tree complex wavelet transform (DT-CWT) based fusion algorithm in discrete and redundant wavelet domain to obtain a high resolute (HR) satellite images.Majorly, there are two stages in this algorithm, which includes the enhancement of a LR satellite images by enforcing the concept of both discrete and redundant wavelet (DRW) transforms together. Afterwards, this enhanced HR satellite image is given as a one of the source images to the approach of DT-CWT based image fusion for further enhancement of HR satellite image. Experimental analysis shown that the proposed fusion based satellite image enhancement is performed superior to the conventional wavelet-based approaches like DWT-RE and DRWT-REin terms of peak signal to noise ratio (PSNR), mean square error (MSE) and structural similarity (SSIM) index.
Key words: Satellite imaging, resolution enhancement, discrete wavelet transform, redundant wavelet transform, complex wavelet transform, dual-tree complex wavelet transform, PSNR, SSIM and MSE.

I. INTRODUCTION

Recent years, there is a rapid growth in satellite imaging due to the demand in satellite applications such as weather forecasting, astronomy and geographical data. These images were captured with the satellite sensors which are ranging from low resolution to high resolution for collecting the desired data into images. Satellite imaging applications have been increasing day by day due to the demand in applications like agriculture, oceanology, regional planning, geology, landscape, biodiversity conservation, forestry, cartography, meteorology and warfare etc.[1]. In order to analyze the satellite images, we need HR satellite images, but these images will be suffered from many factors such as absorption scattering while capturing it through the satellite sensors. These noise elements will create some serious issues for further processing of images in practical applications such as marketing, artificial work, computer vision and also in many fields. Hence, to improve the quality of these images by enhancing the visual quality is an important and challenging task. One must consider several factors to select a speckle reduction algorithm for satellite imagery.

- A digital camera must apply a noise reduction algorithm in a fraction of a second.
- Whether forfeiting few real information is acceptable if it allows more distortion or noise to be removed.

Interpolation is a one of the widely used method for enhancing the image, which is very simple and more popular. These techniques have been cauterized into three parts

1. Nearest neighbor interpolation
2. Bi-linear interpolation
3. Bi-cubic interpolation.

However, these methods were not suitable for all images and also gives more dark or brighter pixels after interpolating the LR images, which in results the quality degradation. There are two types of image resolution enhancement methods, those are: one is Spatial domain, which applies directly on to the pixels i.e., doesn't need to transform the image into other form such as gray level transformation, histogram equalization, neibourhood pixel adjustment etc.[2] and [3]. And second Transform domain, which transforms the LR image into frequency domain and then applies any algorithm to enhance the LR image to HR image such as discrete Fourier transform (DFT) [4], discrete wavelet transform (DWT) [5] and discrete cosine transform (DCT) [6].High frequency details of an image will be preserved by an adaptive anti-aliasing algorithm based on the wavelet Fourier transforms (WFT) [7] and adaptive wavelet shrinkage, which removes aliasing artifacts by shrinkage coefficients. Most effective satellite image enhancement is done by using dual tree complex wavelet transform (DT-CWT) with bicubic interpolation given in [8] and cycle spinning concept is also used to enhance LR image to HR image by merging with CWT or DWT [9] and [10]. However, all the above algorithms have been suffering from lack of reliability, much complex to implement in real time world. Drawback of DWT based

Resolution Enhancement is the down sampling nature of the decomposition of image in the DWT method. An image will be decomposed into four sub bands after applying DWT with 2 factor decimation. These sub bands are with the size of half of original images because of decimation factor. So, the information will be lost after DWT decomposition. For this reason, a new algorithm which employed redundant wavelet along with DWT is presented. Furthermore, we improved the algorithm by including DT-CWT with the algorithm of discrete and redundant WT approach, which, made it more efficient and will improve the PSNR performance.

II. EXISTING METHODS

In the past decades, there are several algorithms have been developed to enhance a LR image with improved performances. In 1974 Hall *et. al.*proposed a gray level transformation in [11], this transformation has been used for image enhancement as well as for normalization process. Later on, several filters have been developed in [12-15] and for enhancing and denoising the LR images. The author in [16] has proposed a fast filtering algorithm for enhancing the LR image, which performs noise smoothing and makes the minimum modifications in the original LR image to obtain HR image by taking the four sub images weighted combination along four major directions. In [8], [9] and [17], a satellite image resolution enhancement method based on DT-CWT, in which the LR image is decomposed into several high frequency bands. Then after these sub bands are interpolated and finally, inverse DT-CWT is used to combine these modified sub bands to get the HR image. Fourier Transform (FT) and Short-Term Fourier Transform (STFT) are the current methods used in the field of image processing. However due to severe limitations imposed by both the FT and STFT in analyzing signals deems them ineffective in analyzing complex and dynamic signals. FT has a drawback that it will work out for only stationary signals, which will not vary with the time period. Because, the FT applied for the entire signal but not segments of a signal, if we consider non-stationary signal the signal will vary with the time period, which could not be transformed by FT. and one more drawback that we have with the FT is we cannot say that at what time the particular event will has occurred. In STFT, the window is fixed. So, we this window will not change with the time period of the signal i.e., for both narrow resolution and wide resolution. And we cannot predict the frequency content at each time interval section. To overcome the drawbacks of STFT, a wavelet technique has been introduced with variable window size. Wavelet analysis allows the use of long-time intervals where we want more precise low-frequency information, and shorter regions where we want high-frequency information.In order to substitute the shortcomings imposed by both the common signal processing methods, the wavelet technique is used. The wavelet technique is used to extract the features in an image by processing data at different scales. The wavelet technique manipulates the scales to give a higher correlation in detecting the various frequency components in an image. In fig.1 it is shown that the comparison of FT, STFT and wavelet transform by considering an example input signal and how the analysis of transformation techniques will apply to get the frequency information of input signal. We can observe that in wavelet analysis the graphical representation shows that the wavelet has a greater number of features than the FT and STFT. Wavelet is also called as multi resolution analysis (MRA).

2.1. Discrete Wavelet Transform (DWT)

Discrete Wavelet Transform (DWT) is a modified version of Continuous Wavelet Transform (CWT). DWT principles are very similar to the CWT however the wavelet scales and positions are based upon powers of two.The basic principle of DWT is to pass the input signal through a group of filters i.e., low pass and high pass filters to get the low frequency (LF) and high frequency (HF) of source signal. Low frequency contents include LL and these coefficients are known as the approximation coefficients [18].

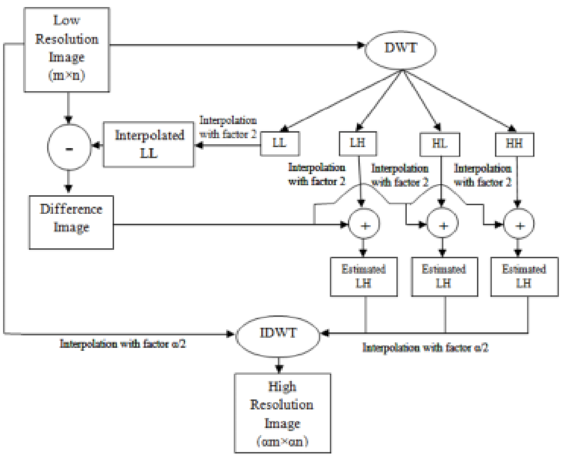


Fig. 1 Existing DWT-RE block diagram

This means the approximations are obtained by using the high scale wavelets which corresponds to the low frequency. The high frequency components which are known as LH, HL and HH of the signal are called the details which will be obtained by using the low scale wavelets which corresponds to the high frequency. The process of DWT filtering includes, first the signal is fed into the wavelet filters. These wavelet filters comprise of both the high-pass and low-pass filter. Then, these filters will separate the high frequency content and low frequency content of the signal. However, with DWT the numbers of samples are reduced according to dyadic scale. This process is called the sub-sampling. Sub-sampling means reducing the samples by a given factor. Due to the disadvantages imposed by CWT which requires high processing power [11] the DWT is chosen due its simplicity and ease of operation in handling complex signals.
Fig. 1 shows the block diagram of existing DWT-RE method. First, the LR image is given as an input to the DWT to decompose it into four sub bands LL, LH, HL and HH, which known as approximation, horizontal, vertical and diagonal coefficients and last three sub bands are also called as detail coefficients. These sub bands size will be half of the LR image due to that the DWT has a decimation property. Hence, we need to interpolate it to further operate it with the LR image.Now, the LL sub band will be interpolated to subtract from the original image i.e., LR image, after this operation a difference image will be obtained. This difference image will be added to the high frequency sub bands LH, HL and HH to improve the high frequency sub bands information. In order to perform addition for these sub bands, we need interpolation to increase the size of decimated sub bands because, the size of difference image equals to the LR image which is an original image. After performing this operation, the estimated or modified LH, HL and HH will be obtained. The after do the interpolation for LR image with a factor of $\alpha/_2$, where the parameter α is an interpolation factor, and do the same for even estimated LH, HL and HHalso. Finally, apply inverse DWT to these four sub bands to get the super resolute image i.e., HR image. However, this approach has been suffering from the decimation property of DWT, because when we apply the DWT decomposition to LR image, it will decompose the image into four sub bands with reducing the size of it to the half of LR image. Here we need to enhance the image quality but due to this decimation we lose some original information while processing with DWT. Therefore, to improve the performance of RE algorithm further, someone needs to gain the lost information and add it with high frequency sub bands to get the modified coefficients.

III. PROPOSED TECHNIQUE

This section gives a brief description about the proposed RE methods using

- DRW transform approach with interpolation
- DT-CWT transform
- Proposed implementation

3.1. DRW Transform

3.1.1. Redundant Wavelet Transform

The redundant wavelet or stationary wavelet transform (RWT) is a wavelet transform algorithm designed to overcome the lack of translation-invariance of DWT. Translation-invariance is achieved by removing the down samplers and up samplers in the DWT and up sampling the filter coefficients by a factor of $2^{(j-1)}$ in the j^{th} level of the algorithm. The RWT is an inherently redundant scheme as the output of each level of RWT contains the same number of samples as the input – so for a decomposition of N levels there is a redundancy of N in the wavelet coefficients. The following block diagram depicts the digital implementation of RWT.

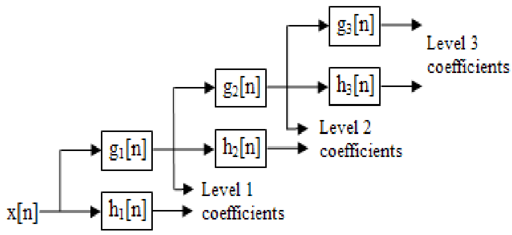


Fig. 2 RWT filter bank with 3 levels

In the above diagram, filters in each level are up-sampled versions of the previous (see figure below).

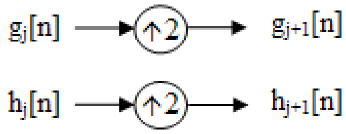


Fig. 3 RWT filters

Fig. 4 shows that the proposed block diagram which includes both discrete and redundant wavelet transforms for improving the image quality. First, the input LR image will be given as an input to the discrete as well as redundant wavelets to decompose them into sub bands. Then we will get the low frequency and high frequency sub bands with the size of half of the LR image and equals to the LR image. Now, added the high frequency sub bands of both wavelet transforms, by using interpolation for increasing the size of decimated LR image sub bands to obtain the new or estimated high frequency sub bands i.e., estimated LH, HL and HH. Finally, these sub bands and LR image were interpolated with the factor of $\frac{\alpha}{2}$ and applied inverse DWT to get the super resolute image with more improved quality than the DWT method in terms of PSNR and MSE.

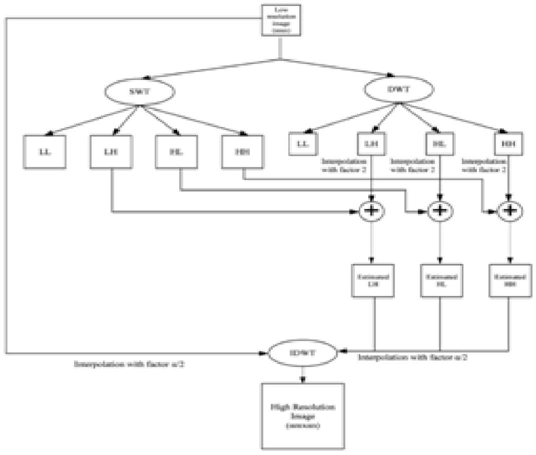


Fig. 4 block diagram of DRWT with interpolation method

3.1.2. Four Problems with Real Wavelets

In spite of its efficient computational algorithm and sparse representation, the wavelet transform suffers from four fundamental, intertwined shortcomings.

Problem 1: Oscillations

Since wavelets are bandpass functions, the wavelet coefficients tend to oscillate positive and negative around singularities. This considerably complicates wavelet-based processing, making singularity extraction and signal modeling, in particular, very challenging. Moreover, since an oscillating function passes often through zero, we see that the conventional wisdom that singularities yield large wavelet coefficients is overstated. Indeed, it is quite possible for a wavelet overlapping a singularity to have a small or even zero wavelet coefficient.

Problem 2: Shift Variance

A small shift of the signal greatly perturbs the wavelet coefficient oscillation pattern around singularities. Shift variance also complicates wavelet-domain processing; algorithms must be made capable of coping with the wide range of possible wavelet coefficient patterns caused by shifted singularities. To better understand wavelet coefficient oscillations and shift variance, consider a piecewise smooth signal $x(t-t_0)$ like the step function

$$u(t) = \begin{cases} 0, & t < 0 \\ 1, & t \geq 0 \end{cases} \quad (1)$$

analyzed by a wavelet basis having a sufficient number of vanishing moments. Its wavelet coefficients consist of samples of the step response of the wavelet

$$d(j,n) \approx 2^{-3j/2}\Delta \int_{-\infty}^{2^j t_0 n} \psi(t)dt \quad (2)$$

where Δ is the height of the jump. Since $\psi(t)$ is a bandpass function that oscillates around zero, so does its step response $d(j,n)$ as a function of n. Moreover, the factor 2^j in the upper limit ($j \geq 0$) amplifies the sensitivity of $d(j,n)$ to the time shift t_0, leading to strong shift variance.

Problem 3: Aliasing

The wide spacing of the wavelet coefficient samples, or equivalently, the fact that the wavelet coefficients are computed via iterated discrete-time down sampling operations interspersed with nonideal low-pass and high-pass filters, results in substantial aliasing. The inverse DWT cancels this aliasing, of course, but only if the wavelet and scaling coefficients are not changed. Any wavelet coefficient processing (thresholding, filtering, and quantization) upsets the delicate balance between the forward and inverse transforms, leading to artifacts in the reconstructed signal.

Problem 4: Lack of Directionality

Finally, while Fourier sinusoids in higher dimensions correspond to highly directional plane waves, the standard tensor product construction of M-D wavelets produces a checkerboard pattern that is simultaneously oriented along several directions. This lack of directional selectivity greatly complicates modeling and processing of geometric image features like ridges and edges.

3.2. DT-CWT Transform

The CWT is a complex-valued extension to the standard discrete wavelet transform (DWT). It is a two-dimensional wavelet transform which provides multiresolution, sparse representation, and useful characterization of the structure of an image. Further, it purveys a high degree of shift-invariance in its magnitude, which was investigated. However, a drawback to this transform is that it is exhibits is the dimension of the signal being transformed) redundancy compared to a separable (DWT).

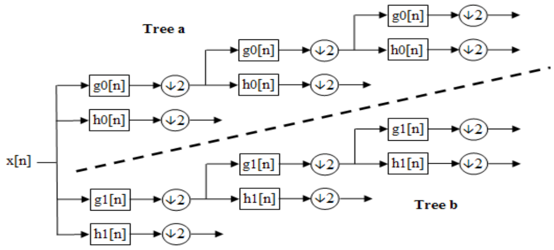


Fig. 5 Block diagram for a 3-level DTCWT

The Dual-tree complex wavelet transform (DTCWT) calculates the complex transform of a signal using two separate DWT decompositions (tree a and tree b). If the filters used in one are specifically designed different from those in the other, it is possible for one DWT to produce the real coefficients and the other the imaginary.This redundancy of two provides extra information for analysis but at the expense of extra computational power. It also provides approximate shift-invariance (unlike the DWT) yet still allows perfect reconstruction of the signal. The design of the filters is particularly important for the transform to occur correctly and the necessary characteristics are:

- The low-pass filters in the two trees must differ by half a sample period
- Reconstruction filters are the reverse of analysis
- All filters from the same orthonormal set
- Tree a filters are the reverse of tree b filters
- Both trees have the same frequency response

3.3. Proposed methodology

In this approach a new methodology of satellite image resolution enhancement has been introduced by using image fusion method, which is based on DT-CWT transform, this algorithm is an extension for all the existing RE methods.The proposed algorithm is described in fig. 6. Here, the output of section 3.1 is considered as the first input image and second one is a reference LR image. Now, we will apply DT-CWT transform to the both images to get the multi resolute coefficients with number of decomposition levels and first order, second order filters, then after we will calculate the new modified coefficients by applying the fusion rule with number of orientations and scales to get the HR image.

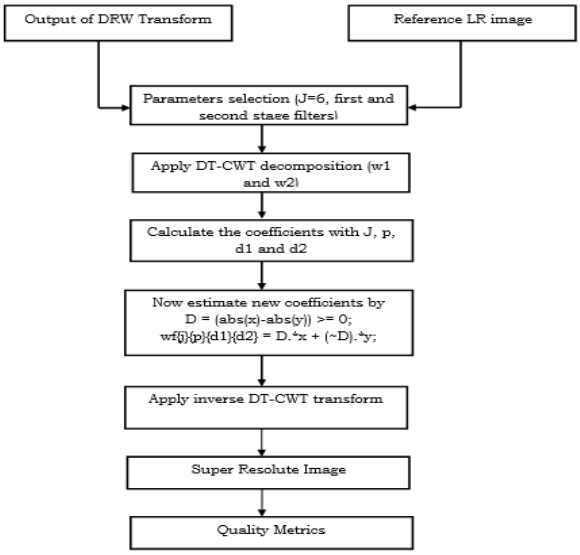
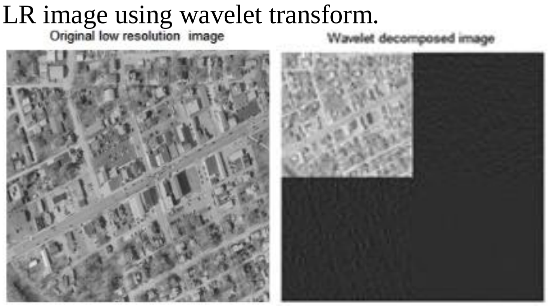


Fig. 6 Proposed RE scheme

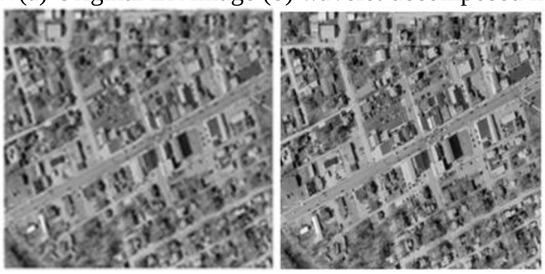
IV. SIMULATION RESULTS

Experimental results have been done in MATLAB 2014a version with 4GB RAM for high speed CPU performance and tested several satellite images taken from various satellite databases. Fig. 7(a) shows that the original LR image which has been taken for testing with proposed and existing RE methods and fig. 7(b) discloses that the decomposed LR image using wavelet transform.



(a)(b)

Fig. 7 (a) Original LR image (b) wavelet decomposed image



(a)(b)

Fig. 8 Obtained HR images (a) DWT-RE method (b) DRWT-RE method

The output of DWT-RE method has shown in fig. 8(a), in which the quality of the image has been increased.Fig. 8(b) shows that the obtained HR satellite image using DRWT-RE algorithm, we can observe that this approach has given better resolute image compared to the DWT-RE method. Further improvement in perceptual quality is achieved by using proposed RE method, which is disclosed in fig. 9.

Fig. 9 Proposed RE method

The quality metrics employed for assessing the quality of HR image over the original LR image is done with PSNR and MSE. DWT-RE method has got a PSNR of 34.9303 dB and DRWT-RE scheme performance is much superior to DWT-RE algorithm with a better PSNR value of 35.2336 dB and 41.348 dB is the obtained PSNR value of proposed RE method which is quite higher than the DWT-RE and DRWT-RE approaches. In addition, MSE is inversely proportional to the PSNR i.e., if the PSNR is high then the value of MSE will be lesser. This section also deals with the image quality assessment (IQA) metrics to measure the quality of resolute images. The IQA metrics used in this project are peak signal to noise ratio (PSNR) and mean square error (MSE).

$$PSNR = 10log10\left(\frac{255^2}{MSE}\right) \qquad (3)$$

Where, $MSE = \frac{1}{M\times N}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}(I-I')^2$

$$SSIM(x,y) = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x{}^2+\mu_y{}^2+c_1)(\sigma_x{}^2+\sigma_y{}^2+c_2)} \qquad (4)$$

Where

μ_x and μ_y are the mean of x and y.

$\sigma_x{}^2$ and $\sigma_y{}^2$ are the variances of x and y.

σ_{xy} is the covariance between x and y.

$c_1 = (k_1L)^2$ and $c_2 = (k_2L)^2$ are two variables to stabilize the division with weak denominator.

L is the dynamic range of the pixel values, $k_1 = 0.01$ and $k_2 = 0.03$

Table 1: Obtained quality metric values of proposed and existing RE schemes

	DWT-RE	DRWT-RE	Proposed
PSNR in dB	34.9303	35.2336	**41.348**
MSE	0.819	0.764	**0.1869**
SSIM	0.928	0.928	**0.966**

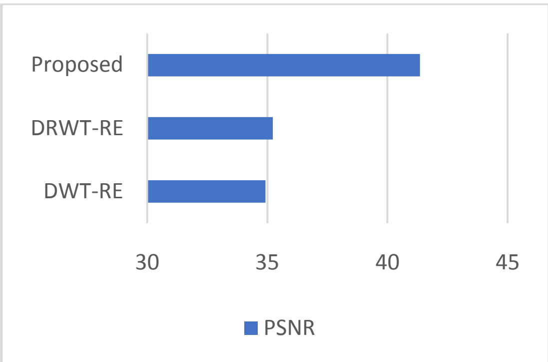


Fig. 10 Comparison of PSNR values with existing and proposed schemes

Table 1 demonstrates that the obtained quality metric values of PSNR, MSE and SSIM by employing the DWT-RE, DRWT-RE and proposed RE methods. The best values of obtained quality metrics is highlighted in bold letter for better visual perception. Moreover, the graphical representation of PSNR is disclosed in fig. 10. In addition, SSIM and MSE also depicted in fig. 11.

Fig. 11 Performance comparison of SSIM and MSE for the obtained resolute images of existing and proposed schemes

V. CONCLUSION AND FUTURE SCOPE

Here, in this a novel satellite image enhancement scheme has been proposed and compared with few existing RE algorithms like DWT and DRWT. Proposed algorithm is based on the fusion scheme which has been developed by using DT-CWT. Simulation results shows that the proposed algorithm has given better enhancement in terms of image quality assessment metrics like PSNR and MSE.In future, this can be improved for the 3D- satellite imaging by implementing more efficacious RE approaches to get HR image.

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