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Satellite Image Compression Using Dual Tree Complex wavelet Transform

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***Abstract**: Satellite images are composed of multiple bands of data covering a large spectrum of reflected light having some GB of data. For such huge amount of data, image compression is particularly important where the images must be compressed and sent over a limited bandwidth before analysis can take place. For various image processing applications, the wavelet transform is a more effective and powerful tool, but it has some limitations like shift invariance, poor directional selectivity and absence of phase information. Complex wavelet transform overcomes these limitations but perfect reconstruction using complex filter is very complicated. Hence approximate shift variant DT-CWT (Dual Tree Complex Wavelet Transform) is implemented in this paper with redundancy of 4:1. This transform provides approximate shift variance and directionally selective filters along with perfect reconstruction. In this paper very efficient DTCWT based (Set Partitioning In Hierarchical Trees algorithm) SPIHT algorithm optimized for progressive image transmission applied for satellite images is presented. It has been shown that proposed method for image compression gives better result in terms of PSNR and hence the image quality as compare to simple DWT.*

***Keywords:** DT-CWT, SPIHT (Set Partitioning in Hierarchical Trees),Wavelet transform, Complex wavelet transform.*

I. Introduction

Satellite image is considered as Multilayer Image which is form by "stacking" the images taken by different sensors from the same area at various wavelengths together [1]. Each component image forms a single layer of the multilayer image. The precise spectral information contained in such image enables better characterization and identification of targets. But sizes of such images are very large ranging from few megabytes to some gigabyte. So it is very expensive to store and slow to manipulate and transmit such huge amount of data. Hence there is need of compression. Image compression techniques are capable of substantially reducing image data, decreasing the costs, and improving user interaction with the information. Compression is nothing but removing redundancy and irrelevancy present in the image. Redundancy reduction means removing duplication from the signal source (image/video).Redundancy can be Spatial (correlation between neighboring pixel values), Spectral (correlation between different color planes or spectral bands) or Temporal (correlation between adjacent frames in a sequence of image).Irrelevancy reduction omits parts of the signal that will not be noticed by the signal receiver. So image compression research aims at reducing the number of bits needed to represent an image by removing the spatial and spectral redundancies as much as possible. Compression may be lossy or lossless. In lossless compression schemes [2], the reconstructed image, after compression, is numerically identical to the original image, but such methods gives very low compression ratio like (3:1) [2]. To achieve higher compression ratio lossless compression methods are used in which a reconstructed image contains some degradation relative to the original image. Compression is accomplished by applying a linear transform to decorrelate the image data, quantizing the resulting transform coefficients, and entropy coding it. The information loss in lossy coding comes from quantization of the data. The previous work carried out for satellite image compression has been reviewed in section-II. Proposed idea behind DTCWT and SPIHT implementation are given in section-III. Section IV presents the experiments carried out on satellite image and their results.

II. Previous Work

The previous approaches to the compression of satellite images include both transform and prediction based methods. In [3] cluster based DPCM method is used for the lossless compression to obtain good quality image. In which compression is mainly divided into three components: clustering, prediction, and coding. The clustering stage referred to the grouping of an image component. Instead of clustering each band, clustering of spectra is done using Linde–Buzo–Gray (LBG) [4] method. And then differences between the clusters indexes are saved instead of the indexes themselves hence called DPCM. Prediction were performed using a linear predictor in which the coefficients are optimized to minimize the mean-squared error inside each cluster, thus different predictor has been used for different cluster. Resulting residual band were entropy-coded, again separately for each cluster. This [3] has given very low compression ratio. To obtain a good encoding performance with limited complexity, many researchers rely on transform coding techniques where a linear transform decorrelate the input data and concentrates most of the power in a few coefficients so that subsequent quantization is more efficient. KLT (Karhunen and Michel Loeve Transform) has high spectral decorrelation property [5]. However, the better performance of the KLT comes at the price of increase in computational cost and at the price of not being scalable as it needs prior statistical information. Ian Blanes [6] used a KLT and multilevel clustered approach together to reduce computational cost of KLT. He had given two multilevel clustering [7] combinations for satellite image compression: Static and dynamic clustering. Lossless compression rates reported with [6] shows that little impact is produced by the use of the static clustered approach but for dynamic cluster approach it produces larger bit streams. Azam Karami [8] considered the spatial correlation along with spectral decorrelation in his work. He considered satellite image as 3D data called as third-order tensor having two spatial dimensions and one spectral dimension. Two dimensional WT is applied to each spectral band by using (9/7) biorthogonal wavelet and then TD (Tucker Decomposition) is applied to the four wavelet sub-images in order to achieve more compression ratio. These elements of the core tensors were coded using adaptive arithmetic coding (AAC). But the total computational complexity [8] found to be very high, given by four times computational complexity of tensor, added with computational complexity of 2D DWT, which further increases with more level of decomposition.

III. Proposed Work

Although the DWT is found to be good for many image processing applications it has some following limitations [9].

- Oscillations of the coefficients at a singularity (i.e. near edges).
- Shift variance where small changes in the input cause large changes in the output coefficients.
- Aliasing due to down sampling and non-ideal filtering during the analysis.
- Lack of directional selectivity in higher dimensions, e.g. inability to distinguish between + 45 degree and – 45 degree edge orientations.

It is found that all the limitations of DWT can be solved effectively by the complex wavelet transform (CWT).The structure of CWT is as shown in fig.1,where out of two ouputs of lowpass and highpass filter, 1 corresponds to real part and other corresponds to imaginary part.CWT filter have complex coefficients and generate complex output samples. Each sample contains a real and imaginary part, thus redundancy of 2:1 is introduced for 1-D signals [10].The important property of these complex wavelet is that their phase varies approximately linearly with input shift. Thus based on measurement of phase shifts, efficient displacement estimation is possible. The extension of complex wavelets to 2-D is achieved by separable filtering along rows and then columns. However, as two adjacent quadrants of the spectrum are required to represent fully a real 2-D signal, we also need to filter the signal with complex conjugate of either the row or column filters. This leads to 4:1 redundancy in the transformed 2-D signal. Complex filters in multiple dimensions provide true dimensional selectivity, for example a 2-D CWT produces six band pass sub images of complex coefficients at each level, which are strongly oriented at angle ±15, ±45, ±75.

For many application it is important that the transform should be perfectly invertible. Unfortunately it is difficult to design an inverse transform, based on complex filters discuss above. Although such filters can be designed to give PR (Perfect Reconstuction) quite easily at level 1 of tree by applying the constrained that the output signal must be real, a similar constraint cannot be applied at further levels where inputs and outputs are complex [10].

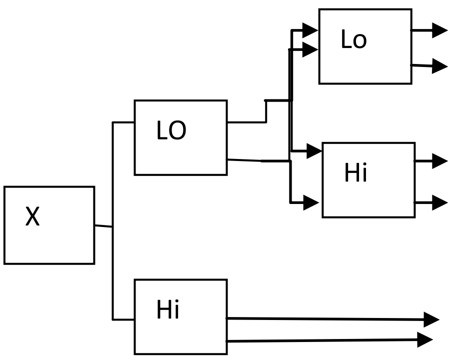

Fig.1. Complex wavelets transform.

Hence a different approach for generating complex coefficients needs to be used. So we have used Dual tree Complex Wavelet Transform (DTCWT), which has following properties [9]:

- Approximate shift invariance;
- Good directional selectivity in 2-dimensions (2-D).
- Perfect reconstruction (PR)
- Limited redundancy, independent of the number of scales, 2 : 1 for 1-D (2m : 1for m-Dimension);

In proposed method we have taken DTCWT (Dual tree Complex Wavelet Transform) of image and then SPIHT algorithm has been applied. DTCWT consist of two conventional DWT filter bank trees (tree a and tree b) working in parallel, with respective filters of both the trees in approximate quadrature to obtain real (from tree a) part and imaginary part (from tree b) of complex wavelet coefficients as shown in fig 2. For encoding we have first found out the magnitude of the coefficients (from real and imaginary part obtained after transform) and then significant coefficient magnitude was coded using SPIHT. SPIHT is progressive encoding method which uses spatial orientation tree structure.The result of this implementation were compared with traditional DWT based SPIHT method. The details of the DTCWT and SPIHT are discussed in following sections.

i. DTCWT

The DT-CWT comprised of 2 parallel wavelet filter bank tree a and tree b, which contain carefully designed filters of different delays to minimize the aliasing effects due to down sampling. Sub-band images of the tree a can be interpreted as the real part of a complex wavelet transform and that of the tree b can be interpreted as the imaginary part as in fig 2, where downward arrow shows down sampling by 2 operation.When designed in this way, the DT-CWT is nearly shift- invariant, in contrast to the classic DWT. Moreover, to achieve the correct relative signal delay, the total delay difference for a given level and all previous levels must sum to one sample period at the input sample rate of the given level. Hence the filters below level 2 in one tree must provide delays that are half a sample different (at each filter's input rate) from those in the opposite tree [11]. For linear phase filters, this requires odd-length filters in one tree and even-length filters in the other [12]. Note that the filters in the first stage of each tree are diferent from the filters in all the later stages. Further there is no complex arithmetic involved in any of the trees. The complex coefficients are simply obtained as (1)

$$X_j^c = X_a + jX_b \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Where Xa represents the coefficients obtained from tree a and Xb are from tree b.The inverse DTCWT is calculated by 2 normal inverse wavelet transforms, one corresponding to each tree and the results of each of the 2 inverse transforms are then averaged to give the reconstructed signal. Again, there is no complex arithmetic needed, since, the $X_j^c(k)$ coefficients are split up into $X_a(K)$ and $X_b(k)$ before they are used in the corresponding inverse transforms [11].

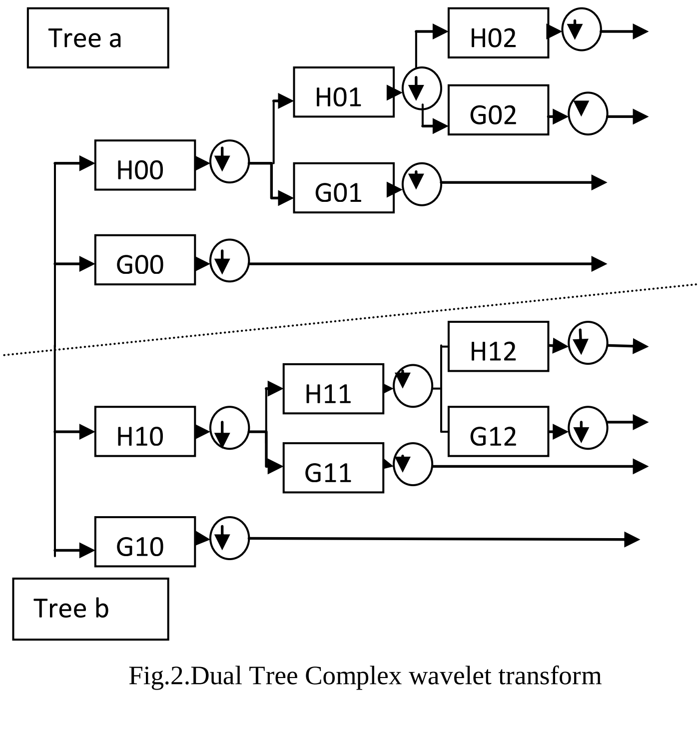

Fig.2.Dual Tree Complex wavelet transform

ii. SPIHT (Set Partitioning in Hierarchical Trees) Algorithm

SPIHT is wavelet based compression method, which is a generalization of the EZW algorithm [13] and was proposed by Amir Said and William Pearlman [14].The SPIHT algorithm uses a partitioning of the trees called spatial orientation trees [15] as shown in fig.3 in a manner that tends to keep insignificant coefficients together in larger subsets.

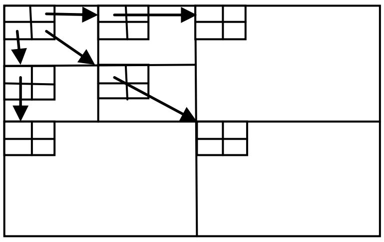

Fig.3. Spatial Orientation Tree

The data structure used by the SPIHT algorithm is similar to that used by the EZW algorithm—although not the same [14]. In order to keep track of the various sets, algorithm uses three list [14]: LIP (List of Insignificant Pixels); one for LSP (List of significant pixel) and LIS (List of significant set). All single coefficients which are not yet tested at the current threshold are put into the LIP. And those which are found to be significant are put into LSP. And sets which are not yet tested at the current threshold are put into the LIS.

The following set of data structure is used to present this coding algorithm:

- O(i, j): set of coordinates of all offspring or child of node (i , j);
- D (i, j): set of coordinates of all descendants of the node (i, j);
- H (i, j): set of coordinates of all nodes in the lowest spatial frequency sub band (roots of tree);
- L (i, j) = D (i, j) − O (i ,j), the grand-descendant set as shown in fig 4.

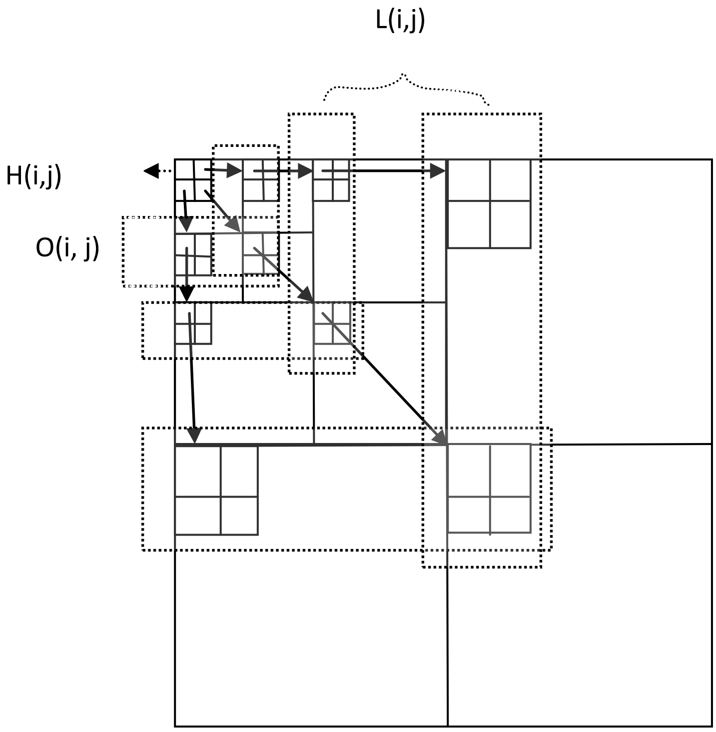

Fig.4. Spatial Orientation Tree showing data structure used

When a tree is splitted, the coordinates of the child nodes go to the LIP, coefficients with their value greater than threshold are moved to LSP and the locator of a grand-descendant set goes to the LIS. Applied SPIHT Encoding algorithm is as given below [12].

iii. Encoding Algorithm:

Step 1: Initialization

n = log2 (max | coefficient |)

LIP = All elements in H
LSP = Empty
LIS = D's of Roots
Significance is tested based on threshold using

$$S_n(i, j) = 1,\ for\left|C_{i,j}\right| \geq 2^n$$

Step 2: Significance Map Encoding ("Sorting Pass")

a) Process LIP: for each coefficient (i, j) in LIP
1. Output Sn (i, j)
2. If Sn (i, j)=1, Output sign of coefficient (i, j): 0/1 = -/+ And Move (i, j) to the LSP
3. End loop over LIP

b) Process LIS: for each set (i, j) in LIS
1. if (type D),then Output Sn (D(i, j))
    i. If Sn (D(i, j))=1, then for each (k, l) $\in$ O(i, j)
    ii. output Sn (k, l)
    iii. if Sn (k,l)=1, then add (k,l) to the LSP and output sign of coefficient: 0/1 = -/+
    iv. if Sn (k, l)=0, then add (k, l) to the end of the LIP
2. if (type L),then Output Sn (L(i,j))
    i. If Sn (L(i, j)) =1,then add each (k ,l) $\in$ O(i,j) to the end of the LIS as an entry of type D
    ii. remove (i, j) from the LIS
3. End loop over LIS

Step 3: Refinement Pass

c) Process LSP
1. for each element (i, j) in LSP – except those just added above, Output the nth most significant bit of coefficient
2. End loop over LSP

Step 4: Update

d) Decrement n by 1 and Go to Significance Map Encoding Step2.

IV. Result And Discussion

Here we are presenting the results of a number of experiments carried out on satellite image. We have used a satellite image composed of six bands, each consisting 512 X 512 pixels with each pixel value represented using 8-bits. To implement this algorithm we have used MATLAB2012a tool. First, we have applied DTCWT [16] to the 2D image to get real and imaginary coefficients and then SPIHT algorithm is applied for coding the significant coefficients. The effectiveness of proposed algorithm has been analyzed using PSNR values calculated using following equation (2) [17];

$$PSNR = \frac{(2^n - 1)^2}{MSE} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Where n is the no. of bit used to represent 1 pixel in the original image and MSE is mean square error given by equation (3):

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(X_{i,j} - X_{ri,j})^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Where Xi,j represents original image and Xri,j represents reconstructed image and M,N are the dimension of image. For decomposition level equal to 4 Table I shows the PSNR values obtained for DWT and that for the DTCWT at different BPP (Bit Per Pixel) rate. Similarly Table IIshows the result for decomposition level equal to 5. Result shows that DCWT outperforms compared to DWT. It has been seen that applying SPIHT separately to real and imaginary parts gives quite improved result than that with applying SPIHT on magnitude of complex coefficients for higher level of decomposition, but at the expense of increase in size of compress image.

TABLE I. COMPARISON FOR LEVEL 4

Rate	Wavelet Transform (level 4)	
	DWT	DTCWT
0.1	15.90	15.85
0.2	17.26	17.41
0.3	18.20	18.21
0.4	18.78	18.80
0.5	19.29	19.37

TABLE II. COMPARISON FOR LEVEL 5

Rate	Wavelet Transform (level 5)	
	DWT	DTCWT(using magnitude)
0.1	16.91	17.18
0.2	17.88	18.15
0.3	18.59	18.81
0.4	19.08	19.40
0.5	19.62	19.99

V. Conclusion

The simulation results for classical Separable DWT and Complex Dual-Tree DWT shows that the proposed method gives significant improvement in terms of image quality and preserves the useful information from the original image. The filter banks in DTCWT for image compression is nearly shift invariant, in contrast with the critically sampled DWT. SPIHT is based on partial ordering by magnitude with a set partitioning sorting algorithm, ordered bit plane transmission, and it takes the advantage of self-similarity across different scales of an images obtained after wavelet transform. So this progressive encoding method based on dual-tree complex wavelet transform gives better results as compare to separable DWT for various applications, with increase in level of decomposition result shows more improvement.

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