Entropy Based Multispectral Image Compression with High Resolution Improved SPIHT Using Symlet Wavelet

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Abstract— The utilization of Multispectral images had gained more popularity in the recent decades due to their current development of image acquisition using multispectral sensors technology. This proposed work explores a rather new way of investigating lossy multispectral compression from a different perspective of extracting their spectral information, referred to as exploitation based lossy compression which further explores the spectral/spatial components to effectively preserve the crucial and vital spectral information of objects. Super resolution transformation based DWT with sym8 wavelet using Improved SPIHT algorithm is proposed to give better performance results for PSNR and Compression Ratio when compared with previous well known compression methods and existing discrete wavelets.

Keywords:
Multispectral Images, DWT, ISPIHT, LIBT, LIST.

1. INTRODUCTION

The multi-spectral cameras are widely used in various applications and they are very expensive when compared with three color RGB cameras, e.g. a resolution of 1360×1024 image comprises of five multispectral sensor cameras which are high in cost with respect to a single sensor RGB camera with less resolution. Most multispectral cameras have a separate array of sensor used for each and every band of the Electro Magnetic spectrum. Large numbers of mechanical and optical parts are used in image acquisition with separate sensor arrays which obviously increases the cost and their size. Many researchers have proposed various methods for compressing the multispectral images with various encoding and decoding schemes. Principal component analysis transforms the images in the spatial and spectral dimensions and its main advantage is that it not only provides the most decorrelated sub bands, but also gives the best energy compaction, which in turn gives best and optimum results for better image classification. The basic disadvantage of the PCA algorithm is its covariance matrix, which is to be decorrelated among various frequency bands, and thus it is very much data dependent. Many of the researchers have used the vector quantization (VQ) and Karhunen-Loeve transform (KLT) on the spectral and spatial dimensions to explore the correlation among various multispectral bands [1]. In this work we propose a new algorithm for the lossy compression of Multispectral images which is based on DWT and Modified SPIHT. This proposed algorithm provides a better picture image quality in metric terms of high PSNR than the other conventional compression methods using symlet wavelets.

The requirement for the Need and Classification of image compression in multispectral images is explained in section 2. The Proposed Compressive Technique for super resolution of multispectral images with Improved SPIHT for Multispectral images using various wavelet based image compression is explained in section 3. To further enhance and substantiate the simulation results, real multispectral image experiments of various datasets are further performed and conducted to evaluate the proposed work in terms of CR, MSE, SSIM, PSNR, Entropy and CC with existing DCT KLT [2], DWT SPIHT [3] algorithms in Section 4. We conclude and present perspectives in Section 5.

2. NEED FOR IMAGE COMPRESSION

Images are compressed mainly to transmit the image data in a more compatible form and to remove the various redundancies which are present in the images to a larger extent. Compression is done to store and to transmit it in a more efficient form. The uncompressed image data is very large in size and to store or retrieve/transmit this uncompressed image requires a considerable amount of storage capacity and transmission bandwidth. Multispectral images comprises of two main types of redundancies called as Spatial Redundancy and Spectral Redundancy. Spatial redundancy refers to the correlation among neighboring pixels. This redundancy is mainly occurred because of the patterning, or self-similarity within an image. Spectral Redundancy occurs between different color planes or spectral bands

3. PROPOSED COMPRESSION TECHNIQUE

A. Super-Resolution

The Image super resolution approach [4]-[5] using a generic image prior like gradient profile prior, is a parametric prior describing its shape and sharpness of the image gradients. Super-resolution is a method to estimate a hi-resolution (HR) image from its low-resolution (LR) input. There are basically three approaches for this problem given by interpolation methods, reconstruction methods, and learning methods. In this proposed method we use bicubic interpolation approach for increasing the resolution of the compressed images.

B. Multiresolution 2-D wavelet decompression

In various image processing applications like image compression, denoising, reconstruction, feature extraction, and image registration [6]-[8], wavelet transform is proven to have more advantages. A two dimensional DWT, comprises of a two dimensional scaling function (x, y), and three two dimensional wavelets, given by φH(x, y), φV(x, y), and φD(x, y).These are used to measure various functional variations, like intensity variations for image along different directions.H is used to measures variations along columns (for example horizontal edges), V is used to measure variations along rows (likes vertical edges) and D is used to measure variation along diagonals.

C. Wavelet Transforms

The information of the signals is transformed into different interpretations using various mathematical transforms for space frequency localization. For example Fourier Transforms convert the signals from time domain to frequency, but the relevant information to a particular class of frequencies at specific intervals is not provided. This shortcoming is overcome by means of window based STFT technique where both time and frequency information at different parts of the signal and at different instants of time is obtained. However due to Heisenberg's uncertainty principle the image resolution gets much worse in frequency domain as and when the resolution of the signal gets improved in time domain by zooming at different sections of the signal. Thus multiresolution provides the required enhancement for the major parts of the signal both in time domain and the remaining parts in frequency domain. The image is expressed as a sum of wavelet functions with different image scales and locations with the support of Wavelet Transform which exhibits a high ratio of energy compaction with decorrelation properties.

D. Wavelet families

Different family of wavelets are mathematically designed and developed for discrete wavelet transform with compactly support by means of low pass and high pass analysis and synthesis filters for optimum orthogonality and biorthogonality. Haar wavelet, Daubechies wavelet, Symlets wavelet, Coieflets wavelet, Meyer wavelet, Biorthogonal wavelet and Morlet wavelet etc are a few families of wavelets available. These wavelets are highly supported by the orthogonal and biorthogonal wavelets. Based on the particular application and its analyzing functionality a wavelet is chosen to perform its operation to give optimum results.

E. Symlet wavelets

Since Daubechies wavelets are used to select the minimum phase square root whose energy is concentrated nearly at the starting point of the support of the signals and are they are not symmetric in nature. When compared to other wavelets symlets are nearly symmetric wavelets which are proposed by Daubechies. These are the modifications to the existing Db family of wavelets which are used to select each other set of roots for closer symmetry with linear complex phase. The other properties of Daubechies and symlets families are very much similar apart from their symmetry. The peak signal to noise ratio (PSNR) of the reconstructed and decompressed image is improved using symlets wavelets.

F. Improved Set Portioning of Hierarchical Trees

The SPIHT algorithm is an efficient implementation of EZW (Embedded Zero Wavelet) [9] algorithm which was developed by Shapiro. There are manly two passes in this algorithm given by the sorting pass and the refinement pass. The ISPIHT encoding process uses three lists *LIBT* (List of Insignificant Block Test) which contains individual coefficients as a block and has magnitudes lesser than the thresholds, *LIST* (List of Insignificant Sets Test) which contains set of wavelet coefficients that are well defined by their tree structures and nearly found to have magnitudes lesser than the threshold,*LSP* (List of Significant Pixels) which has a list of pixels found to have magnitudes larger than the threshold (significant) and *VT* (vector Tree) corresponding to *LIST*. The sorting pass [10] is well performed on the above three lists as shown in Fig.1.

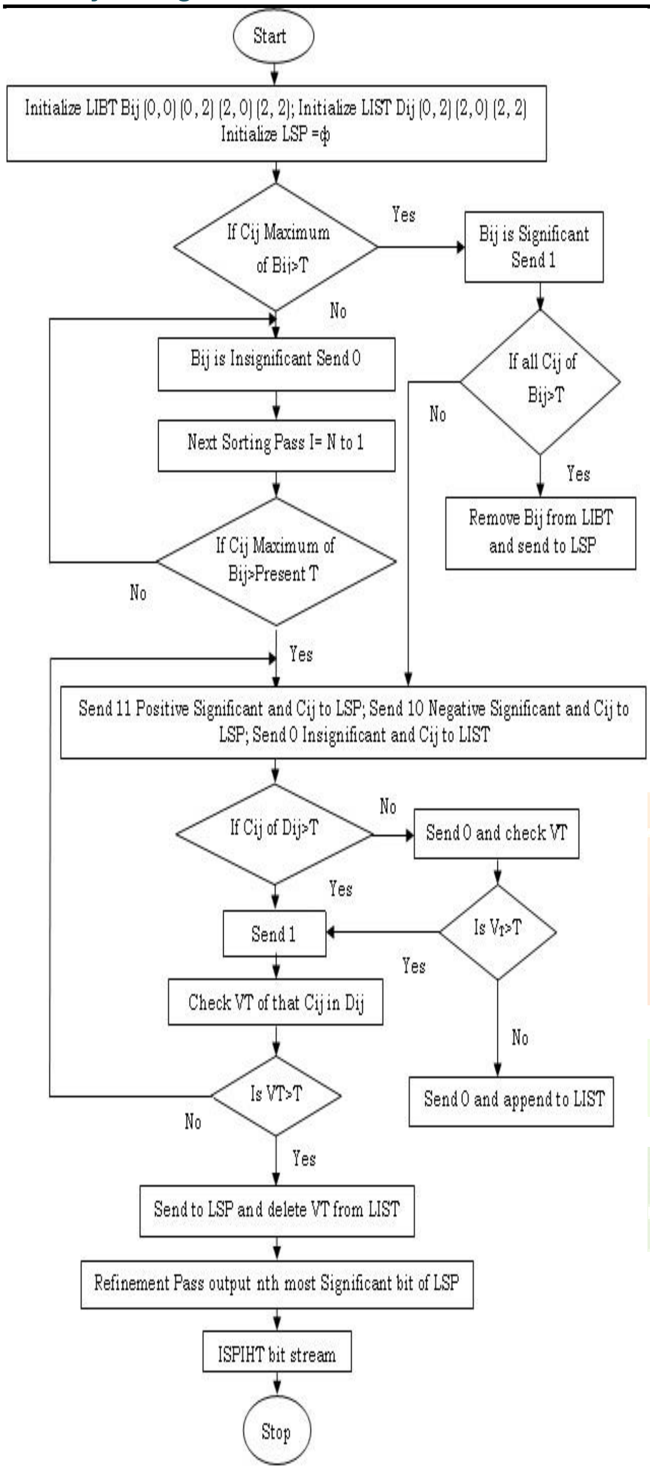

Fig.1. Flow chart of ISPIHT algorithm

Algorithm: ISPIHT Coding

Initialization: LIBT={B(0,0), B(0,2), B(2,0), B(2,2)}, LIST={D(0,2), D(2,0), D(2,2)}, T=2n, Cij is wavelet matrix coefficient and LSP is empty.

n = |log 2(max(i,j) |Ci,j|)| (1)

$C_{i,j}$ is the matrix coefficient after DWT and (i, j) is the coordinate of $C_{i,j}$.

Sorting pass:

For I=1 to N

Output: Bit stream

Input: Wavelet co-efficient or data matrix to be coded, A, the number of threshold levels, N.

Assign LIBT={ A(0,0), A(0,2), A(2,0), A(2,2)}

Assign LIST with VTs for coordinates (0, 2), (2, 0) and (2, 2) as type-0 descendent trees.

Compute Vm, M, VT (Vector Tree), Threshold (as described in the Initialization).

Assign LSP=0;

LIST Testing:

For each pixel in the LIST

If a pixel is found to be significant
Send a 1, followed by a sign bit.
Delete the pixel form LIST and append its absolute value to LSP.
Else
Send a 0
End if
End For each
For each VT in LIST
If the type of VT is 0
If VT is significant
Send a 1
For each of the four pixels associated with the node of the VT.
If a pixel is significant,
Send a 1 followed by sign bit.
Append the absolute value of the pixel to LSP.
Else
Send a 0
Append the pixel to LIST
End If
End For each
If VT has more than 1 element
Neglect the first element, change its type to 1 and append to LIST.
End If
Else
Send a 0
End If
Else
If VT (of type-1) is significant
Send a 1
Generate VT corresponding to the four top leftmost pixel co-ordinates of the four 2x2 sub-matrices associated with current node.
Delete the VT from the LIST.
Else
Send a 0
End If
End If
End For each
Refinement Pass:
For r=1 to LSP
If (LSP(r) –Threshold)>=Threshold/2
Send a 1
Else
Send a 0
End if
End For
Lp1=No. of pixels in the LSP
Threshold=Threshold/2;
End For

4. PERFORMANCE EVALUATION

This work describes discrete wavelet transform when applied on the image matrix to get the wavelet coefficients whose magnitudes are then quantized and encoded and decoded using ISPIHT algorithm. Experiments have been conducted on various Real multispectral image datasets like the LAN file of little co river which is captured using the MATLAB(R) function multiband read. The proposed technique with Improved SPIHT exploits the symmetrical quality of symlet8 wavelet and explicitly compresses the image data with good quality when compared to the conventional methods like DCT KLT, DWT SPIHT in terms of PSNR, MSE, CR, Entropy, SSIM and CC which are implemented in mat lab R2016b as shown in Fig.2.Their comparative results for PSNR,MSE,CR and Entropy, SSIM, CC for DCT KLT, DWT SPIHT and Proposed method in terms of various multispectral Images are shown in Table I and Table II respectively. The comparative results of various multispectral images are shown from Fig.3 to Fig.7 respectively as taken from the database.
In the MSE measurement the total squared difference between the original signal and the reconstructed one is averaged over the entire signal. Mathematically,

$$MSE = \frac{1}{N}\sum_{i=0}^{N-1}\left(\hat{x}_i - x_i\right)^2 \qquad (2)$$

Where $\hat{x}_i$ is the reconstructed value of x_i , N is the number of pixels. The mean square error is commonly used because of its convenience. A measurement of MSE in decibels on a logarithmic scale is the Peak Signal-to-Noise Ratio (PSNR), which is a popular standard objective measure of the lossy codec.

$$PSNR = 10 \log_{10} [255^2 / MSE] \quad (3)$$

The entropy is the measure of amount of information of the pixels contained in an image given by

$$H = -\sum_{k=0}^{M-1} p_k \log_2(p_k) \quad (4)$$

where M is the number of gray levels and p_k is the probability associated with gray level k.
The correlation coefficient (CC) is given by

$$r = \frac{\sum_i (x_i - x_m)(y_i - y_m)}{\sqrt{\sum_i (x_i - x_m)^2}\sqrt{\sum_i (y_i - y_m)^2}} \quad (5)$$

where, xi and yi are intensity values of ith pixel in 1st and 2nd image respectively. Also, xm and ym are mean intensity values of 1st and 2nd image respectively. The correlation coefficient has the value r =1 if the two images are absolutely identical, r= 0 if they are completely uncorrelated and r= -1 if they are completely anti-correlated.
Compression Ratio can be determined as the ratio of the original dataset to the compressed dataset
CR=Bits of original image/Bits of compressed image (6)

Table I: Comparative Results of various Multispectral Images for 0.4 bpp in terms of PSNR, MSE and CR

Image	METHOD	PSNR	MSE	CR
Little Co river	DCT KLT	27.337	120.05	1.2020
	DWT SPHIT	30.294	60.761	1.5181
	PROPOSED	**40.308**	**6.0571**	**3.0151**
Paris City	DCT KLT	35.561	18.070	1.8572
	DWT SPHIT	32.447	37.012	1.2065
	PROPOSED	**44.317**	**2.4064**	**2.0312**
Vizag City	DCT KLT	19.704	696.05	1.0090
	DWT SPHIT	22.627	355.08	2.3168
	PROPOSED	**31.451**	**46.554**	**4.9292**
Forest Image	DCT KLT	20.419	590.40	1.5229
	DWT SPHIT	21.375	473.75	2.4911
	PROPOSED	**34.305**	**24.127**	**4.3676**
Montana	DCT KLT	36.238	15.462	1.0436
	DWT SPHIT	36.623	14.150	0.8712
	PROPOSED	**44.306**	**2.4123**	**2.1167**

Table II: Comparative Results of various Multispectral Images for 0.4 bpp in terms of Entropy, SSIM and CC

Image	METHOD	Entropy	SSIM	CC
Little Co river	DCT KLT	1.5228	-0.009	-0.028
	DWT SPHIT	6.2776	0.9893	0.9410
	PROPOSED	**6.2876**	**0.9812**	**0.9942**
Paris City	DCT KLT	2.3175	-0.020	-0.014
	DWT SPHIT	4.9235	0.9943	0.7940
	PROPOSED	**4.5337**	**0.9308**	**0.9847**
Vizag City	DCT KLT	1.1911	0.0078	-0.0930
	DWT SPHIT	7.8168	0.9272	0.9581
	PROPOSED	**7.6288**	**0.9158**	**0.9955**
Forest Image	DCT KLT	1.2905	-0.003	-0.0124
	DWT SPHIT	7.3113	0.8838	0.9119
	PROPOSED	**6.4468**	**0.8371**	**0.9953**
Montana	DCT KLT	2.0763	-0.0599	-0.0889
	DWT SPHIT	4.8719	0.9985	0.8973
	PROPOSED	**5.1882**	**0.9937**	**0.9918**

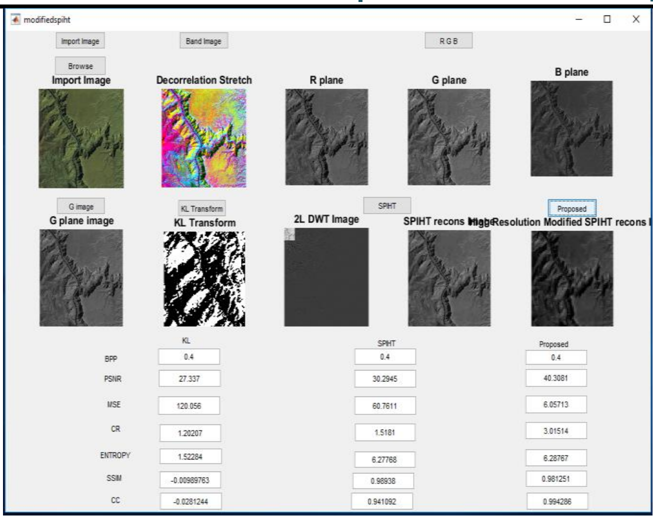

Fig.2. MATLAB Results for sym8 wavelet transform for 0.4 bpp of little co river multispectral image

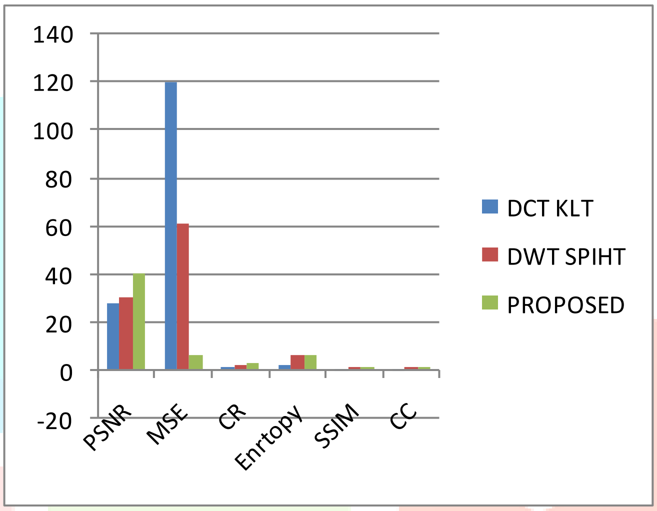

Fig.3. Comparative Results of various methods for Little Co river Land sat Multispectral Image for 0.4 bpp

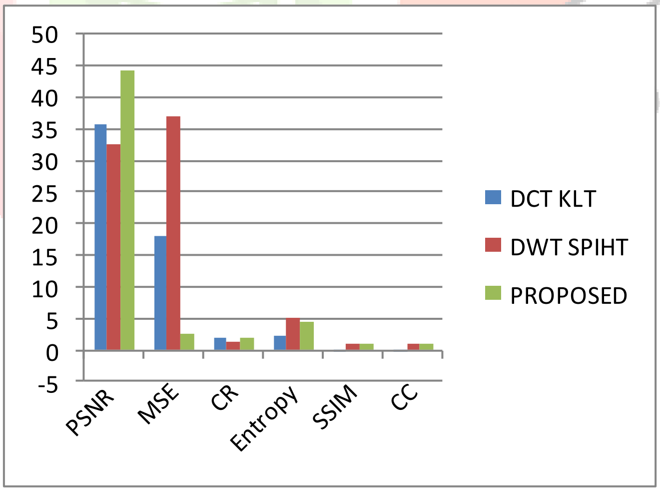

Fig.4. Comparative Results of various methods for Paris City Land sat Multispectral Image for 0.4 bpp

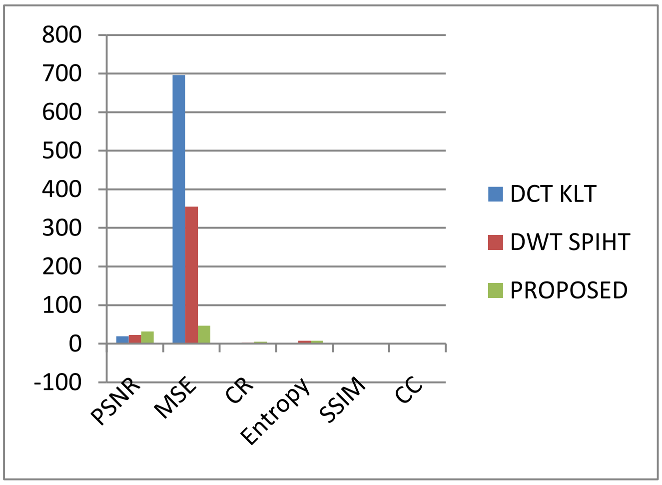

Fig.5. Comparative Results of various methods for Vizag City Land sat Multispectral Image for 0.4 bpp

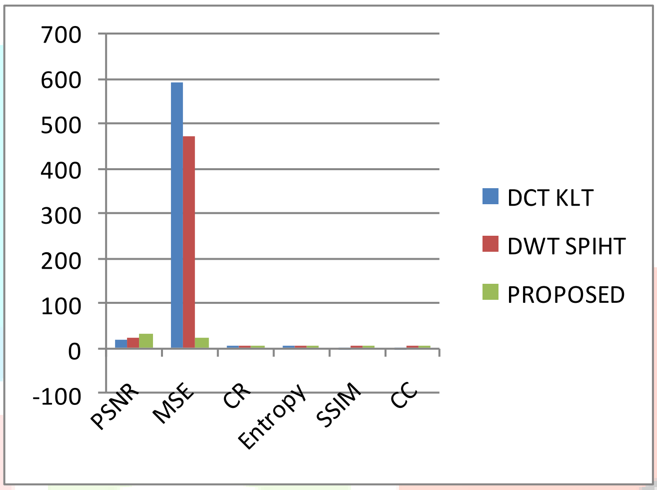

Fig.6. Comparative Results of various methods for Forest Land sat Multispectral Image for 0.4 bpp

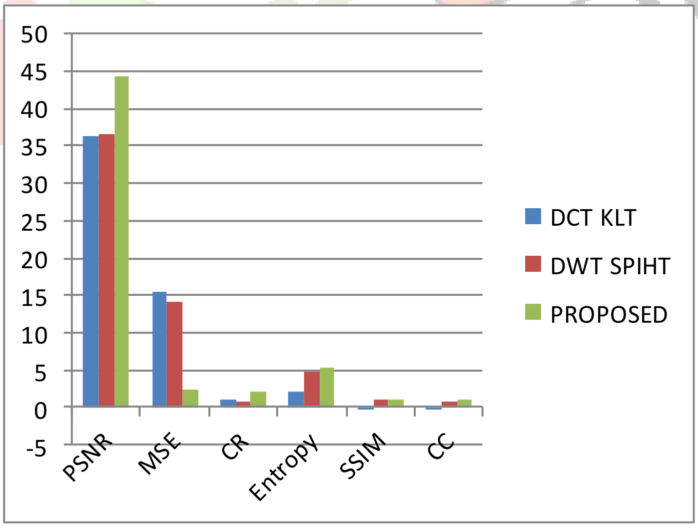

Fig.7. Comparative Results of various methods for Montana Land sat Multispectral Image for 0.4 bpp

5. CONCLUSION

This proposed work is comprised of using a discrete wavelet called symlet8 along with Improved SPIHT algorithm for bit allocating to the encoded and decoded bit stream of multispectral images optimally at the time of compressing and decompressing the images. There exists a spectral correlation among the subclasses of the biorthogonal wavelet which effectively quantizes the wavelet coefficients of the DWT. The above work is compared with the traditional techniques like DCT KLT, DWT SPIHT and superior results were obtained with the proposed algorithm. The compression can be done to a larger extent even by exploiting spatial, spectral and temporal correlations as well. This frame work can be extended to compressive sensing, denoising applications and video compression.

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