Low Complexity DCT-based DSC approach for Hyperspectral Image Compression with Arithmetic Code

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Abstract

This paper proposes low complexity codec for lossy compression on a sample hyperspectral image. These images have two kinds of redundancies: 1) spatial; and 2) spectral. A discrete cosine transform (DCT)- based Distributed Source Coding(DSC) paradigm with Arithmetic code for low complexity is introduced. Here, Set-partitioning based approach is applied to reorganize DCT coefficients into wavelet like tree structure as Set-partitioning works on wavelet transform, and extract the sign, refinement, and significance bitplanes. The extracted refinement bits are Arithmetic encoded, then by applying low density parity check based (LDPC-based) Slepian-Wolf coder is implement to our DSC strategy. Experimental results for SAMSON (Spectroscopic Aerial Mapping System with Onboard Navigation) data show that proposed scheme achieve peak signal to noise ratio and compression to a very good extent for water cube compared to building, land or forest cube.

Keywords: Image compression; hyperspectral image; distributed source coding (DSC); discrete cosine transform (DCT); Arithmetic code; low complexity.

1. Introduction

Hyperspectral imaging is a powerful technique and has been used in large number of applications, such as geology,earth-resource management, pollution monitoring, meteorology, and military surveillance. Hyperspectral images are three-dimensional data sets, where two of the dimensions are spatial and the third is spectral. These images are acquired by observing the same object (area or target) in multiple narrow wavelength slices at the same time and reveal the reflection, transmission, or radiation features of the observed object in multiple spectral bands.

The 2D- DCT technique was proposed by Z. Xiong, O Guleryuz, M T Orchard[1], for transform coefficients coding. Owning to high correlation of hyperspectral image, in particular the correlation across frequency bands, DSC is applied into hyperspectral image to obtain a lowly complex and highly effective lossy compression. For DSC can shift the complexity between encoder and decoder, compared to traditional source coding. Slepian and Wolf have proved the feasibility of DSC scheme and ensure that such encoder can theoretically gain the same efficiency of the joint one as shown if fig 1[2].

In [3], Wyner and Ziv provide the lossy extension of Slepian-Wolf coding. The application of DSC theory to hyperspectral image has been widely used recently. Enrico Magli proposed two different lossless compression DSC-based ways [4][5][6]. N.-M. Cheung puts forth the DSC based lossy method in DWT domain, named set-partitioning in hierarchical tree with Slepian-Wolf coding (SW-SPIHT) [7,8]. It demonstrates that the presented application is very promising.

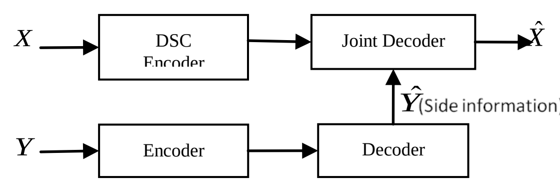

Figure 1 DSC based compression scheme.

In the above context, the present research work proposes low complexity hyperspectral image compression on the basis of DSC in DCT domain, rather than DWT domain. It is found that hyperspectral image is highly correlated not only in DWT domain but also in DCT domain. Moreover, the complexity of DWT is inferior to that of DCT. It is well known that DCT-based coder is much easier than DWT-based one. [9,10] show that the calculation quantity of DCT is much smaller. Jianrong Wang, Rongke Liu modifies the Zixiang Xiong’s embedded zerotree discrete cosine transform (EZDCT) algorithm [11]. The proposed

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approach the zerotree quantizer in SPIHT and choose the SPIHT coder instead of EZW coder. It is used to extract bitplanes of reordered DCT coefficients. Arithmetic code is also introduced, arithmetic coding depends mainly on the estimation of the probability model that the coder use and the arithmetic coding approach the entropy of the source[12]. The smaller the entropy of the input data is, the higher the compression ratio is. According to DSC theory, the inter-band correlation of DCT domain can be exploited at the decoder side to attain the same compression ratio as the joint compression of the various bands. The refinement bitplanes are Arithmetic encoded. Afterwards, [6] LDPC-based Slepian-Wolf coder is adopted to the Arithmetic codes and sign bits in order to generate syndromes. These syndromes are conveyed to the decoder, while the significance bits are transmitted straightly.

2. Codec Design

It has been observed that DCT-based coder has lower complication than its DWT-based one. This paper, bring forth low complexity DSC-based hyperspectral image compression in DCT domain with Arithmetic code. For one thing, the implementation of DCT is less expensive than that of WT. Besides, the regrouped DCT coefficients with waveletlike tree structure and high dependency help us not merely employ wavelet-based coder to obtain better reconstruction quality than traditional DCT-based ones and EZW coder, but also apply DSC technique at lower cost than most wavelet-based ones.

2.1 DCT-Based Subband Representation

Fig.2 states the process of regrouped 8×8 DCT coefficients [13]. First, an image (N×N) is divided into n×n blocks. Second, each of the blocks is transformed to DCT domain and can be treated as an L (L=log2n) level tree. Third, the corresponding coefficients from all DCT blocks are rearranged together into a new wavelet like subband.

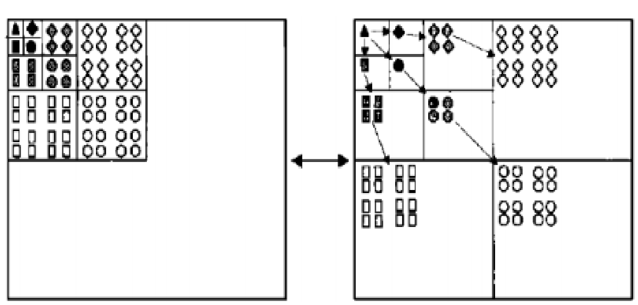

Figure.2 Process of DCT coefficients regrouping.

2.2 DCT-Domain Correlation Analysis

For close relationship between source and side information is the vital factor of DSC principle, therefore this paper discuss whether there is dependency in the reorganized DCT domain. The intra-band (i.e., spatial) and inter-band (i.e. spectral) correlation are analysed, the correlation coefficient with normalization and discretization are defined as follows.

$$R(l,k)=\frac{\sum_{x=1}^{M}\sum_{Y=1}^{N}\left[f(x,y)-u_f\right]\times\left[f(x+1,y+k)-u_f\right]}{\sum_{x=1}^{M}\sum_{y=1}^{N}\left[f(x,y)-u_f\right]^2} \quad (1)$$

Where,
$R(l,k)$ = intra-correlation value; M×N = *size*, $f(x,y)$ = pixel grey value labeled with space coordinate (x,y); uf = the image's average grey value; l and k = the distance of analyzed pixels.

$$H(l,k)=\frac{\sum_{x=1}^{M}\sum_{y=1}^{N}f(x+l,y+k)g(x,y)}{\sqrt{\left\{\sum_{x=1}^{M}\sum_{y=1}^{N}[f(x,y)]^2\right\}\left\{\sum_{x=1}^{M}\sum_{y=1}^{N}[g(x,y)]^2\right\}}} \quad (2)$$

Where,
$H(l,k)$ = inter-correlation value; $f(x,y)$ and $g(x,y)$ = the pixel grey value of two different bands; l and k = the relative distance of analyzed pixels between the two bands.

The inter band correlation results are shown in Fig.3. The x-axis represents band number of hyperspectral image and y-axis represents correlation coefficient. Fig.3 illustrates that most bands have a correlation coefficient close to one, except those noisy bands. The relationship at the corresponding point is much closer than that of other positions. This suggests the feasibility of DSC principle.

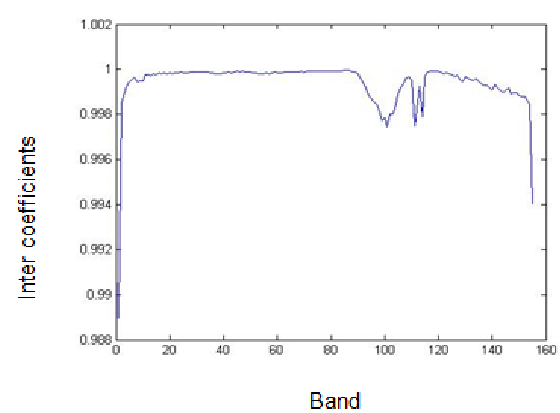

Figure 3 Spectral correlation curve of hyperspectral SAMSON image

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From the above graph, it is observed that the first few bands have low spectral correlations. Whereas, the bands after 11th band are highly correlated with each other.

3. The proposed Architecture

The hardware (or software) implementation of DCT transform is less expensive compared to that of DWT. Zixiang Xiong's EZDCT[14] algorithm is better than most DCT-based coder like baseline JPEG and improved JPEG, and even better than Shapiro's wavelet-based EZW coder [8]. Moreover, it is available of Arithmetic code to exploit bit level's correlation and reduce the corresponding error bit rate. Hence, referring to EZDCT, DSC-based method in DCT domain with Arithmetic code is applied to satisfy our compression requirement.

The scheme is composed of transforming, estimation, bitplanes extraction via set partitioning algorithm, Arithmetic encoding, LDPC-based Slepian-Wolf coder and reconstruction. Three crucial procedures are DCT transform instead of Wavelet transform, improvement of side information by estimation, and bitplane technique with Arithmetic code. The following describes in detail about the proposed paradigm showed in Fig.4. Take into consideration two adjacent highly correlated hyperspectral bands, the current band to be coded and the previous band coded already, symbolized as X_i and X_{i-1} respectively.

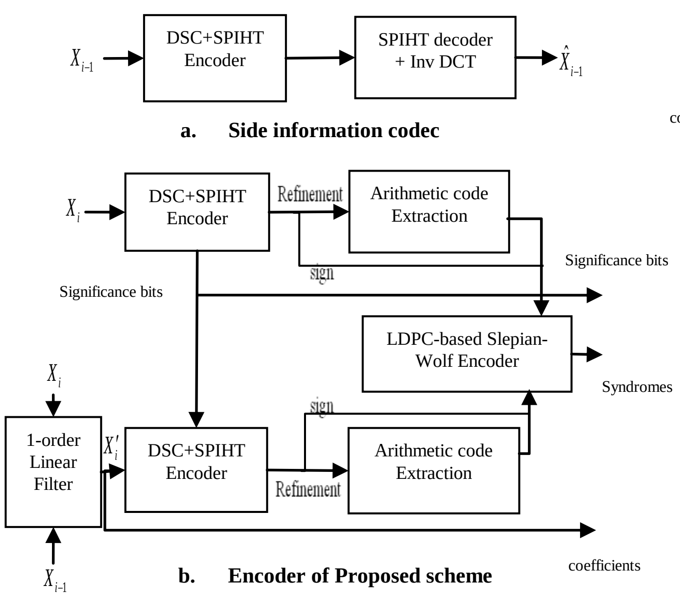

Figure 4 Encoder block diagram of proposed scheme

Fig.4.a diagrammatically stated that the reference band X_{i-1} is transmitted by modified EZDCT, and its reconstructed image $\hat{X}_{i-1}$ is generated and offered at the decoder. More particularly about the modification, zerotree quantizer in SPIHT algorithm is use and substitute SPIHT coder for EZW coder.

Fig.4.b shows the model of the encoder, which is applied to the band X_i to be coded by DSC approach in DCT domain. First, set-partitioning method is adopted to extract bitplanes of regrouped DCT coefficients, generating significance, sign and refinement. Then, Arithmetic code is introduced to encode refinement bits. Arithmetic code is then applied directly to extract all bitplanes in conventional approach. So as to realize the DSC strategy, LDPC-based Slepian- Wolf coder is then employed to encode sign and refinement bits to yield syndromes. The compression ratio relies on the value of crossover probabilities. The crossover probabilities are considered in the corresponding bitplane location of X_i and X_i', representative of the predicted *Xi* obtained by the linear filter. So the significance tree of X_i *is applied* to the regrouped DCT coefficients of X_i' to extract sign and refinement bitplanes. These generated sign and refinement bits are compared to those of X_i and calculate the rate. The need to transmit the coefficients of the one-order linear filter is required because it is unknown to the decoder. Along this way, more precise version of band X_i, i.e. $\tilde{X}_i$ can be generated.

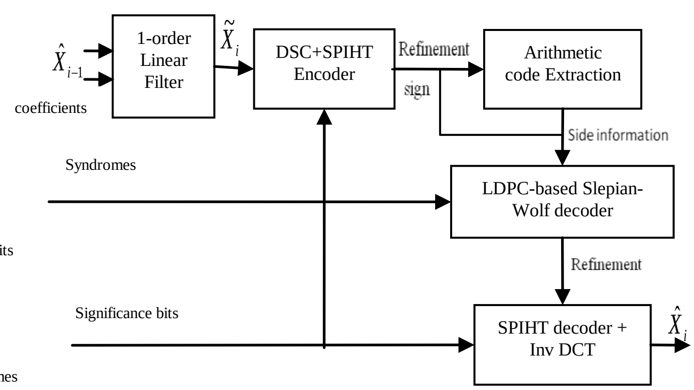

Figure 5 Decoder block diagram of proposed scheme

As is showed in Fig.5, at the decoder side, the estimated value $\tilde{X}_i$ is adopted, instead of directly using $\hat{X}_{i-1}$. This is useful in DSC method because the quality of the side information decides the compression ratio to a degree. Once the significance bits produced at the encoder are passed to the decoder, the $\tilde{X}_i$'s sign and refinement bits are reconstructed and are available as side information. Then, with the precise side information and conveyed syndromes,

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LDPC-based Slepian-Wolf decoder is introduced to reconstitute sign and refinement bits.

4. Techniques used in DSC-based coder

Hyperspectral image exhibit a significant amount of dependency, and one-order liner filter, i.e. $X_i^{'} = a \times X_{i-1} + b$ provides an approximate version of X_i at the encoder, so that the difference between X_i and X_{i-1} can get smaller. By this means, the Slepian-Wolf coder can obtain better performance due to DSC theory. Pixels between the X_i and X_{i-1} are applied to calculate the coefficient a and b that fits the data best in a least squares sense.

For our DSC-based strategy, the bitplanes are extracted to reorganized DCT coefficients into binary data because the using LDPC-based coder performs best for binary form. This process generates sign and refinement bitplanes, and significance bitplanes which represent the waveletlike tree structure. Besides the coefficients' correlation at the corresponding location between the two bands is the highest. Therefore the significance bits of X_i are use to index the structure of X_{i-1} and generate sign and refinement bits of X_{i-1}.Particularly $\widetilde{X}_i$,the estimated reconstructed X_{i-1}, as substitute of X_{i-1}, is applied at the decoder. These produced sign and refinement bits are provided as side information of DSC-based framework.

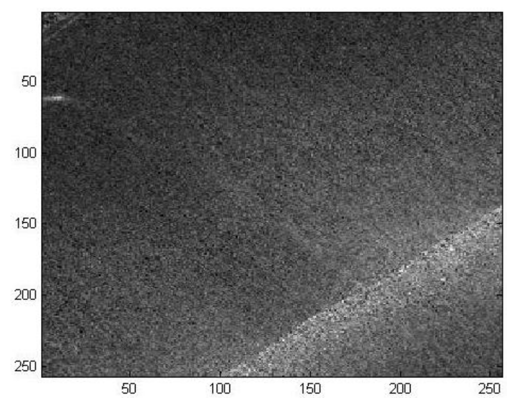
Moreover, the Arithmetic encoding is use to enhance the relationship of source and side information. In DSC system, higher correlation between source and side information can achieve better coding efficiency. In most cases, natural binary code is employed. However, this natural binary code is inappropriate when the values of source and side information are very close but the binary representations are remarkably diverse. Hence natural binary code potentially degrades the correlation, and Arithmetic code is obviously used to replace natural binary code. So as to further fulfill the scheme's requirement for easily implementation, Arithmetic encoding is adopted to all DCT coefficients directly. It is merely applied to represent the refinement bits rather than all bitplanes, which can not only significantly reduce the amount of Arithmetic codes, but also make full use of the advancements of Arithmetic code. It is noticed that the sign bits are not Arithmetic encoded. Because sign bitplane is merely one bitplane, and the difference between source and side information hardly exists, Arithmetic encoding is not essential.

5. Results and discussion

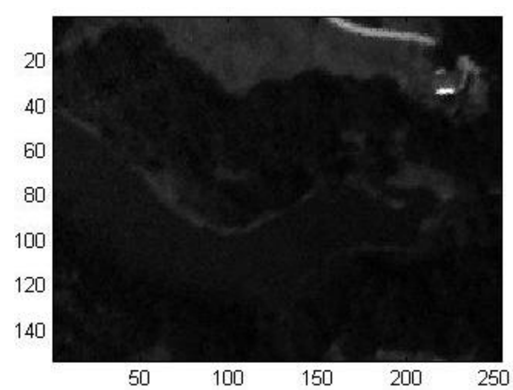
The software implementation of the algorithm is written in a Matlab environment using Matlab7.7 software. The hyperspectral dataset used, is generated by the SAMSON sensor. It covers the spectral range of 400nm-900nm with a band width of 3.2nm. The data was collected by the Florida Environmental Research Institute as part of the GOES-R sponsored experiment.

The instrument flown during the collect is the SAMSON, a push-broom, visible to near IR, hyperspectral sensor. This sensor was designed and developed by FERI [15]. They have 156 contiguous bands and 952X952 pixel resolution. The 256X256 up left corner is extracted for the experiments. Each pixel in each band has 8 bits of radiometric information.

Four HIC's are shown below. While the land image was utilized as test data. All the scenes consist of 156 spectral bands covering the visible and near-infrared spectral window (wavelengths from 400nm to 700nm). Band 1 of each scene is shown in Figure 5.4. The scene are of different spatial sizes- 257×256, 153×253, 257×157, and 151×257 for "water", "forest", "building" and "land" images, respectively. Each pixel in each band has 8 bits of radiometric information.



(a)"Water" cube



(b)"Forest" cube

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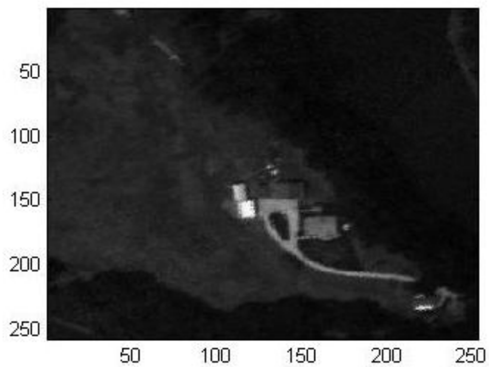
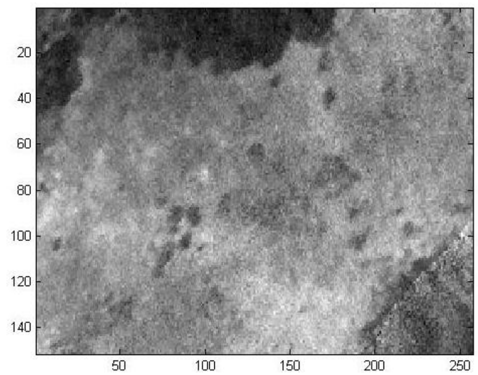


(c)"Building" cube



(d)"Land" cube

Figure 6 Examples of different scenes or cube(band 1).

5.1 Quality Measurement Definitions

There exist different performance measures for verification of coding algorithms. In order to make a fair comparision between the techniques, the same performance measure must be used, preferably on the same hyperspectral data. It is known that this type of imagery is not necessarily viewed by human visual system (HVS). Although the reconstructed cubes were examined also by a subjective quality criterion (visual quality, artifacts like blockiness, smoothness etc.), it is obvious that the true quality can be measured mainly according to the specific application the encoding is used for.

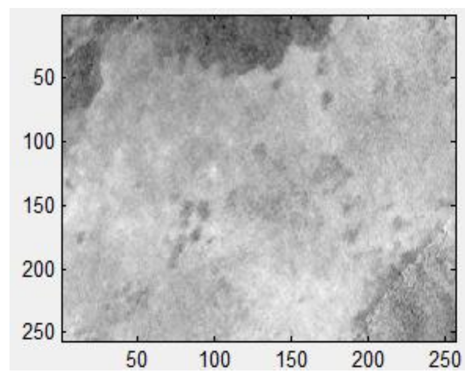
In this paper it was decided to measure the performance with the following performance measures:
Peak signal-to-noise ratio (PSNR): This is a commonly used quantitative fidelity criteria (in image processing applications). Let X_i be the original pixel in spatial position of the spectral band b (of size N×M) and $\hat{X}_i$ the respective reconstructed pixel, then for each spectral band $1 \le b \le 156$, $PSNR_b$ is defined by

$$PSNR_b = 10\log_{10}\left(\frac{255^2}{\frac{1}{NM}\sum_{x=1}^{N}\sum_{y=1}^{M}\left[X_i - \hat{X}_I\right]^2}\right) \qquad (3)$$

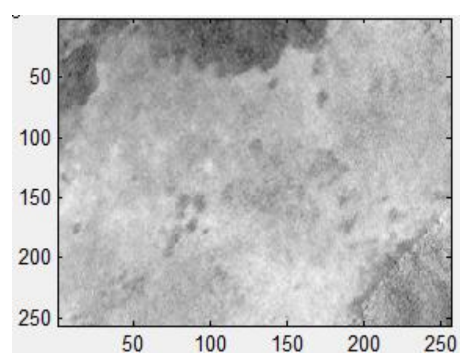
An average PSNR is obtained as the quality measure, where the averaging is performed over B spectral bands:

$$\overline{PSNR} = \frac{1}{B}\sum_{b=1}^{B} PSNR_b \qquad (4)$$

(B=156 in our image).
The higher PSNR would normally indicate that the reconstruction is of higher quality. It is measured in decibels (dB).



(a) Original land cube band 1



(b)Reconstructed band 1(PSNR= 51.0184dB, at 0.2bpp,CR= 49.45%)

Figure 7 Examples of the algorithm used for performance measurement of land cube.

Fig.8 shows the average PSNR for hyperspectral SAMSON image as 42.66dB.
This figure shows PSNR obtained by the implemented algorithm on land image.

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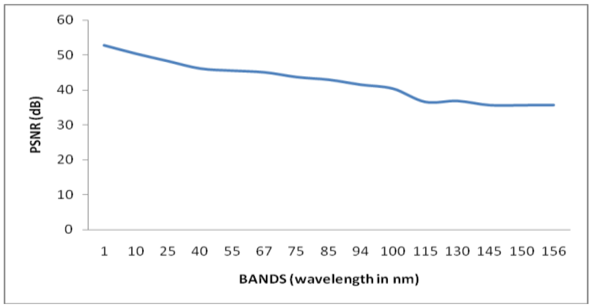
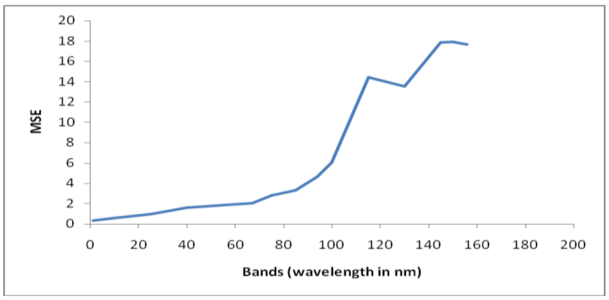
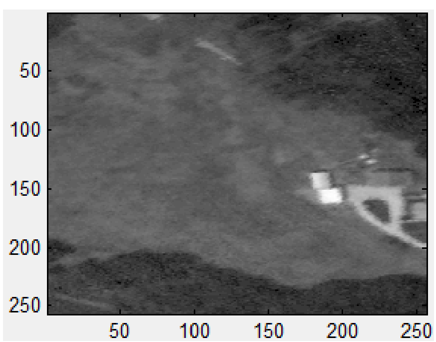


(a) PSNR of hyperspectral land image at different wavelengths



(b) MSE of hyperspectral land image at different wavelengths

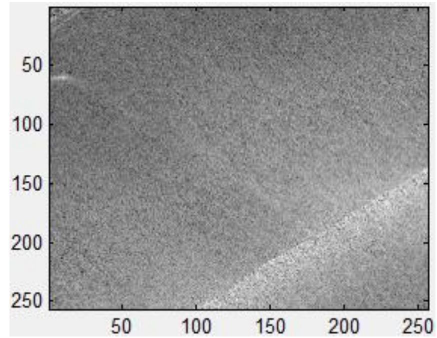
Figure 8 PSNR and MSE at different wavelength(400nm to 900nm)



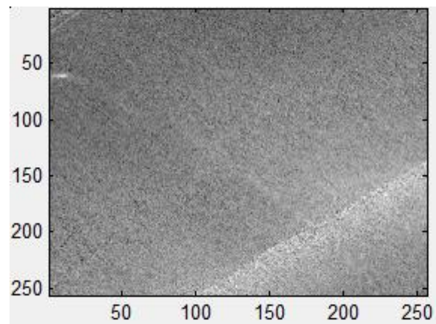
(a) Original building cube band 1

(b)Reconstructed band 1(PSNR= 48.3266dB, at 0.2bpp,CR= 35.09%)

Figure 9 Examples of the algorithm used for performance measurement of building cube.



(a) Original water cube band 1



(b)Reconstructed band 1(PSNR= 52.7722dB, at 0.2bpp,CR= 52%)

Figure 10 Examples of the algorithm used for performance measurement of water cube.

Table 1: PSNR of different image cubes at different wavelengths(bands)

BAND	***PSNR***		
	WATER	***BUILDING***	***LAND***
1	52.7722	48.3266	51.2961
10	52.1164	45.1874	48.8515
25	50.5957	42.8504	46.4606
40	47.4585	40.8409	44.1433
55	47.1728	40.0821	43.0656
67	49.546	38.5117	41.3444
75	50.0125	37.4868	40.3314
85	51.534	36.3623	38.8738
94	51.4536	35.2795	37.6516
100	53.7355	34.5676	36.9302
115	53.7355	31.2275	33.3583
130	53.7355	31.6653	33.755
145	53.7355	30.4444	32.4173
150	53.7355	30.4901	32.4041
156	53.7355	30.6178	32.4969

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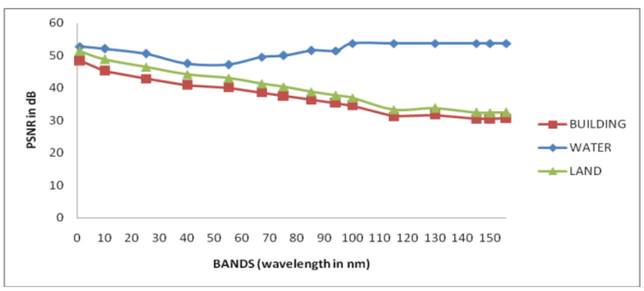
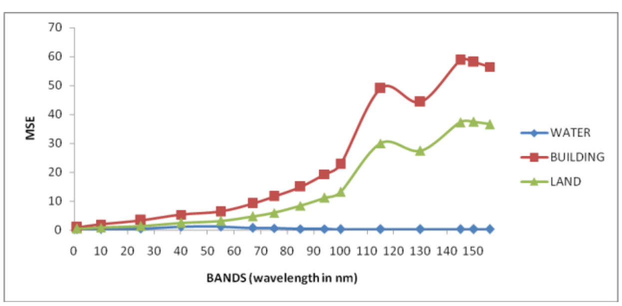
Table 2: MSE of different image cubes at different wavelengths(bands)

BAND	***MSE***		
	WATER	***BUILDING***	***LAND***
1	0.34345	0.95591	0.48247
10	0.39943	1.9695	0.84708
25	0.56691	3.3732	1.469
40	1.1674	5.3579	2.5046
55	1.2468	6.3808	3.2101
67	0.72191	9.1604	4.7713
75	0.64838	11.5984	6.0248
85	0.45675	15.0263	8.4275
94	0.46529	19.2811	11.1666
100	0.27512	22.7155	13.1843
115	0.27512	49.0156	30.0091
130	0.27512	44.3154	27.3895
145	0.27512	58.7	37.2692
150	0.27512	58.0857	37.3827
156	0.27512	56.4023	36.5924



(a) PSNR of hyperspectral land image, water image and building image at different wavelengths.



(b) MSE of hyperspectral land image, water image and building image at different wavelengths

Figure 11 PSNR and MSE of different image cubes at different wavelength(400nm to 900nm)

6. Conclusions

Discrete cosine transform is a versatile tool in hyperspectral remote sensing which is utilized for various applications such data compression. DCT and SPIHT are the most widely used methods for compression of hyperspectral image. In this paper, DCT based DSC technique using arithmetic code was conducted in order to estimate their performance on hyperspectral imagery.

The DCT based DSC using arithmetic code were examined using SAMSON hyperspectral sample data. The performance of these algorithms is evaluated based on PSNR of the compressed image and compression ratio.
PSNR= 42.66152 dB, CR = 48%
From MSE, it is observed that the difference between original and reconstructed image is very small. A higher PSNR indicate that the reconstruction is of higher quality. It can also be stated from the observation that PSNR is good for Water cube as compared to building cube may be due to spectrometer range.

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