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Hyperspectral Image Compression Using Prediction-based Band Reordering Technique

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Abstract—The hyperspectral image represents various spectral properties Because it consists of broad spectral information of ground materials that can be used for various applications, These images are collected as large amounts of data that must be processed and transmitted to the ground station. These acquired images contain redundant spectral information that has to be reduced in order to reduce transmission and storage capacity. This work focuses on preserving their quality while compressing them using band reordering techniques and prediction coding. This can be accomplished by preprocessing in which sub-bands are decomposed and bands are reordered into unsequenced compression can be accomplished through using the technique of linear prediction. The report discusses the Pavia University hyperspectral image data cube, which was acquired via a sensor known as a reflected optics system imaging spectrometer (ROSIS-3) over the city of Pavia, Italy**.**

Keywords— band reordering, compression techniques, Hyperspectral image, prediction-based techniques, transformation-based techniques.

1. Introduction

Remote sensing technology works with materials to identify and describe their properties using light, and the interaction of light with materials is known as spectroscopy. It investigates how light behaves in the target and uses the spectral signature to identify the material. A spectral signature identifies a spectrum material. The amount of light at various wavelengths is referred to as the spectrum. A spectrometer splits the incoming light into a spectrum. This reflecting spectrometer is commonly employed in hyperspectral imaging (HSI). The hyperspectral camera is used to capture HSI, which is used in imaging spectrometers. Which produces an image by measuring dozens or hundreds of thousands of spectra. Each spectrum contains data. This gathered spectrum contains a massive quantity of data and is shown in Fig.1 as 3D. As a result, transporting this data requires more bandwidth, so the amount of information must be reduced.

Remote sensing plays an important role in a variety of applications that require reliable data processing, such as medical diagnosis, environmental monitoring, pharmaceuticals, forensic science, food, and so on. It is challenging to store and transmit hyperspectral images. To reduce the challenges of hyperspectral images ie, a huge amount of data, it is necessary to use more efficient lossless or lossy compression techniques [6]. The use of lossless compression algorithms preserves all information and allows the user to restore the original spectrum data from the compressed data, but it is difficult to achieve and fulfil the problems of onboard data transmission [6].

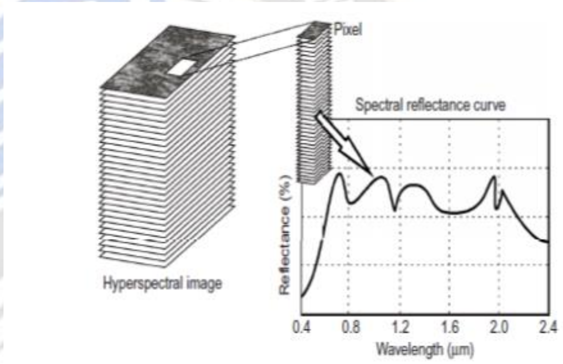

Fig. 1. Spectral Image

However, hyperspectral image data was collected using hundreds of continuous bands. Because of transmission bandwidth and storage limitations in remote sensing, it is extremely difficult to transmit raw data. There is a significant relationship between the spatial and spectral bands in this image; therefore, an efficient compression strategy is necessary to decrease the spatial and spectral correlations.

There are three types of hyperspectral image compression techniques: prediction-based techniques, vector quantization, and transformation techniques based on lossy and lossless image compression [16].

Lossy compression, on the other hand, provides a high compression ratio, this ratio is achieved by sacrificing the low distortion rate; This means that more losses will appear on the reconstructed data; this causes losses affecting the process of earth's object identification [22]. Another way to compression is known as lossless; this approach achieves a higher

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compression ratio than the lossless approach and lower distortion than lossy compression approaches.

Researchers are currently searching for the ideal solution that will fit within satellites. Most of the research focuses on using either the spectral or spatial redundancy of hyperspectral data; spatial redundancy results from the same spatial dimensions that will be present when capturing a particular area, and these properties are extensively investigated. Due to this, we have wavelet transformation and discrete cosine transformation, which make use of spatial redundancy in images. However, since spectral redundancy is a relatively new aspect of hyperspectral imaging, numerous studies have been conducted to examine the best ways to deal with it . This fact has led to a new area of research and analysis of the spectral structure of hyperspectral data, which will provide the main outlines and solutions for how to use inter-band spectral correlation most effectively [1] [10] in hyperspectral data.

This study is focused on lossless compression with prediction-based reordering technique. The predictor in prediction-based algorithms predicts the similarities between a neighboring pixel and spectral bands. the predictor will carry out a decorrelator for all of the original data, and the coder will calculate the prediction error. This study developed a discrete wavelet transform [5], which decomposed or normalized bands. A greedy approach based on a structural similarity index matrix and correlation coefficient [4] is used to rearrange bands, which is then converted into one-dimensional data using image scanning techniques. Finally, prediction-based coding is used to predict future values based on previous sequences, as well as the estimated error frame, for greater compression. This stage yields two results: predicted value and error value. and These errors are encoded and compressed in the output. The output of this may be sent to the decoding stage. The reverse operation is used on the receiver side to obtain the original image.

The paper is organized as follows: Section II describes the proposed methodology, which deals with DWT, Band Normalization, Section III describes band reordering, which deals with Structural Similarity, Greedy algorithm, and rearranging Bands, Section IV provides the Compression technique using Huffman encoding, Section V results, and discussion, and the concluding remarks are given in Section VI.

2. Proposed Methodology

This study is a band reordering algorithm in the preprocessing stage. This study begins with a preprocessing stage that results in strongly correlated unidimensional sequences. This sequence is used at the step of prediction-based compression. This stage produces prediction coefficients and prediction errors. These errors are encoded and compressed in the output. The output of this is passed to the decoding stage. The decoder stage involves reconstructing unidimensional data that is similar to the output of the preprocessing stage, whereas the post-processing stage involves the reconstruction of original data using transformation techniques. Fig. 2 depicts the process flow of the suggested methodology.

2.1. 2D-Discrete Wavelet Transform

For better compression, discrete wavelet transforms are used. This gives images with a spatial-frequency domain as well as eliminating noise and redundancy.

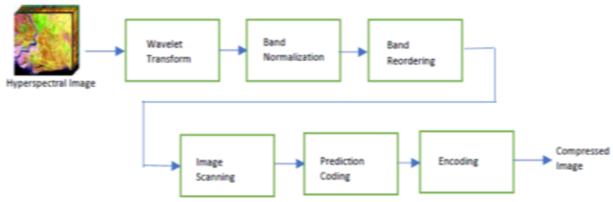

Fig. 2. Process Flow

Subband decomposition is discussed in this study. Discrete Wavelet Transform (DWT) [5][19] employs filter banks, which are typically applied to dimensional images. However, because the data in each band is two-dimensional, this filter bank approach is only applicable to 2D images. This can be accomplished by first applying a one-dimensional filter bank on the row of two-dimensional images and then moving along the column of images, or vice versa.

The original image is considered to be at the highest resolution, so it is decomposed into four parts Low Low, Low High, High Low, High High bands, shown if Fig 4.and then we repeat the process with the LL subband coefficients and decompose into four parts again [7-8]. After decomposition, each image at each level of the decomposition retains only one-fourth of the total image samples, allowing us to obtain finer resolution. The primary goal of wavelet analysis is to extract the spatial and frequency localization. Subband decomposition can be used to determine whether spatial locations have high and low frequencies.

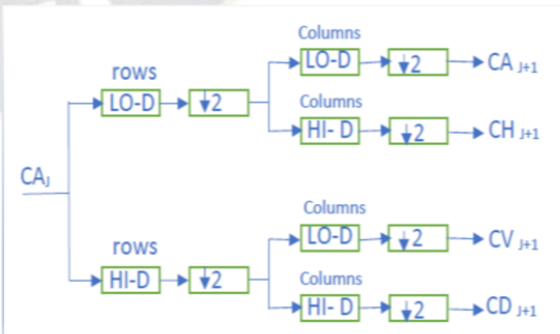

Fig. 3. Subband decomposion

Low Low Image (CA)	Low to High Image (CH)
High to Low Image (CV)	High to High Image (CD)

Fig. 4. Sub-band decomposition

2.2. Band Normalization

Band normalisation is a procedure that alters the range of image intensity values by converting all input values into ranges set between minimum and maximum values [9]. Band normalization uses scaling methods to scale values down to the given range. All of the pixel input values in the band are scaled within the desired range. Image normalisation works in the same way. Linear normalisation is used in band normalisation and is achieved using eq (1).

$$\text{Image Normalization} = \text{Original image} - \left[\text{Min Image value}\left(\frac{\text{New Max Value} - \text{New Min Value}}{\text{Max ImageValue} - \text{Min Image Value}}\right)\right] + \text{New Min Value} \quad (1)$$

The input to the band normalisation stage is the result of a discrete wavelet transform. where Min Image value and Max Image value of eq (1) are the minimum and maximum input image values. The New min and New max value of an image is the specified value. The value of Newmin is 0 and the value of Newmax is 1. As a result, each pixel in the image is translated into a range defined by the minimum and maximum values, 0 and 1. In a band, the greatest pixel value is transformed to a maximum value, while the lowest pixel value is changed to a minimum value between the range of 0 and 1. This normalised value's output is given to Preprocessing techniques to calculate the Structural Similarity Index matrix.

3. Band Reordering

Band Reordering is evaluated based on a greedy algorithm using structural similarity index measure (SSIM) and Correlation coefficient [2] [3][20].

3.1. *Structural similarity index measure (SSIM)*

The band normalisation output samples of all pixels in the band fall between the minimum and maximum values. The presence of redundant information in the bands is possible. As a result, minimising redundant spectral information is critical for compression. To accomplish this, a technique known as structural similarity index measure (SSIM) [1] evaluates the correlation between spectral bands. The coefficient between the bands is large, indicating that they are closely connected.

The quality assessment of SSIM [10] is based on the luminance term, the contrast term, and the structural term as shown in fig.5. the overall term is calculated on the multiplicative of all three terms. SSIM Is evaluated using the above said three terms are given in eq (2),(3),(4),(5) respectively.

$$SSIM(x,y) = [l(x,y)]^{\alpha}.[c(x,y)]^{\beta}.[s(x,y)]^{\gamma} \quad (2)$$

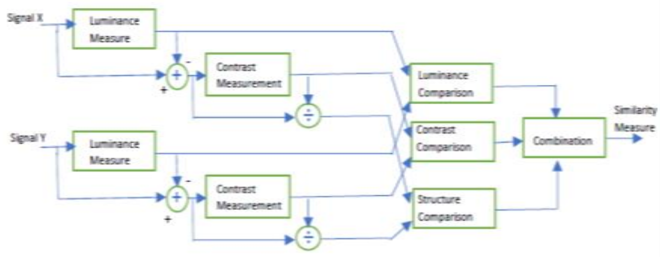

Fig. 5. Structural Similarity Index matrix

Where,

$$l(x,y) = \frac{2\mu_x\mu_y + c_1}{\mu_x{}^2 + \mu_y{}^2 + c_1} \quad (3)$$

$$c(x,y) = \frac{2\mu_x\mu_y + c_2}{\sigma_x{}^2 + \sigma_y{}^2 + c_2} \quad (4)$$

$$s(x,y) = \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3} \quad (5)$$

Where $\mu_x\mu_y$ − local means

$\sigma_x, \sigma_y, \sigma_{xy}$ are standard deviation and c_1, c_2, c_3 are the cross − correlation of images x, y.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x{}^2 + \mu_y{}^2 + c_1)\ (\sigma_x{}^2 + \sigma_y{}^2 + c_2)} \quad (6)$$

The mean of SSIM is calculated and Band reordering is done using a greedy algorithm.

3.2 Greedy Algorithm

Captured Image orders are changed based on the greedy algorithm as follows.

1. Initialize the original spectral bands of an image as set A and the Reference Image as set R

2. Calculate the coefficient of each band in sets A and R using eq (7)

3. Identify the pair which is having highest correlation coefficient which is moved into Set R and considered this as a new reference

4 Do the procedure until A set is empty.

Merge sort algorithm are used to order the bands in ascending or descending order.

Correlation coefficients calculated by using the Formula

$$p(x,y) = \frac{1}{N-1}\sum_{i=1}^{N}\left(\frac{x_i - \mu_x}{\sigma_x}\right)\left(\frac{y_i - \mu_y}{\sigma_y}\right) \quad (7)$$

$$p(x,y) = \frac{cov(x,y)}{\sigma_x\ \sigma_y} \quad (8)$$

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$$SD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}|x_i - \mu|^2} \qquad (9)$$

μ_x , μ_y are mean of x & y image

σ_x , σ_y are Standard Deviatuion (SD) of x & y image

3.3 .Rearranging the Bands using the merge sort algorithm

The Reference image R contains Bands is not in the sequence manner [11], so to order the bands Merge and Sort algorithm are used. Referece Image R is assigned to vector X.Sort the vector X using the merge sort algorithm. The result of the vector X contains sorted values of X in ascending order. But it requires extra memory for merging the result. The merge Sort Algorithm is as follows,

1.Divide the vector X having n samples into two sub-sequences namely a, b having n/2 samples each.

2.Sort samples of a and b individually.

3.Merge the sorted subsequences of a & b and generate the final sorted sequence and it is assigned into O.

Hence, the output of the bands is rearranged in either ascending or descending order.

3.4 .Image scanning

Image scanning is used to normalize the image and this normalized image will pass to the prediction coding for better compression. This paper deals with a zig-zag algorithm. which converts two-dimensional data to dimensional data. the purpose of the Zig-zag [14] Scanning is to group low-frequency coefficients on top of a vector.

Steps:

1.Initially Divide the bands in the data cube into several blocks namely block 1, block 2, and block 3…. wrt different sizes. ex. 5x5, 8x8, 20x20…

2.Scan the bands of block 1 using zig-zag scanning converted into one-dimensional data. Which contains 25,64,400 data wrt to the above example.

3.Concatenate block 1 of all other bands. so block size of 5x5 which gives you 25 data each. Similarly for all other bands.

4.Do the procedure for all other bands in the image.

A01	B01	C01	D01	E01
A02	B02	C02	D02	E02
A03	B03	C03	D03	E03
A04	B04	C04	D04	E04
A05	B05	C05	D05	E05

Fig. 6. Band 1 of 5x5 matrix

A11	B11	C11	D11	E11
A12	B12	C12	D12	E12
A13	B13	C13	D13	E13
A14	B14	C14	D14	E14
A15	B15	C15	D15	E15

Fig.7. Band 2 of 5x5 matrix

$$N = \{A01, B01, A02, \ldots \ldots A11, B11, A12, \ldots \ldots E15\} (10)$$

Fig.6 shows the band1 of the 5x5 matrix which gives a total of 25 elements. Similarly, Fig.7 shows band2 of a 5x5 matrix, a total of 25 elements. In eq (10) N value gives the concatenation of band1 and band2 of block size 5. Finally, the output of the Zigzag algorithm gives the concatenates of all the bands of the 5x5 matrix, 8x8 matrix, and 20x20 matrix. This output is supplied to linear prediction for better compression performances.

4. Compression Stage

4.1. Linear prediction coding (LPC)

Linear prediction coding (LPC) [13] is a mathematical technique that uses past samples to predict future values. The autocorrelation approach of autoregressive (AR) modelling is used by LPC to estimate the filter coefficients. The idea behind LPC is that an input sample can be approximated as a linear mixture of previous samples. A unique set of predictor coefficients can be determined by minimising the sum of the squared differences between actual input samples and linearly predicted ones [2].

The equation is related to the input samples.

$$S(n) = \sum_{k=1}^{p} S(n-k) \qquad (11)$$

$$\overline{s(n)} = \sum_{k=1}^{p} \alpha_k \, s(n-k) \qquad (12)$$

(a) (b)

nth sample can be viewed as a linear combination of p past samples.

If we process the output of the linear predictor and predictor coefficient are αk and the predictor output is S. Error between the actual signal and error predicted value is given by

$$e(n) = s(n) - \overline{s(n)} \qquad (13)$$

4.2. *Huffman Encoding:*

Huffman coding is a lossless encoding algorithm [15] that is used to reduce data size. To save costs and transmission bandwidth, data must be compressed. This use variable length encoding. The variable length of the code is applied to all characters, and the length of the code for each character is

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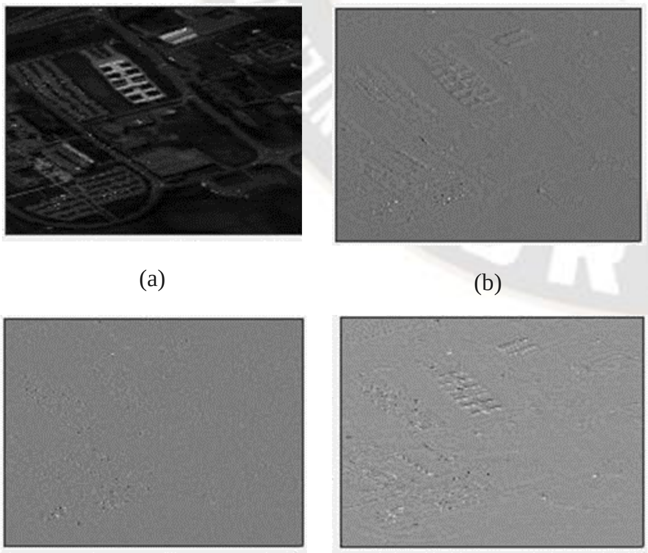
determined by how frequently it appears in the given input. The shortest code is the most common, while the largest code is the least common. It's called Huffman encoding. Huffman coding is applied to each mistake frame from the linear prediction stage. The basic notion behind Huffman coding is that if a symbol in a sequence repeats, a very short codeword is required. Decompression is also carried out in reverse.

5. Results & Discussion

5.1.About Dataset:

This paper deals with the hyperspectral image datacube of Pavia University which was captured by a sensor known as a reflective optics system imaging spectrometer (ROSIS-3) over the city of Pavia, Italy. The image consists of 610×340 pixels with 103 spectral bands covering the wavelength ranging from 0.43 to 0.86 μm.

Fig. 8. Original image of Pavia University



(a) (b)

(c) (d)

Fig.9. a) Low Low Region b) Low High Region c)High Low Region d) High High Region

Each band in the hyperspectral images is decomposed into 4 subsamples. The original image consists of 610x340x103 and each band represents 610x340 decomposed into four subsamples are Approximate coefficient (LL) contains 305x170, Horizontal Coefficient (LH) contains 305x170, Vertical Coefficient contains (HL) 305x170 and Diagonal Coefficient (HH) contains 305x170 pixels as shown in Fig.9. we know that more information will be available in low low regions. so, further estimation LL region is considered.

Each band after decomposition is normalized. The original captured order of image is {1,2,3,4,5……103}. It is Reordered using a greedy algorithm is {3,2,6,7, 8,9,10,12,15,18,21,23,25,27,28,30,33,36,37,39,35,34,31,33,38 ,40,1,43,46,47,48,49,45,46,47,52,53,55,56,57,58,57,62,……41}. The output of the linear prediction stage is predicted value and error sequences as shown in Fig 10 & Fig,11. The mean value of Prediction error is 6.27 compared with [21] shaobiao xie et, al proposed an Adaptive quantization of prediction error is 6.3. Compression results are tabulated in Table 1. The compression ratio of the proposed method is 3.83 for the Bit per Pixel is 4.4.

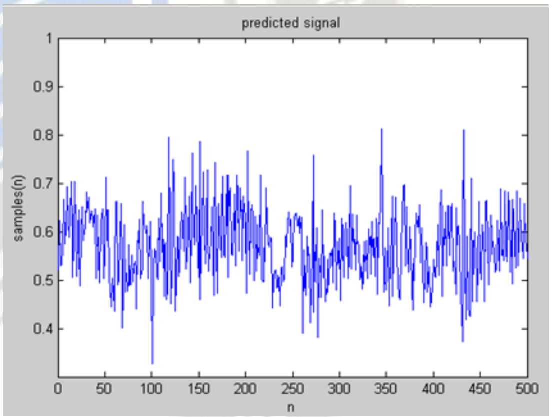


Fig. 10. Predicted Sequence

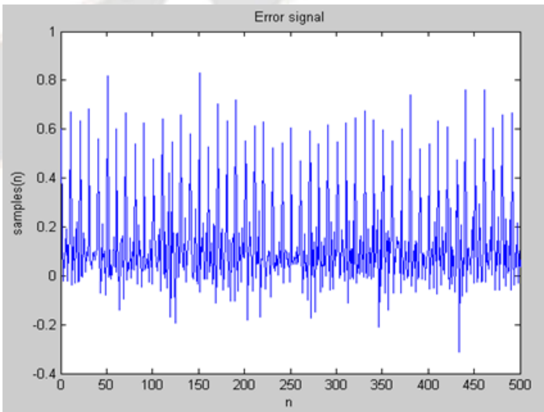


Fig.11 . Error sequence

Table 1 shows the comparison table of the proposed method with the other methods. The proposed method achieves the compression performance with the prediction based on band reordering techniques achieved using the structural similarity index. Jarno Mielikainen et, al proposed A clustered differential pulse code modulation with linear prediction [16]. The lookup table (LUT) was proposed with the band-interleaved-by-line (BIL) format to increase the search speed.

Table 1. comparison of CR for Pavia image

Algorithm	Compression Ratio
D-PCM	3.42
LUT	3.36
Preprocessing+Compression	3.63
Proposed method	3.83

6.Conclusion:

The proposed paper presented band reordering based on structural similarity using a greedy algorithm. Compression is achieved by preprocessing in this sub-bands decomposition is done and bands are reordered into unsequenced, compression is achieved by using linear prediction. Experiments show that the proposed prediction-based band reordering is beneficial to hyperspectral image compression.

References:

[1] Zhou, W., A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli. "Image Quality Assessment: From Error Visibility to Structural Similarity." IEEE Transactions on Image Processing. Vol. 13, Issue 4, April 2004, pp. 600–612.

[2]. Pekka Toivanen, Olga Kubasova, and Jarno Mielikainen, "Correlation-Based Band-Ordering Heuristic for Lossless Compression of Hyperspectral Sounder Data" IEEE Geoscience and remote sensing letters, Vol.2, No.1,2005, pp 50-54.

[3]. Jing Zhang and Guizhong Liu" An Efficient Reordering Prediction-Based Lossless Compression Algorithm for Hyperspectral Images" IEEE Geoscience and remote sensing letters, Vol.4, no.2, April 2007, pp.283-287

[4]. Rui Li & Zhibin Pan & Yang Wang," The linear prediction vector quantization for hyperspectral image compression", Multimedia Tools and Applications, 2019, pp.11701–11718,

[5]. I. Blanes, M. Albinet, R. Camarero & J. Serra-Sagristà, "Almost fixed quality rate-allocation under unequal scaling factors for on-board remote-sensing data compression", International Journal of Remote Sensing, 2018, pp. 514–526

[6]. Worku Jifara & Feng Jiang & Bing Zhang& Huapeng Wang & Jinsong Li & Aleksei Grigorev & Shaohui Liu , Hyperspectral image compression based on online learning spectral features dictionary, Multimedia Tools and Applications, 76, pp.25003–25014, 2007.

[7]. Toreyin, B. U., Yilmaz, O., & Mert, Y. M. "Evaluation of on-board integer wavelet transform based spectral decorrelation schemes for lossless compression of hyperspectral images". 2014 6th Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing,

[8].Toreyin, B. U., Yilmaz, O., Mert, Y. M., & Turk, F." Lossless hyperspectral image compression using wavelet transform-based spectral decorrelation". 7th International Conference on Recent Advances in Space Technologies (RAST), 2015

[9] Chen, L., Bei, C., Zhai, Y., & Wu, J. " Efficient Wavelet-Based Compression for Hyperspectral Images Using Precompression Algorithm". International Conference on Multimedia and Signal Processing,2011.

[10] Zhao, D., Zhu, S., & Wang, F," Lossy hyperspectral image compression based on intra-band prediction and inter-band fractal encoding". Computers & Electrical Engineering, 54, 494–505.

[11] Hagag, A., Hassan, E. S., Amin, M., Abd El-Samie, F. E., & Fan, X. " Satellite multispectral image compression based on removing sub-bands". 2011,Optik, 131, 1023–1035.

[12] Rolando Herrero, Vinay Kingle "Ultraspectral image preprocessing with tridimensional space-filling curves", open transaction on information processing, 2014. Pp-27-42

[13] Makhoul, J.: Linear prediction: a tutorial review. Proc. IEEE 63(4), 561-580 (1975)

[14] Ruslan Yuzkiva, Vladislav Sergeeva, "Transform-based coding method for remote sensing hyperspectral data compression" 3rd International Conference "Information Technology and Nanotechnology", ITNT-2017, 25-27, pp 249–257

[15]. Licciardi, G. A.." Hyperspectral compression. Hyperspectral Imaging", (2020) 55–67.

[16] Mielikainen, J., & Toivanen, P. "Clustered DPCM for the lossless compression of hyperspectral images". IEEE Transactions on Geoscience and Remote Sensing, 2003, pp. 2943–2946.

[17].J. Mielikainen, "Lossless compression of hyperspectral images using lookup tables," IEEE Signal Process. Lett., vol. 13, no. 3, 2006,pp. 157–160,

[18]. Rui Li & Zhibin Pan & Yang Wang, "The linear prediction vector quantization for hyperspectral image compression". Multimedia Tools and Applications". 78,2019, pp.11701–11718.

[19].K Pranitha , G Kavya, "An efficient image compression architecture based on optimized 9/7 wavelet transform with hybrid post processing and entropy encoder module", Microprocessors and Microsystems
Volume 98, April 2023.

[20]. Masud Ibn Afjal, Palash Uddin, Al Mamunc and Abu Marjan," An efficient lossless compression technique for remote sensing images using segmentation based band reordering heuristics", International journal of remote sensing 2021, VOL. 42, NO. 2, 756–781

[21].Shaobiao Xie, Ning Zhang,Lei Zhang," Near-Lossless Multispectral and Hyperspectral compression based on Adaptive Prediction Error", TEST Engineering Mannagement,2020, Volume 83,pp 22075-22083.

[22].G. che u o - ar ortea a es o e -Ruiz, V.Camps-Valls, a a a erra-agrist "On the Impact of LossyCompression on Hyperspectral Image Classification and Unmixing,"IEEE Geoscience and Remote Sensing Letters,8(2),253–257,2011