LOW MEMORY WAVELET-BASED HYPERSPPECTRAL IMAGE CODING USING 2D DYADIC WAVELET TRANSFORM

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ABSTRACT

The proposed hyperspectral image compression algorithm employs 2D dyadic wavelet transform to transform spectral frames and encode each plane using the 3D-Low Memory Block Tree Coding algorithm starting from the higher bit plane to the lower bit plane. The 3D dyadic wavelet transform which employees a significant memory in the transformation process, posing a challenge to the resource constraint hyperspectral image sensors. The results show that the proposed algorithm requires a low memory while maintaining the coding gain and complexity at par to the 3D wavelet transform based hyperspectral image compression algorithms.

Key words: Wavelet Transform, Image Coding, Hyperspectral Image, Compression Algorithm, Transform Based Compression.

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1. INTRODUCTION

In the last couple of decades, there is significant growth in computational technology. These computer-based machines generate a lot of data, and this data has been sent to the wireless channel. According to the report by CISCO, the mobile data has been reached up to 11.2 2

Exabytes in 2017, which is around fivefold data growth as on 2012. It has been noted that the data is growing at a rate of 66% yearly [1-2].

Computer vision is one of the fastest-growing fields of computer science that has various applications in agriculture, automotive, banking, healthcare, remote sensing, security, etc [3]. The computer vision technology had been developed from the grayscale image to the hyperspectral (HS) image during a couple of decades. The single HS image is the collection of the hundreds of images that are taken for the electromagnetic spectrum from visible range to infrared range. It has been known that a single HS image can capture the fine detail of the elements present in the scene. This vast image data is a challenge for any HS image sensor. So, the HS image compression becomes a necessary process to save the sensor memory and energy, to increase its performance (efficiency), and reduce the data bandwidth with transmission time [4]. There are two types of redundancy exist in the HS images, namely spectral redundancy and spatial redundancy. The spectral redundancy exists due to the correlation between the two consecutive frames of HS image while the spatial redundancy exists due to the spatial variation of the pixels in the frame. The high correlation exists between the continuous frames of HS images that need to be exploited by reducing the redundancy [5].

The HS image compression algorithms (HSICA) can be classified into two different categories on the basis of data loss and coding process. Based on data loss, the HSICAs can be subdivided into the two groups named as lossy HSICAs and lossless HSICAs [6] while in the view of coding process of the algorithm, HSICA can be divided into three different groups called as the predictive coding, the vector quantization, and the transform coding [7].

The transform-based HS image coding algorithms are one of the most popular HS image coding algorithms that enable the medium complexity with high coding gain and flexible to the definition of hyperspectral image quality policies [8]. Meanwhile, in recent years, there is a rise in the transform coding algorithm for HS images, which includes explicitly transform-based set partition coding algorithms. Set partition coding algorithms can achieve a state of art performance with the embedded nature. The set partitioning algorithms can be categorized on the basis of partitioning rule or list implementation. On the basis of the partitioning rule, it can be subdivided into the three subcategories named as block cube partitioning (3D-SPECK and 3D-LSK), tree partitioning (3D-SPIHT and 3D-NLS) and block cube tree partitioning (3D-WBTC and 3D-LMBTC). While for the list implementation, it can be divided into two subcategories named as having lists (3D-SPECK 3D-SPIHT and 3D-WBTC) or having no list (3D-LSK, 3D-NLS, and 3D-LMBTC) [9]. In the block cube partitioning, the whole HS image data is divided into the eight continuous block cubes, and each block cube is tested for the significance. If any element in the block cube is significant, then the whole block cube is tested and it is divided into 8 sub-blocks, and the process is repeated till it reaches to the single coefficient level, while for the tree partitioning, the whole HS image data is partitioning into the spatial orientation trees form in which the significance of the coefficient has been tested, and if any coefficient found significant, then the whole tree will be tested for significance. In the block cube tree set partitioning algorithms, the whole HS image data is partitioned into the continuous coefficient block cubes, and then block cube trees are formed with the root in the topmost subband. An algorithm that uses the list to track the coefficients is called the list based set partitioning HS image compression scheme while the compression algorithm uses the markers for tables to track the significance of the block cube or tree. The listless HS image compression algorithms are relatively fast, but they are memory consuming with reference to their list base versions [10].

The transform process and the coding process of the transform-based HSICA either the two stages run in parallel or sequentially. It has been observed that the 3D dyadic wavelet transform or any other 3D wavelet transform consumes a lot of memory, which needs to be

reduced for the resource constrain HS image sensors. In this paper, we proposed a novel HSICA that reduces the transformed memory keeping the coding gain and complexity near to the 3D-DWT based 3D-LMBTC. The proposed algorithm is compared with the other state of art HSICAs on the basis of five metrics: the transformed memory, the coding memory, the peak signal to noise ratio (PSNR), the encoding time, and the decoding time taken by the proposed algorithm. The peak signal to noise ratio is a measurement of the distortion of the image, which is related to the compression ratio of the HS image. It also indicates the total quality of the reconstructed image with reference to the original image.

The paper is organized into four sections. The second section is dedicated to the proposed HSICA, which is adapted to the raw and processed HS images. The third section outlines the comparative results between the state of the art HSICAs with the proposed algorithm on the basis of the mentioned five parameters. Finally, the conclusions are given in Section IV.

2. PROPOSED METHOD

In the past few years, many significant efforts have been taken to reduce the memory requirement of the transform-based HS image coders. The memory requirement of the hyperspectral image order is divided into two parts transform memory and coding memory. The transform memory is a memory required for the wavelet transform and inverse wavelet transform, while the coding memory is the memory requirement for the encoding and decoding process of wavelet coefficients. Overall, any transform-based HSICA memory is either the sum of two memories or the maximum of both depending upon whether both stages run in parallel or they run in sequential form.

Dyadic Wavelet Transform: In this section, we have proposed the 2D dyadic wavelet transform based HS image compression algorithm, which is the low memory solution for the HS image. It reduces the memory requirement during the 2D wavelet transform due to the nature of transform with the cost of slightly higher complexity and slightly lower coding gain with reference to its 3D version. The traditional 3D dyadic wavelet transform requires a large memory, while the 2D dyadic wavelet transform needs less memory for the computation of the wavelet coefficients [9-11].

3D Low Memory Block Tree Coding (3D-LMBTC) : The 3D-Low Memory Block Tree Coding (3D-LMBTC) is a transform-based set partitioned HSICA that is an appropriate candidate for the low memory HS image sensors [9]. It is a listless version of 3D-Wavelet Block Tree Coding (3D-WBTC), which uses the excellent features of block cube-based algorithm and tree-based algorithm for an HS image. The algorithm uses four different types of markers for the tracking of the significance of the coefficients and sets, which reduce the complexity and coding memory of the compression scheme. The significance testing of the block cube and block cube tree with the help of equation 1 and equation 2. For the n^{th} bit plane, the threshold is given as $T=2^n$.

$$S_n(B) = \begin{cases} 1 & \text{if } T \leq \max_{i \in B} [C_i] \leq 2T \\ 0 & \text{if } \max_{i \in B} [C_i] < T \\ \text{Null} & \text{if } \max_{i \in B} [C_i] \geq 2T \end{cases} \quad (1)$$

$$S_n(BT) = \begin{cases} 1 & \text{if } T \leq \max_{i \in BT} [C_i] \leq 2T \\ 0 & \text{if } \max_{i \in BT} [C_i] < T \end{cases} \quad (2)$$

3. EXPERIMENTAL RESULTS AND ANALYSIS

All transform-based set partitioned HSICAs are applied to the same computer platform having the working memory of 8 GB and 4th generation i3 processor on the numerical computing simulation software. The two raw images (Yellowstone uncalibrated scene 3 and Yellowstone uncalibrated scene 10) have been taken for the analysis having a dimension of 128 for each dimension. The HS image data can be seen as the three dimensions of x, y, and z, where x and y are the spatial dimensions and z, is known as a spectral dimension of the HS image, which corresponds to the different wavelengths [9]. The HS images are transformed dyadic wavelet transform (3D or 2D) as mentioned, and then it's floating-point transform coefficients are quantized to the nearest integer. After that, it reads into a linear index array which is the one-dimensional matrix through the Morton mapping [6].

Coding Efficiency : The coding efficiency is a measurement of rate-distortion performance of any HS image compression algorithm, which is measured in terms of bit per pixel per band to achieve a minimum desire quality of the reconstructed HS image. The peak signal to noise ratio is a parameter which measures the quality of the reconstructed HS image is defined mathematically [12] in equation 3

Figure 1 (a) Peak Signal to Noise Ratio of the Yellowstone uncalibrated scene 3 for fifteen different bit rates.

Figure 1 (b) Peak Signal to Noise Ratio of the Yellowstone uncalibrated scene 10 for fifteen different bit rates.

$$PSNR = 10 \log_{10} \left[\frac{\text{Maximum Signal Power}}{MSE} \right] \quad (3)$$

where MSE is a mean square error of the reconstructed HS image [13-14] defined in equation 4

$$MSE = \frac{1}{N_{pix}} \sum_{x,y,z} [f(x,y,z) - g(x,y,z)]^2 \quad (4)$$

N_{pix} is a total number of pixels in all frames for each HS image. The $f(x, y, z)$ is the original HS image, and $g(x, y, z)$ is the reconstructed HS image.

It has been observed that the coding train gain been reduced from 0.1 dB to 0.5 dB at different bit rates, as shown in Fig 1 (a) and Fig 1 (b) with increased complexity due to application of the 2D-DWT frame by frame. However, at the low bit rates below 0.2 bpppb (bit per pixel per band) [9], the proposed algorithm works at par with 3D- DWT based 3D-LMBTC. Fig 1 (a) and Fig 1 (b) are the comparative analysis of proposed algorithm with the 3D dyadic wavelet transform based 3D-SPECK [15], 3D-SPIHT [16], 3D-LSK [17], 3D-WBTC [6] and 3D-LMBTC [9].

Computation Memory : Table 1 gives a comparative analysis of the different set partitioning based HSICAs. It has been observed that the proposed scheme is using the same memory as the 3D-DWT based 3D-LMBTC, and it is fixed, which is dependent on the size of the HS image. Due to the listless approach, it requires a fix size memory, which is depended on the size of HS image. It needs a fixed size memory of 12 KB for the tracking of the sets and the coefficients.

Table 2 gives the comparative analysis of working memory required by five-level of 2D dyadic wavelet transform and 3D dyadic wavelet transform. It has been clearly observed that there is a multiple fold increase in the consumption of the memory of 3D-DWT compare to 2D-DWT. This is because that the 2D dyadic wavelet transform requires less memory because it applied to the two dimensions only, while the 3D dyadic wavelet transform is applied to the three-dimension which increases the size and more computational memory is needed to calculate the wavelet coefficients.

Complexity Analysis : The computational complexity of the proposed HSICA is calculated by estimating the computation time required for the encoding of wavelet transform coefficients and for decoding the generated bit-stream at the given bitrate. The complexity of the proposed HS image compression is compared with other states of the art HS image compression algorithms in table 3 and table 4 for the different bit rates. From table 3 and table 4, it is observed that for each algorithm, the encoding and decoding time increases as the bit rate increases. This is an expected outcome because more coefficients needed to be encoded, and hence the encoding time as well as decoding time increases as the bit rate increases.

It has also been evident from Table 3 and Table 4 that the listless coding algorithms have lower computation time than their corresponding list base coding algorithms. The list base coding algorithms use the linked list to keep track of the transform coefficients and sets, and it will grow exponentially with the increase bit rate. The management and processing of these linked lists need higher computational demands, and it has longer computational time. The listless algorithms use the fixed-size state tables instead of a linked list. These fix size state tables do not require any memory or operational management; therefore, they require less time for the encoding of the transform coefficients. The proposed algorithm is a variant of 3D-LMBTC, which uses the four types of markers for the tracking of the coefficients.

Table 1 Comparative Analysis of memory consumption by the different HSICAs at the coding stage

Memory of Yellowstone uncalibrated scene 3 for the different compression scheme							Memory of Yellowstone uncalibrated scene for the different compression scheme					
bpppb	3D-DWT + 3D-SPECK	3D-DWT + 3D-SPIHT	3D-DWT + 3D-WBTC	3D-DWT + 3D-LSK	3D-DWT + 3D-LMBTC	2D-DWT + 3D-LMBTC	3D-DWT + 3D-SPECK	3D-DWT + 3D-SPIHT	3D-DWT + 3D-WBTC	3D-DWT + 3D-LSK	3D-DWT + 3D-LMBTC	2D-DWT + 3D-LMBTC
0.00625	16.3	16.9	8.2	512	12	12	19.1	14.7	11.2	512	12	12
0.0125	25.9	28.4	20.1	512	12	12	33.3	37.3	34.3	512	12	12
0.025	71.1	73.0	62.6	512	12	12	64.6	71.4	64.2	512	12	12
0.0375	78.2	80.7	71.6	512	12	12	111.8	115.6	101.1	512	12	12
0.05	116.9	124.1	109.4	512	12	12	162.8	123.3	113.3	512	12	12
0.1	205.4	204.1	185.6	512	12	12	276.4	288.7	281.5	512	12	12
0.2	396.9	413.7	378.1	512	12	12	447.9	489.0	446.0	512	12	12
0.3	677.9	682.5	621.2	512	12	12	822.3	832.6	826.1	512	12	12
0.4	725.9	752.6	708.4	512	12	12	919.9	881.2	891.4	512	12	12
0.5	947.4	946.7	894.3	512	12	12	1038.4	1055.3	1036.6	512	12	12
0.6	1119.2	1155.4	1090.9	512	12	12	1352.1	1388.6	1355.1	512	12	12
0.7	1234.2	1243.4	1120.9	512	12	12	1633.8	1561.4	1592.3	512	12	12
0.8	1343.5	1323.5	1282.4	512	12	12	1681.0	1652.4	1633.6	512	12	12
0.9	1439.0	1473.2	1400.1	512	12	12	1741.3	1709.9	1712.3	512	12	12
1	1498.0	1517.2	1440.1	512	12	12	1825.2	1813.1	1824.5	512	12	12

Table 2 Comparative Analysis of memory used by in transform stage

Memory required for the Transform (5 Level)	
3D Dyadic Wavelet Transform	38.346 MB
2D Dyadic Wavelet Transform	348.991 KB

Table 3 Comparative Analysis of encoding time consumed by the different HSICAs

Encoding Time of Yellowstone uncalibrated scene 3 for the different compression scheme							Encoding Time of Yellowstone uncalibrated scene 10 for the different compression scheme					
bpppb	3D-DWT + 3D-SPECK	3D-DWT + 3D-SPIHT	3D-DWT + 3D-WBTC	3D-DWT + 3D-LSK	3D-DWT + 3D-LMBTC	2D-DWT + 3D-LMBTC	3D-DWT + 3D-SPECK	3D-DWT + 3D-SPIHT	3D-DWT + 3D-WBTC	3D-DWT + 3D-LSK	3D-DWT + 3D-LMBTC	2D-DWT + 3D-LMBTC
0.00625	0.9	1.0	0.5	0.7	0.4	0.7	1.8	0.6	0.8	0.3	0.9	1.1
0.0125	1.6	1.1	1.3	0.4	1.1	1.4	2.5	1.1	1.4	0.4	1.2	1.4
0.025	2.9	1.6	1.8	0.5	1.4	1.8	5.0	1.5	1.7	0.4	1.5	1.6
0.0375	5.0	2.2	2.4	0.5	1.7	2.1	5.1	2.2	2.1	0.5	1.7	1.9
0.05	6.7	4.3	2.7	0.6	2.1	2.5	8.5	3.3	3.5	0.6	2.0	2.2
0.1	18.2	9.9	7.1	0.8	3.2	3.7	18.8	8.0	5.9	0.7	3.0	3.3
0.2	57.3	24.3	25.0	1.2	5.5	5.9	83.5	29.0	23.5	1.0	5.0	5.4
0.3	97.1	39.9	47.9	1.4	6.7	8.2	110.2	50.3	32.5	1.3	6.6	7.7
0.4	205.5	104.1	122.3	1.8	9.3	10.3	326.5	181.1	198.7	1.7	9.2	10.1
0.5	302.7	130.9	176.7	2.2	10.5	11.7	471.9	241.5	294.1	1.9	11.5	11.8

0.6	348.8	140.5	190.4	2.5	11.5	13.1	588.3	263.7	363.2	2.2	11.3	12.8
0.7	706.4	337.8	528.3	2.7	14.3	15.2	678.3	281.3	398.3	2.5	12.5	13.8
0.8	835.1	408.4	601.1	3.0	15.7	17.2	1150.8	531.0	771.8	2.9	15.8	17.2
0.9	980.8	414.4	633.2	3.4	16.8	18.4	1745.2	883.0	1223.2	3.1	17.1	18.9
1	1372.9	632.4	976.9	3.7	19.9	21.1	2557.6	1034.1	1517.0	3.3	18.3	20.2

Table 4 Comparative Analysis of decoding time consumed by the different HSICAs

bpppb	Decoding Time of Yellowstone uncalibrated scene 3 for the different compression scheme						Decoding Time of Yellowstone uncalibrated scene 10 for the different compression scheme					
	3D-DWT + 3D-SPECK	3D-DWT + 3D-SPIHT	3D-DWT + 3D-WBTC	3D-DWT + 3D-LSK	3D-DWT + 3D-LMBTC	2D-DWT + 3D-LMBTC	3D-DWT + 3D-SPECK	3D-DWT + 3D-SPIHT	3D-DWT + 3D-WBTC	3D-DWT + 3D-LSK	3D-DWT + 3D-LMBTC	2D-DWT + 3D-LMBTC
0.00625	0.7	0.8	0.2	0.5	0.4	0.5	0.8	0.3	0.2	0.2	0.5	0.7
0.0125	0.9	0.8	0.4	0.3	0.5	0.8	1.9	0.3	0.4	0.3	0.9	1.2
0.025	1.6	1.2	0.6	0.4	0.7	1.0	2.3	0.7	0.7	0.4	0.7	1.5
0.0375	3.5	1.5	1.2	0.4	0.9	1.3	2.8	1.2	0.9	0.4	0.8	1.7
0.05	4.6	2.6	1.6	0.5	1.1	1.5	5.9	2.2	2.3	0.5	1.0	1.9
0.1	14.5	6.6	9.5	0.7	1.9	2.2	12.8	6.5	4.4	0.6	1.8	2.4
0.2	49.3	22.3	17.6	1.0	3.5	4.7	62.2	25.8	21.6	1.0	3.3	3.7
0.3	81.9	31.6	40.0	1.4	5.1	7.1	80.0	47.3	29.2	1.2	4.9	6.2
0.4	189.6	90.4	109.7	1.7	6.7	8.4	306.7	171.6	175.3	1.4	6.7	8.1
0.5	284.1	117.7	155.8	2.0	8.1	10.5	441.3	218.6	262.2	1.7	7.6	9.4
0.6	321.1	128.3	176.2	2.4	9.4	11.2	555.1	229.7	319.1	1.9	9.0	10.8
0.7	684.0	308.8	576.7	2.5	11.0	13.7	609.3	246.5	358.5	2.2	10.5	12.1
0.8	821.8	373.0	552.6	2.7	12.5	15.1	1080.0	496.2	717.3	2.5	11.8	14.4
0.9	859.6	399.7	588.7	3.2	13.9	16.3	1692.5	817.9	1130.1	3.0	13.3	15.7
1	1258.0	589.2	849.3	3.4	15.6	18.7	2179.1	929.9	1384.1	3.4	14.7	17.2

The computational time for the 3D-LSK is less than 3D-LMBTC because there is one more step for the significance testing of block cubes, which lead to the increase in computational time. The proposed algorithm is taking more time than the original 3D-LMBTC because of the use of a two-dimensional dyadic wavelet transform which is applied frame-by-frame; thus it increases time for encoding process and decoding process.

4. CONCLUSION

In order to meet the constraint of low-cost HS image sensors and associated multimedia devices, also a low memory image coder is an essential requirement. In this paper, we propose a low memory algorithm that is suitable for the memory constraint image sensors. The use of a two-dimensional dyadic wavelet transform, the transform memory is reduced significantly, and the memory used in the algorithm reduced by the 3D-LMBTC, which is the low memory HS image compression scheme. From the simulation result, it is observed that the 2D dyadic wavelet transform requires only 349-kilobyte memory. But its 3D version utilize the 40 MB memory, which is significantly large in multifold. So, the combination of applying 2D dyadic wavelet transform frame by frame and use of the 3D-LMBTC is the optimum solution for the low memory HS image sensors.

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