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3D modified wavelet block tree coding for hyperspectral images

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ABSTRACT

A novel wavelet-based efficient hyperspectral image compression scheme for low memory sensors has been proposed. The proposed scheme uses the 3D dyadic wavelet transform to exploit intersubband and intrasubband correlation among the wavelet coefficients. By doing the reconstruction of the transform image cube, taking the difference between the frames, it increases the coding efficiency, reduces the memory requirement and complexity of the hyperspectral compression schemes in comparison with other state-of-the-art compression schemes.

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1. INTRODUCTION

Hyperspectral Imaging (HSI) sensors capture the hundreds of continuous image frames for a single scene in the spectral range of 400 nanometers to 2500 nanometers with a nominal spectral sepration between the two frames of 10 nanometers. A single pixel of the hyperspectral image is represented by the multiple values which is correspondence to the associated wavelength,-contains the useful spectral information about the pixel [1].

This spectral information acquired in hundreds of bands allows recognizing any small change in the scene. Due to above-mentioned properties of HSI, it is used in the multiple applications such as agriculture, biotechnology, environmental monitoring, food product analysis, forensic science, material identification, medical diagnose, mineral mapping & extraction, pharmaceuticals, surface investigation, remote sensing, security and defence services, space science, township planning, verification of documents etc [2].

Earth observation remote sensing is the one of the most remarkable application that takes the benefit of the information obtained from HSI sensors to identify, measure, and monitor constituents of the Earth's interior, exterior and it's climate. Hyperspectral remote sensing image can be viewed as a 3D data cube, with first two dimensions representing spatial coordinates on the Earth’s surface, while the third dimension representing the frequency. Due to the large size of the hyperspectral image & limited onboard memory availability of HSI sensor, it is necessary to apply the image compression scheme to save onboard hardware memory capacity, reduce network downlink transmission bandwidth and time [3-4].

The hyperspectral image compression scheme is the process of encoding information using fewer bits or other information-bearing units than an unencoded representation. Performance parameters & compression ratio of hyperspectral images compression is stated in terms of bit per pixel per band (bppbp).

There are many compression schemes are proposed for hyperspectral images which can be classified into three categories: predictive coding, vector quantization, and transform-based compression schemes. Predictive coding schemes are based on the elimination of the inter-pixel redundancies of the closely spaced pixel by extracting and coding the new information in each pixel. This new information is the difference between the actual and predicted value of that pixel. It can be two type lossy or lossless. In the image compression scenario, the prediction of a hyperspectral image pixel for a current frame or group of pixels of current frame maybe drive from the previously transmitted pixels of that frame. The predicted pixel value is subtracted from the original pixel and a different signal is obtained. Differential Pulse Code Modulation (DPCM) is commonly used in predictive coding for image compression. Vector Quantization (VQ) is a lossy image compression scheme. VQ is a process of mapping multiple vectors into a single vector that has a smaller value. A vector of the image represents the small sub-image or a block of pixels. In VQ, it treats one entire sub-image as a single entity and quantized it by reducing total number of bits required to represent the sub-image. It is done by using a code book which stores the fix sets of vector and then coding the sub-image is performed by using the codebook.

Transform based compression scheme consist the two stages: transform and coding stage. The transform stage compact the energy of the hyperspectral image into the few coefficients of spatial and spectral domain. The coding stage of the transformed image is coded according to the values of the transform image coefficients [5]. The wavelet transform is widely employed due to its excellent clustering in time and space, computationally fast, it compresses images without appreciable degradation. 3D wavelet transform is applied to the 3D HSI cube using 1D wavelet transform employed in all direction in the row, column & width fashion. Obtained wavelet coefficients are arranged in the pyramidal shape in which high energy coefficients are placed at the top. 3D dyadic wavelet transform is a mathematical way of encoding information in the layered structure according to the level of detail [6]. A single level 3D-Wavelet Transform divides the hyperspectral image in eight non-overlapping coefficient band known as LLL, LLH, LHL, LHH, HLL, HLH, HHL & HHH. Wavelet transform based hyperspectral image composition schemes are broadly divided into two groups: Zerotree hyperspectral image compression schemes and Zeroblock hyperspectral image compression schemes. Spatial orientation trees (SOTs) are formed by the group of wavelet coefficients corresponding to the same spatial location for the zerotree hyperspectral image compression schemes. A SOT is zerotree when there is no significant wavelet coefficient above than current threshold level. In zeroblock schemes, contiguous blocks are formed from the transform hyperspectral image by dividing it according to the level of the transform. The significance test is done for the individual block. A block is zeroblock when there is no significant coefficient with reference to the current threshold. The new category of the compression scheme is combining the features of both zerotree compression schemes and zero block compression schemes. Zeroblocks of the partitioned image are formed and then block trees are formed with the roots in the topmost subband in the zerotree fashion [7-8].

Present manuscript has four sections. Section II describes the detail version of the 3D-Modified Wavelet Block Tree Coding (3D-MWBTC) for hyperspectral image compression. Section III gives the comparative simulation results of proposed 3D-MWBTC with the 3D-SPECK [6], 3D-SPIHT [9], 3D-LSK [10] & 3D-WBTC [11] for four available hyperspectral images [12] on the five different parameters peak signal-to-noise ratio (PSNR), new significant bit found in the first ten pass, cumulative number of bits generated in the first ten pass, memory consumed by compression schemes, encoding time & decoding time.

2. RESEARCH METHOD

Each frame of the hyperspectral image corresponds to the same scene. There is a high level of correlation between the different nearly placed frames of the hyperspectral image [13, 14]. This correlation property is exploited and the reconstructed hyperspectral image is generated. The cube structure of 3D gives the superior performance than the cuboid structure because of the partition of the cube will give the similar 8 subcubes (same dimension). The proposed 3D-MWBTC generates an embedded bit-stream like 3D-SPIHT [9, 15].

Let's consider a hyperspectral image cube of dimension 'x' is transformed with five levels 3D dynamic wavelet transform. The 3D dyadic wavelet transform exhibit the pyramid subband structure in which low frequency (high energy) terms are present at the top portion. This transform image cube (dimension ‘x’) goes for the reconstructed phase. In the reconstruction phase of the transform image cube, the cube is divided (spectral dimension) in the sets having the eight continuous frames. The first frame of the set is preserved without any change, but for the 2^{nd}, 3^{rd} till 8^{th} frame of the set, the changes are done with the difference of current frame and the previous frame. This is done for rest all frames present in the hyperspectral image cube. It has been observed that the performance characteristics have been obtained with taking the eight frames together is better than taking the 4 or 16 frames in a set together. After the reconstruction of the hyperspectral image cube the 3D-wavelet block tree coding (3D-WBTC) scheme is applied. This 3D- wavelet block tree scheme has the best features of tree base coding schemes and block-based coding schemes which make it a perfect choice for the compression scheme. There are many benefits of the reconstruction of hyperspectral image cube it reduces the maximum value of the hyperspectral image cube, which let the elimination of the top bit plane. The elimination of the top bitplane increases the peak signal ratio value as well as it will also reduce the complexity of the composition scheme. 3D-MWBTC has many advantages over zerotree base compression schemes (eg. 3D-SPIHT). It is a block-based compression scheme which saves memory with reference to the pixel based compression schemes. Intersubband correlation and spectral band correlations are exploited due to the pyramid structure obtained after the 3D wavelet transform. It combines multiple zerotrees which may occur in highest priority bitplane which lead the creation of the zerotree with more coefficients.

3D-MWBTC has three order list name as, a list of insignificant block cubes (LIBC), list of insignificance block set cubes (LIBSC) and list of significant pixels (LSP). In the initialization phase, block cubes present in LLL band are added to the LIBC and those with the descendents are added to the LIBCS as type 'A' blocks. The LSP initialized with the empty list. Type 'A' blocks are those blocks who are not significant and their children are not significant to the current threshold. While type 'B' blocks are those blocks who are not significant but their children are significant.

The encoding process has two stages within each bitplane sorting followed by refinement phase. The encoding process starts from the most significant bit plane. In the sorting pass, first, it will check the LIBC list. If the block cube is present in the list, the significance of the block cube will be tested against the current threshold level. Only one bit is used for the significance of the block. If the block cube is found insignificant then, it is zero block and '0' is sent. The block cube will remain in the LIBC. There will be no further partitioning and no new bits will be generated for the block. If the block is found significant against the current threshold level, then it is non zero block and '1' is sent. A significant block is partitioned into the eight subcubes using octuple-tree partitioning rule. The partition operation recursively repeated until no further partition is needed or the smallest possible block cube size (2*2*2). At this stage, eight coefficients and their significance are individually tested. If a coefficient is insignificant, then '0' is sent and the position is moved to LIBC as a single coefficient block. If the coefficient is significant than '1' is sent, a sign bit is also coded and this coefficient is moved to LSP. After performing the testing of all eight individual coefficients in a block cube, the current block cube is removed from the LIBC. Then encoder tests the block cube sets present in the LIBCS and performs the significance test for each block cube sets. Significant block cube sets are divided into the subsets while insignificant block cube sets remain in LIBCS.

A significant type ‘A’ set is partitioned into eight type ‘B’ sets and eight offspring block cubes. The type ‘B’ set is added to the end of the LIBCS while eight offspring block cubes are tested for their significance in the same manner as they are present in the LIBC. A significant type ‘B’ block cube is partitioned into eight type ‘A’ block cube and all of them are added to the end of the LIBCS. After each sorting pass, all the coefficients present in the LSP before the starting of the current biplane, are refined with one bit. This process repeats the above process by decreasing the threshold level by the factor of 2 until the bit budget is available.

The decoder follows the same procedure as the encoder with no changes and an additional step of significance testing of coefficient or block cube sets to identify coefficient or block sets containing coefficients requiring refinement.

3. RESULTS AND ANALYSIS

The performance of the proposed compression scheme 3D-MWBTC is compared with the 3D-SPECK [6], 3D-SPIHT [9], 3D-LSK [10] & 3D-WBTC [11]. Parameters are evaluated on four different standard hyperspectral images which are Washington DC (1280x307x191), Culprit (250x190x224), Jasper Ridge (100x100x224) & Urban (307*307*210). Hyperspectral images are taken in the size of the cube of the dimension 128. The padding has been performed with '0' for the hyperspectral images who does not have the cube shape of the mention dimension. Hyperspectral images are cropped from the initial to get the desired cube size. The simulation of the different hyperspectral images compression schemes have been implemented using the Matlab 2016A version and executed on Windows 8.1 operating system. Compression is needed to save the power of onboard sensors & data transmission bandwith [16-17].

3.1. Coding Efficency

The coding efficiency of the hyperspectral images is measured by the parameter peak signal to noise ratio (PSNR). This parameter shows the quality of reconstructed hyperspectral images with reference to the original hyperspectral images. It is defined by equation (1) & (2) [18].

$$\mathrm{PSNR} = 10\log_{10}\left[\frac{(\text{Maximum Signal Power})}{\mathrm{MSE}}\right] \tag{1}$$

where MSE is the mean square error of the reconstructed hyperspectral images with the original hyperspectral images. It is calculated with the equation (2).

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

Table 1 is the comparative performance of the proposed composition scheme with the other state of art hyperspectral image compression which is taken at the bppbp of 0.1 to 1. It is clearly evident that the proposed compression scheme 3D-MWBTC is outperforms the compression schemes. This is due to the elimination of the highest bit plane of the hyperspectral images which leads the significant increment of the PSNR for all hyperspectral images. It has been observed that the proposed compression scheme 3D-MWBTC has been outperformed with other compression scheme but according to the maximum pixel value of the hyperspectral image cube. 3D-MWBTC is significantly better than the other compression scheme at low bit rates (bppbp). The main reason behind this performance is that when high priority bit planes are coded, the majority of coefficients are insignificant and proposed compression scheme combined a large volume of insignificant coefficient together represented by a single bit.

Table 1. PSNR (in db) comparison of M-3D-WBTC with 3D-SPECK [6], 3D-SPIHT [9], 3D-LSK [10], 3D-WBTC [11] at various bit rates for the four different hyperspectral images Washington DC, Jasper Ridge, Cuprite & Urban [12]

bpppb	3D-SPECK	3D-SPIHT	3D-LSK	3D-WBTC	M-3D-WBTC	3D-SPECK	3D-SPIHT	3D-LSK	3D-WBTC	M-3D-WBTC
			Washington DC					Jasper Ridge		
0.1	38.53	38.28	38.35	38.7	45.47	35.08	35.11	35.29	35.67	48.65
0.2	41.54	41.34	41.29	41.72	47.81	39.35	39.13	39.40	39.60	52.47
0.3	43.51	43.3	43.55	43.69	49.20	41.72	41.89	41.95	42.40	54.96
0.4	45.26	45.11	44.79	45.45	51.61	44.52	44.41	44.55	44.81	57.41
0.5	46.81	46.6	46.36	47.01	54.58	45.91	46.33	46.26	46.78	59.12
0.6	48.45	48.24	48.42	48.63	55.42	48.17	48.19	48.41	48.62	61.01
0.7	49.76	49.53	49.43	49.74	56.33	49.94	50.06	50.05	50.53	62.70
0.8	51.12	50.84	50.7	51.29	57.02	51.13	51.74	51.71	52.20	63.52
0.9	52.24	52.06	52.24	52.42	58.31	52.97	53.09	53.30	53.51	64.98
1	53.52	53.32	53.49	53.71	59.93	54.77	54.72	54.86	55.13	66.04
			Cuprite					Urban		
0.1	25.64	24.67	25.65	25.57	33.01	57.04	56.94	57.04	57.02	62.35
0.2	30.92	29.44	30.88	31.03	39.76	58.95	58.80	58.76	58.95	63.18
0.3	34.55	33.36	34.55	34.58	43.87	60.43	60.29	60.43	60.42	64.90
0.4	38.05	37.04	38.05	38.15	46.54	61.77	61.67	61.54	61.76	65.88
0.5	41.27	40.51	41.32	41.37	48.32	62.95	62.79	62.69	62.94	66.30
0.6	43.46	42.58	43.47	43.57	50.19	64.16	64.00	64.05	64.16	67.41
0.7	45.55	45.00	45.78	45.57	51.51	65.37	65.27	65.35	65.37	68.84
0.8	47.12	46.43	47.07	47.26	52.85	66.33	66.21	66.09	66.34	69.19
0.9	48.74	47.95	48.75	48.85	54.26	67.36	67.25	67.03	67.36	70.26
1	49.83	49.24	49.86	49.98	55.48	68.40	68.23	68.11	68.40	71.07

Table 2 represents the newly significant bits found in the first ten passes of the four different hyperspectral image compression schemes. It has been observed that propose compression scheme sucessfully identify more significant bits than the other hyperspectral image compression schemes due to the reconstructed hyperspectral image cube. This has been done by the proposed compression scheme by keeping the high PSNR values with reference to the other compression scheme.

Table 2. New significant bit found in the first ten pass of 3D-SPECK [6], 3D-SPIHT [9], 3D-LSK [10], 3D-WBTC [11] at various bit rates for the four different hyperspectral images Washington DC, Jasper Ridge, Cuprite & Urban [12]

Pass	3D-SPECK	3D-SPIHT	3D-LSK	3D-WBTC	M-3D-WBTC	3D-SPECK	3D-SPIHT	3D-LSK	3D-WBTC	M-3D-WBTC
	Washington DC					Jasper Ridge				
1	17	17	17	17	22	7	7	7	7	12
2	50	50	50	50	59	30	30	30	30	44
3	65	65	65	65	84	71	71	71	71	84
4	178	178	178	178	198	217	217	217	217	311
5	533	533	533	533	612	636	636	636	636	818
6	1786	1786	1786	1786	1918	1671	1671	1671	1671	1801
7	5558	5558	5558	5558	6018	5602	5602	5602	5602	5948
8	18159	18159	18159	18159	19185	18286	18286	18286	18286	20022
9	48342	48342	48342	48342	51235	37407	37407	37407	37407	39948
10	108519	77842	78941	71878	75356	72574	72574	72574	72574	77121
	Cuprite					Urban				
1	5	5	5	5	8	33	33	33	33	59
2	50	50	50	50	51	58	58	58	58	201
3	219	219	219	219	255	70	70	70	70	297
4	537	537	537	537	702	156	156	156	156	548
5	5099	5099	5099	5099	5323	745	745	745	745	2073
6	10324	10324	10324	10324	11002	3002	3002	3002	3002	9285
7	22424	22424	22424	22424	23874	11305	11305	11305	11305	37475
8	46681	46681	46681	46681	49128	35333	35333	35333	35333	92623
9	79986	79986	79986	79986	82079	108506	108506	108506	108506	169220
10	120660	120660	120660	112854	119756	252166	252166	252166	252166	275708

3.2. Memory

Table 3 represents the memory requirement of the 3D-MWBTC for different bit per pixel per band rate (bppbp) with 3D-SPECK [6], 3D-SPIHT [9], 3D-LSK [10], 3D-WBTC [11]. As shown in the Table 3, 3D-MWBTC has less memory requirement with other hyperspectral image compression schemes. It is clear that memory requirement of all five compression scheme in top priority bitplane is more significant than lower low priority bitplane because at the lowest threshold level more sets will be significant and 3D-MWBTC will result in more entries in LIBC.

Table 3. Memory (kb) use by the 3D-SPECK [6], 3D-SPIHT [9], 3D-LSK [10], 3D-WBTC [11] at various bit rates for the four different hyperspectral images Washington DC, Jasper Ridge, Cuprite & Urban [12]

bppbp	Washington DC					Jasper Ridge				
	3D-SPECK	3D-SPIHT	3D-LSK	3D-WBTC	M-3D-WBTC	3D-SPECK	3D-SPIHT	3D-LSK	3D-WBTC	M-3D-WBTC
0.1	243.84	263.28	512	250.09	241.30	241.36	245.86	512	245.83	227.25
0.2	416.29	437.97	512	416.00	402.17	439.95	445.74	512	443.73	411.69
0.3	701.05	628.55	512	704.03	635.99	541.29	555.28	512	549.26	512.66
0.4	733.80	723.55	512	732.97	805.79	729.56	759.53	512	741.59	662.86
0.5	1048.80	1060.50	512	1049.00	1075.85	821.57	808.88	512	827.94	799.90
0.6	1191.10	1222.60	512	1195.40	1075.85	1099.85	1123.21	512	1106.71	985.66
0.7	1191.90	1222.60	512	1195.60	1262.85	1099.85	1123.21	512	1106.71	1012.95
0.8	1407.70	1415.30	512	1404.40	1587.01	1178.85	1192.71	512	1189.12	1087.48
0.9	1702.50	1725.50	512	1704.60	1603.14	1443.24	1467.97	512	1450.32	1221.44
1	1802.50	1826.70	512	1724.60	1669.57	1443.24	1467.97	512	1450.32	1221.44
bppbp	Cuprite					Urban				
	3D-SPECK	3D-SPIHT	3D-LSK	3D-WBTC	M-3D-WBTC	3D-SPECK	3D-SPIHT	3D-LSK	3D-WBTC	M-3D-WBTC
0.1	277.73	277.60	512	282.79	185.33	293.23	299.44	512	294.27	251.79
0.2	414.52	434.27	512	417.15	248.51	478.12	529.82	512	483.45	534.85
0.3	544.29	514.74	512	546.27	333.95	841.20	863.95	512	842.73	679.98
0.4	601.93	576.49	512	594.45	496.66	841.20	866.95	512	842.73	981.90
0.5	671.18	701.89	512	674.51	751.95	1076.59	1110.29	512	1076.96	981.90
0.6	854.01	783.74	512	857.57	834.04	1419.37	1444.85	512	1424.83	1200.32
0.7	854.02	783.74	512	857.57	885.65	1563.42	1586.39	512	1564.13	1477.50
0.8	1065.30	964.62	512	1057.30	1003.91	1563.42	1586.39	512	1564.13	1477.50
0.9	1158.50	1182.40	512	1159.50	1173.22	1590.25	1586.39	512	1589.81	1481.34
1	1158.50	1182.40	512	1159.60	1173.22	1889.49	1906.35	512	1808.87	1747.06

3.3. Complexity Analysis

Table 4 and Table 5 are the encoding and decoding time of the 3D-MWBTC with the comparative analysis of 3D-SPECK [6], 3D-SPIHT [9], 3D-LSK [10], 3D-WBTC [11]. This time has been calculated for different bit per pixel per band (bppbp) values. The time of wavelet transform and inverse wavelet transform is not included in the encoding and decoding time. It has been cleared that the proposed scheme is taking less encoding and decoding time with reference to other compression schemes due to the low value of the highest pixel value present in the image cube.

Table 4. Encoding Time (sec) of the 3D-SPECK [6], 3D-SPIHT [9], 3D-LSK [10], 3D-WBTC [11] at various bit rates for the four different hyperspectral images Washington DC, Jasper Ridge, Cuprite & Urban [12]

bppbp	3D-SPECK	3D-SPIHT	3D-LSK	3D-WBTC	M-3D-WBTC	3D-SPECK	3D-SPIHT	3D-LSK	3D-WBTC	M-3D-WBTC
			Washington DC					Jasper Ridge		
0.1	24.98	7.47	0.77	6.51	5.17	21.10	7.62	0.93	6.36	5.15
0.2	57.94	25.76	1.08	24.81	16.31	54.19	20.56	1.16	17.71	13.62
0.3	92.12	37.47	1.53	32.03	45.25	100.62	39.43	1.49	42.77	26.12
0.4	269.74	117.89	1.99	195.46	70.26	150.94	47.77	2.21	70.67	71.05
0.5	414.80	140.13	2.53	194.19	77.97	315.28	101.56	2.64	182.38	78.88
0.6	576.03	166.40	2.91	247.89	311.97	355.95	115.33	3.03	227.51	185.58
0.7	887.48	405.70	3.16	625.02	404.48	426.13	232.29	3.15	480.85	325.46
0.8	1130.50	474.16	3.80	710.20	456.71	585.74	382.31	3.69	676.43	362.20
0.9	1334.60	555.72	4.04	746.00	592.91	701.17	415.02	3.98	771.90	450.15
1	1497.50	574.96	4.38	804.00	704.88	757.32	425.38	5.05	942.81	659.52
			Cuprite					Urban		
0.1	17.26	6.29	0.85	4.69	4.48	15.64	6.79	1.58	6.85	6.15
0.2	55.82	26.01	1.21	16.61	9.76	49.54	19.74	2.97	19.09	20.54
0.3	107.91	45.52	1.98	39.06	16.95	85.71	48.89	4.11	26.36	45.59
0.4	182.28	75.55	2.09	68.19	25.45	312.36	202.14	5.64	191.77	56.80
0.5	276.14	95.44	2.19	93.32	36.70	416.21	198.11	7.07	253.64	232.62
0.6	298.42	161.67	3.44	155.69	85.63	886.92	206.67	8.84	300.34	277.05
0.7	438.80	179.18	3.85	202.24	135.15	605.09	211.86	9.48	371.65	294.26
0.8	558.74	198.45	4.21	358.46	155.02	1125.15	541.76	11.09	788.74	548.23
0.9	656.09	282.84	4.42	370.97	271.57	1542.71	774.09	12.69	1067.05	801.75
1	905.06	364.00	4.97	652.46	481.80	1702.79	780.18	14.37	1184.45	857.14

Table 5. Decoding Time (sec) of the 3D-SPECK [6], 3D-SPIHT [9], 3D-LSK [10], 3D-WBTC [11] at various bit rates for the four different hyperspectral images Washington DC, Jasper Ridge, Cuprite & Urban [12]

bppbp	3D-SPECK	3D-SPIHT	3D-LSK	3D-WBTC	M-3D-WBTC	3D-SPECK	3D-SPIHT	3D-LSK	3D-WBTC	M-3D-WBTC
			Washington DC					Jasper Ridge		
0.1	17.42	6.12	0.71	5.03	3.52	15.31	7.41	0.75	4.57	3.43
0.2	48.77	24.84	1.12	22.45	14.39	36.99	17.63	1.12	15.32	11.35
0.3	75.39	34.77	1.50	28.50	43.39	84.67	37.14	1.43	39.95	22.45
0.4	264.22	106.26	1.72	180.43	69.66	128.79	44.96	2.08	68.97	70.31
0.5	339.07	135.44	2.17	191.65	75.40	290.76	98.51	2.61	178.42	74.42
0.6	532.38	130.56	2.64	244.64	306.66	330.90	155.55	2.80	229.76	181.47
0.7	807.58	427.07	2.64	558.00	400.22	386.40	232.15	3.02	432.08	319.98
0.8	1058.10	468.88	3.08	675.31	469.02	487.76	382.18	3.50	608.44	356.30
0.9	1142.30	486.23	3.17	725.00	597.09	667.35	402.73	3.55	673.47	461.30
1	1289.66	503.96	3.68	874.00	689.27	726.86	421.31	4.28	923.14	642.32
			Cuprite					Urban		
0.1	13.38	5.00	0.66	3.14	2.78	11.78	4.28	1.50	4.76	4.85
0.2	46.66	22.08	0.99	14.57	9.76	41.59	16.83	2.39	16.38	18.32
0.3	93.70	40.23	1.77	35.41	16.95	72.29	42.50	3.24	23.17	43.17
0.4	162.48	70.08	1.87	65.81	25.45	292.17	218.31	4.65	194.48	53.97
0.5	236.13	88.29	2.02	91.52	36.70	388.44	198.82	5.35	243.21	228.35
0.6	319.20	160.90	2.86	148.97	85.63	487.20	197.21	6.14	294.68	271.86
0.7	435.00	175.79	3.10	196.82	135.15	592.70	199.07	8.20	365.65	289.21
0.8	525.89	195.33	3.79	315.96	155.02	1066.72	528.92	8.80	771.74	546.03
0.9	599.22	273.50	4.04	366.90	271.57	1506.41	749.75	9.37	1052.34	798.03
1	884.44	346.64	4.49	595.98	481.80	1661.79	3908.40	10.04	1173.39	853.29

4. CONCLUSION

The work has been demonstrated that the high signal to noise ratio can be achieved by the proposed hyperspectral image compression scheme with limited loss of critical information according to the compression point of view. In this scheme the hyperspectral image cube is reconstructed and the top priority bit plane is eliminated by the taking difference between the consecutive frames of hyperspectral image cube. This compression scheme is suited for the sensors which needs high PSNR at the low bit per pixel per band rate. It has the relatively less coding memory requirement with the other compression scheme as shown in the Table 3.

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