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Original Article

Contourlet Transform Based Listless Set Partitioned Embedded Block Coding Algorithm for Wireless Multimedia Sensor Networks

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Abstract *- The coding efficiency of any compression algorithm at a low bit rate is challenging. It is a crucial performance metric for reconstructing the hyperspectral image after compression. Many wavelet-based compression algorithms have been proposed, but they either have low coding efficiency, extortionate coding memory requirements, or high coding complexity. In the present manuscript, the proposed compression algorithm utilized the property of contourlet transform to represent the image's geometrical features. This led to an increase in the coding efficiency of the proposed compression algorithm. Using markers it has low and fixed memory requirements and coding complexity. The simulation presented that the proposed compression algorithm gains 2% to 5% in coding efficiency.*

Keywords *- Hyperspectral image compression, Coding algorithm, Lossy compression, Transform coding, Set Partitioned.*

1. Introduction

Hyperspectral (HS) imaging is an advanced technology that combines a spectrometer and a camera sensor to capture multi-band spectral images by examining the reflection or radiation data (spatial and spectral information) for a single scene across successive wavelengths of visible to infrared and beyond (400 nm to 2500 nm with spectral spacing of 5 nm to 10 nm) [1-3].

With such detailed information in HS images, HS imaging has great potential in multiple applications ranging from astronomy [4], biotechnology [5], biomedical [6], chemical imaging [7], corrosion detection (infrastructure) [8], cultivation [9], defence [10], environment [11], forestry [12], forensic [13], geology [14], healthcare [15], mining (mineralogy) [16], oceanography [17], pharmaceuticals [18], remote sensing [19], township planning [20] etc.

The refined analysis enhances comprehension of the HS image, leading to more well-founded judgments [21]. Remote Sensing (RS) collects information about objects from a distance, utilizing technology to detect characteristics such as temperature and radiation [22]. Given the extensive information available in hyperspectral images, scientists are developing computational algorithms in different research fields ranging from band reduction [23], classification [24], change detection [25], compression [26], denoising [27], dimension reduction [28], feature extraction [29], feature selection [30], fusion [31], image inpainting [32], object identification/recognition [33], segmentation [34], target detection [35], unmixing [36] etc.

Each HS image occupies around 150 MB of storage space. Hence, saving the HS image data in the onboard sensor memory requires memory [37]. An efficient compression algorithm is required to compress the HS image data before the transmission from the onboard station to the earth station to save the onboard sensor memory, curtail the HS image data processing time (complexity), lower the data bandwidth and reduce the energy requirement [38-39].

Two forms of redundancy exist in HS images: spatial redundancy (due to the correlated coefficient present in one frame) and spectral redundancy (due to the pixels present at the same spatial location in adjutant frames) [40]. Redundancy should be minimized to achieve compression in any image [41].

The compression algorithms, or the HyperSpectral Image Compression Algorithm (HSICA), are divided into categories based on HS image data loss or coding process. Based on HS image data loss it is subdivided into three types: lossless, near lossless, and lossy [42,43]. While based on HS, the image coding process is subdivided into seven types: Predictive Coding (PC) [44], Vector Quantization (VQ) [45], Transform Coding (TC) [46], Compressive Sensing (CS) [47], Tensor Decomposition (TD) [48], Learning-Based Compression (LC) [49] and hybrid compression algorithms [50].

Among the above-mentioned types of HSICAs, transform coding based HSICA has optimum performance as these HSICAs can work with lossy and lossless compression. Because of coding efficiency, LC-based HSICA has the best coding efficiency. Except for TC-based HSICAs, the rest of the HSICA work with lossless compression only [51].

In this manuscript, focusing on the previously discussed challenges, a novel mathematical (contourlet) transform-based lossy compression algorithm for HS images addresses image sensors' difficulties. This manuscript makes a significant contribution to the following sub-areas,

- The contourlet transform is a geometric image transformation method designed to capture and represent contours and textures in HS images effectively.
- Due to the listless version of the compression algorithm, the fixed coding memory was required independent of the bit rate and depended only on the size of the HS image under test.
- The proposed compression algorithm (3D-CT-LSK) has a lower coding complexity than other state-of-the-art HS image compression algorithms.

However, this research analysis is carried out using seven research sections. Section 2 introduced the principle of contourlet transform with a short survey of different mathematical transform-based compression algorithms. Section 3 gives the detailed architecture of the proposed compression algorithm with associated pseudo code.

Section 4 discusses the implications of the results, deployment considerations, and outstanding challenges. Section 5 provides this study's main conclusions and identifies potential future research directions.

2. Related Work

In this section, the associated work with the compression algorithm is defined. The first sub-section describes the contourlet transform, while the second section covers a detailed description of the set partition-based HS image compression algorithm with a short survey.

2.1. Contourlet Transform

It has been known that a single HS image is a combination of highly correlated HS image frames that have many intrinsic geometrical structures [52]. Fourier, cosine, and wavelet transform have limited ability to identify the smoothness of curves present in any image [53]. Thus, a new transform is required, which is more powerful for representing the curve's smoothness [54]. The contourlet transform, an extension of the wavelet transform, has multiresolution, localization, directionality, critical sampling, and anisotropy properties [55].

The basic functions of contourlet transform are multiscale and multidimensional [56]. The contourlet transform builds upon the curvelet transform while incorporating principles of human visual perception, enabling effective representation of image contours with diverse elongated geometries and multidirectional orientations [57].

The contourlet transform is successfully applied in multiple algorithms related to hyperspectral image fusion [58], denoising [59] and feature extraction [60].

2.2. Mathematical Transform-Based Set Partition Hyperspectral Image Compression Algorithms

Mathematical transform-based set partition compression algorithms are a special type of compression algorithms that utilise the set structure of wavelet transform of HS image to define the large number of insignificant coefficients at high bit rates. It has been clear from the energy compaction property of the wavelet curvelet or contourlet transform that this mathematical transform packs the energy into the few low-frequency uncorrelated transform coefficients [61-62].

This mathematical transform works as a decorrelator, which acts as a decorrelate for the HS image [63]. These mathematical transform compression algorithms can work for the lossy (till the bit budget is available with the compression algorithm) and lossless compression [43, 64].

Among these mathematical transform-based compression algorithms, a special type of compression algorithm that exploits the property of wavelet transform (energy compaction) or its advanced version of transform (curvelet, shearlet, etc.) and uses the set structure to define much insignificant coefficient at the high bit level to achieve the high coding efficiency. Apart from this property, low coding complexity, small coding memory requirement and embeddedness are the significant properties of these compression algorithms [51].

From the orientation of the set structure (grouping of the insignificant coefficients), these algorithms are divided into the zerotree, zero block cube and zero block cube tree [43]. 3D-SPECK [65], 3D-LSK [68] and 3D-ZM-SPECK [72] are the major zero block cube-based compression algorithms. Similarly, 3D-SPIHT [66], 3D-NLS [69] and 3D-BPEC are the major zerotree based compression algorithms. In the same way, 3D-WBTC [67] and 3D-LMBTC [70] are the major zero block cube tree compression algorithms.

3. 3D Contourlet Transform Based Listless SPECK (3D-CT-LSK)

A transform-based sub-band ‘δ’ whose coefficient ‘η’ is located at the position (α, β, γ) is denoted as $C_{\alpha, \beta, \gamma}$ in the linear array. Any sub-block cube ‘B’ of sub-band ‘δ’ is significance is as per Equation (1) concerning the bit plane ‘n’

$$\max_{(\alpha,\beta,\gamma) \in B} \left[\left| C_{\alpha\,\beta\,\gamma} \right| \right] \geq 2^n \tag{1}$$

The other condition is insignificance and will be mentioned as ‘0.’

$$\Gamma_n(B) = \begin{cases} 1 & if\ 2^n \leq \ \leq 2^{n+1} \\ 0 & else \end{cases} \tag{2}$$

3D-CT-LSK uses the block cube structure to define the insignificant coefficients. Three markers are used to define the significant/insignificant sets or coefficients.

The compression algorithm is started from the initialization of the fixed size of coding memory ‘SB’ of $N_{pix}/8$ (N_{pix} is total coefficients in HS image) elements with SB (0) stated as ‘MIB’ and SB (N_{pix} / 8^{L+1}) stated as MI with rest of the elements are denoted as ‘0’. The initial Threshold is denoted as ‘T’. Each bit plane has two passes: the sorting pass and the refinement pass. ‘MRB’ represents that all eight coefficients of the block cube are found significant in the previous bit plane.

The sorting pass of the bit plane is initiated by scanning all elements present in the ‘SB’, SB(k) = ‘MIB’. The size of an S block is determined by counting the consecutive '0' elements in SB (representing block cubes of fixed size). The S block is then evaluated against a threshold, and its significance is encoded.

- If the S block is deemed insignificant, it is omitted, and the SB index is adjusted accordingly.
- When the S block is significant, it undergoes splitting into eight segments, and the corresponding entries in SB are tagged as 'MIB' (Marked for Further Partitioning).

The resulting octa blocks are then tested against the Threshold.

- Quad-tree partitioning is applied to significant octa-blocks, continuing until a base '2 × 2 × 2' block cube is obtained.
- When a '4 × 4 x 4' block reaches significance, it transitions to an 'MNB' state, initiating individual coefficient evaluation against the Threshold with parallel significance encoding.
- Their sign information is included in the encoding for coefficients that meet the significance threshold.

This process ensures efficient hierarchical encoding of significant data while skipping irrelevant regions. In the refinement pass of any bit plane, the refinement bits are generated for all past significant coefficients (last bit planes). In the last bit plane, state ‘MNB’ denoted that this block cube of size ‘8’ is significant in the current bit plane and requires no refinement. For a block marked as 'MSB', each coefficient requiring refinement (i.e., those with a magnitude greater than twice the current Threshold) has its refinement bit encoded. Once all coefficients in the block have been refined, the block's state is updated from 'MSB' to 'MRB' (Marked as Refinement Completed), indicating that no further refinement is needed for that block at the current Threshold. This ensures efficient progressive refinement while tracking the completion status of each block.
In Table 1, the pseudo-code for the introduced compression algorithm is given.

Table 1. Algorithm outline for the proposed compression algorithm

Algorithm: HS image data encoding workflow in the proposed compression approach
Input: Transform HS image (cube) ‘Z’ of size ‘N x N x N’ with ‘L’ level of transform applied
Bit rate is defined as Bit Per Pixel Per Band (BPB)
Output: Embedded Bit Stream
Initialization : Number of coefficients contained in the HS image cube after transformation
A 1D array representation of the 3D HS image cube is generated via Morton ordering from its original 3D form.
Number of binary (bit plane) planes $n = \log_2[\max\{max\{\max\{Z\}\}\}]$
Number of coefficients in the array (embedded bit stream) λ = ‘N x N x N x bob’
Maximum (initial) Threshold T = 2^n
Size of linear array $N_{pix} = 8^n$
Initial SB size = ($^{N_{pix}}/_{8^L}$)
Set : SB(0) = ‘MIB’
Set : SB(8^{m-L-1}) = ‘MI’
Set: The rest of the coefficient is marked as ’0’

Sorting Pass

```
for (i = 0 : 2^N x 2^N x 2^N – 1)
{
    if (mark[i] = MIP)
    {
        Output S(i)
        if (S(i) = 1)
        {
            Calculate the sign bit to the coefficient C αβγ
            Mark [i] = MNP
            i = i+1
            else
            {
                if (mark [i] = MNK )
                {
                    Scan block cube B for every coefficient
                    if (Γn (δ) = 1)
                    {
                        Partition the block cube into eight new block cubes.
                        else
                        {
                            FindNext()
                        }
                    }
                }
            }
        }
    }
    i = i +1
}
```

.

Refinement Pass

```
For (i = 2^N x 2^N x 2^N – 1)
{
    if (mark [i] = MSP)
    then
    {
    {
        Output the nth most significant bit of the block
    }
    i = i +1
    Elseif (mark [i] = MNP)
    {
        then
        {
            mark [i] = MSP
        }
    i = i +1
}
```

Quantization Step

Decrement of n (bit plane) by 2 and go to the sorting pass till the bit budget is available.

4. Experiment Result

The proposed compression method is benchmarked against leading compression algorithms, considering coding efficiency, memory requirements, and processing complexity. The simulation work has been carried out on the four publicly named Washington DC Mall (Image I), Yellowstone Scene 0 (Image II), Yellowstone Scene 3 (Image III), and Yellowstone Scene 18 (Image IV), available with Matlab simulation tool. The HS image is cropped from the top of the left-hand side and made into an HS image cub used in the experiment. The performance metrics Peak Signal to Noise Raito (PSNR), Structural Similarity Index (SSIM) and Feature Similarity Index (FSIM) are used for the calculation of the coding efficiency while BD-PSNR is the derive comparative performance metric for the determine performance of proposed compression algorithm [43]. Coding memory is measured by the memory in kilobytes [72]. Coding complexity is calculated by the time required to calculate the encoding and decoding of the coefficients [73]. All the simulation experiments were conducted on the i5 (11th generation) processor, which has 20 GB RAM with a Windows 11 operating system.

Nine different HSICAs are used for the simulation test with the proposed compression algorithm on the four different HS images. 3D-SPECK (CA-I) [65], 3D-SPIHT (CA-II) [66], 3D-WBTC (CA-III) [67], 3D-LSK (CA-IV) [68], 3D-NLS (CA-V) [69], 3D-LMBTC (CA-VI) [70], 3D-LCBTC (CA-VII) [71], 3D-ZM-SPECK (CA-VIII) [72] and 3D-LBCSPC (CA-IX) [73] are set partition based compression algorithms used for the simulation test and simulation result shows the comparative analysis with proposed compression algorithm.

4.1. Coding Efficiency

The Compression Ratio (CR) measures how much the original Hyperspectral (HS) image is reduced in size after compression [70]. It is a smaller parameter. The mathematical equation in Equation (3) defines CR.

$$CR = \left[\frac{Size\ of\ original\ HS\ image}{Size\ of\ reconstrcuted\ HS\ image}\right] \tag{3}$$

PSNR is the ratio of the maximum possible power of a signal, which is the original image, to the power of noise, which is based on the disparity between the original and processed HS images [74]

$$PSNR = 20\ \log_{10}\left[\frac{Max}{MSE}\right] \tag{4}$$

The highest possible pixel value of the HS image is denoted by the letter 'Max' and the Mean Square Error (MSE) of the reconstructed HS image compared to the original HS image. It is calculated as Equation (5)

$$MSE = \frac{1}{N_{pix}}\sum_{x,y,z}[f(x,y,z) - g(x,y,z)]^2 \tag{5}$$

The results in Table 2 indicate that the proposed algorithm delivers superior PSNR performance over other leading compression algorithms. It is clear from Table 3 that the proposed compression algorithm had a greater number (sum) of Newly Significant Coefficients (NSC) and Refinement Coefficients (RC) at the mentioned bit rates. Also, it has a slightly high number of refinement coefficients, which makes the coding efficiency higher than the other compression algorithms. The HS Image Quality (HSIQ) is defined in PSNR terms.

3D Contourlet Transform Based Listless SPECK has no list (listless) and has only markers; a short comparative analysis of PSNR has been covered in Table 4 for coding efficiency of the different listless compression algorithms for the higher bit rates, which is almost similar for every algorithm. This is because the HS image is reconstructed at a higher bit rate. BD -PSNR gain has been covered in Table 5 for the seven-bit rates.

SSIM and FSIM are the other performance-measuring metrics for determining the coding efficiency of compression algorithms [75-77]. It has been clear from Table 6 (for SSIM) and Table 7 (for FSIM) that 3D-CT-LSK performs better than other compression algorithms because it fetches a significant coefficient at a higher bit level. Due to the contourlet transform's property, it can capture the geometrical variation more efficiently than the other mathematical transform.

Table 2. Performance comparison of the 3D-CT-LSK with other transform-based set-partitioned HSICA techniques in terms of PSNR

BR	CR	CA-I [65]	CA-II [66]	CA-III [67]	CA-IV [68]	CA-V [69]	CA-VI [70]	CA-VII [71]	CA-VIII [72]	CA-IX [73]	3D-CT-LSK
Image I											
0.001	14000	26.28	26.28	26.25	26.14	25.90	26.26	26.41	26.32	26.39	27.11
0.005	2800	28.95	28.95	28.93	28.71	28.71	28.70	28.66	28.73	29.01	29.78
0.01	1400	30.08	30.08	30.04	29.99	29.83	29.98	30.01	29.99	30.14	30.94
0.05	280	34.23	34.23	34.21	34.04	33.81	33.99	34.29	34.06	34.37	35.02
0.1	140	37.22	37.22	37.20	36.96	37.00	36.83	37.34	36.87	37.29	37.98
0.25	56	42.17	42.17	42.16	41.62	41.69	41.34	42.28	41.37	42.01	43.02
0.5	28	48.02	47.99	47.97	47.01	47.79	47.51	48.11	47.55	47.74	48.89

Image II											
0.001	16000	27.11	26.75	27.09	26.83	26.61	26.75	26.87	26.82	27.19	28.01
0.005	3200	29.45	29.31	29.43	29.27	29.25	29.24	29.41	29.25	29.55	30.34
0.01	1600	30.28	30.19	30.27	30.27	30.15	30.31	30.53	30.33	30.38	30.96
0.05	320	33.76	33.61	33.73	33.56	33.59	33.51	33.69	33.54	33.87	33.64
0.1	160	35.57	35.44	35.56	35.49	35.41	35.45	35.55	35.46	35.67	36.31
0.25	64	39.30	39.19	39.29	39.26	39.17	39.22	39.37	39.23	39.29	40.09
0.5	32	43.62	43.65	43.51	43.57	43.26	43.55	43.62	43.58	43.68	44.59
Image III											
0.001	16000	27.82	27.49	27.8	27.78	27.28	27.88	28.07	27.92	27.97	28.69
0.005	3200	30.24	30.09	30.22	30.03	30.03	30.01	30.44	30.02	30.38	30.87
0.01	1600	31.27	31.14	31.25	31.17	31.1	31.13	31.42	31.14	31.37	31.94
0.05	320	34.57	34.39	34.55	34.58	34.27	34.44	34.67	34.51	34.71	35.21
0.1	160	36.63	36.49	36.64	36.42	36.49	36.35	36.74	36.37	36.81	37.27
0.25	64	40.83	40.63	40.84	40.46	40.59	40.29	40.81	40.31	40.65	41.51
0.5	32	45.88	45.66	45.87	45.39	45.57	45.13	45.58	45.15	45.69	46.32
Image IV											
0.001	16000	28.11	27.94	28.06	28.08	27.88	28.07	28.14	28.16	28.21	28.94
0.005	3200	30.44	30.32	30.43	30.27	30.03	30.26	30.22	30.28	30.51	31.21
0.01	1600	31.41	31.29	31.39	31.32	31.1	31.29	31.57	31.43	31.55	32.02
0.05	320	34.46	34.3	34.45	34.41	34.27	34.25	34.62	34.28	34.54	35.15
0.1	160	36.43	36.29	36.43	36.25	36.49	36.19	36.51	36.2	36.53	37.08
0.25	64	40.08	39.93	40.07	39.92	40.59	39.8	40.19	39.84	39.82	40.79
0.5	32	44.51	44.47	44.5	44.31	44.46	44.22	44.63	44.22	44.24	45.04

Table 3. Image quality of 3D-SPECK [65], 3D-LSK [68], 3D-ZM-SPECK [72], 3D-LBCSPC [73] and proposed 3D-CT-LSK

BR	Image I														
	3D-SPECK [65]			3D-LSK [68]			3D-ZM-SPECK [72]			3D-LBCSPC [73]			3D-CT-LSK		
	HSIQ	NSC	RC	HSIQ	NSC	RC	HSIQ	NSC	RC	HSIQ	NSC	RC	HSIQ	NSC	RC
0.001	26.28	2601	883	26.14	2413	685	26.32	2495	833	26.39	2681	927	27.11	2711	951
0.005	28.95	16563	4134	28.71	14905	4134	28.73	14297	4174	29.01	16821	4194	29.78	16997	4219
0.01	30.08	29621	12018	29.99	27742	12018	29.99	27034	17916	30.14	30817	12918	30.94	31102	12992
0.05	34.23	159915	36960	34.04	154678	36960	34.06	144247	107342	34.37	161495	95823	35.02	164002	96008
0.1	37.22	330216	112621	36.96	314919	112621	36.87	291818	231642	37.29	337414	123568	37.98	339574	123002
R	Image II														
	3D-SPECK [65]			3D-LSK [68]			3D-ZM-SPECK [72]			3D-LBCSPC [73]			Proposed Algorithm		
	HSIQ	NSC	RC	HSIQ	NSC	RC	HSIQ	NSC	RC	HSIQ	NSC	RC	HSIQ	NSC	RC
0.001	27.11	3780	1577	26.83	3348	1577	26.82	3094	1913	27.19	3894	1624	28.01	3916	1684
0.005	29.45	17212	7129	29.27	15469	7129	29.25	14481	9433	29.55	18002	8154	30.34	18111	8267
0.01	30.28	29247	12415	30.27	29196	12415	30.33	27583	13814	30.38	30017	12989	30.96	30958	13344
0.05	33.76	170267	47234	33.56	158703	47234	33.54	148700	46602	33.87	165268	47008	33.64	168714	47108
0.1	35.57	314698	142703	35.49	302729	142703	35.46	290236	142472	35.67	310523	143651	36.31	315108	146222

Table 4. Coding efficiency of listless HS image compression algorithms at the higher bit rates

BR	CA-IV [68]	CA-V [69]	CA-VI [70]	CA-VII [71]	CA-VIII [72]	CA-IX [73]	3D-CT-LSK	CA-IV [68]	CA-V [69]	CA-VI [70]	CA-VII [71]	CA-VIII [72]	CA-IX [73]	3D-CT-LSK
	Image I							**Image II**						
1	55.96	56.1	55.42	55.64	55.44	56.04	56.06	49.51	49.53	49.25	49.47	49.26	49.55	49.54
2	66.75	66.77	66.01	66.18	66.02	66.78	66.97	59.52	59.29	59.49	59.51	59.51	59.61	59.67
3	75.72	75.47	75.48	75.41	75.50	75.69	76.02	66.66	66.71	66.07	66.24	66.08	66.7	66.69
4	82.99	83.07	82.75	82.64	82.76	83.04	83.25	72.43	72.50	71.60	71.97	71.60	72.5	72.5
5	87.9	87.43	88.43	88.17	88.44	88.27	88.41	78.92	78.76	77.77	78.08	77.78	78.9	78.91
6	95.68	95.17	95.68	95.61	95.68	95.71	95.77	84.51	84.41	84	84.09	84.00	84.6	84.61
7	96.8	96.71	96.72	96.52	96.77	96.84	96.89	89.12	88.88	89.21	89.28	89.21	89.2	89.25
8	97.71	97.65	97.87	97.58	97.69	97.88	97.9	96.94	96.02	96.94	96.91	96.94	96.9	96.9
	Image III							**Image IV**						
1	53.38	53.15	52.89	53.08	52.93	53.49	53.51	50.96	53.15	50.43	50.47	50.45	51.21	51.22
2	64.15	63.91	64.15	64.16	64.11	64.31	64.31	61.12	60.91	60.62	60.94	60.63	61.28	61.3
3	70.59	70.70	70.44	70.52	70.45	70.68	70.7	67.98	67.82	67.50	67.61	67.51	67.95	67.95
4	76.27	76.10	75.97	76.09	75.97	76.41	76.44	73.81	73.65	72.94	73.24	72.95	73.91	73.9
5	82.39	82.21	82.16	82.11	82.17	82.41	82.47	79.86	79.68	78.60	79.37	78.61	79.88	79.87
6	87.17	87.00	87.26	87.29	87.27	87.22	87.23	85.27	85.12	84.68	84.91	84.68	85.37	85.36
7	96.15	95.87	96.35	95.97	96.15	96.39	96.39	90.55	90.1	90.7	90.77	90.71	90.67	90.66
8	98.07	97.67	98.01	98.01	97.89	98.14	98.14	96.6	95.53	96.6	96.51	96.6	96.6	96.61

Table 5. Rate-distortion performance evaluation: Average PSNR gains (BD-PSNR) of the novel HS compression approach versus benchmarks across seven bitrate levels

HS Images under Test	CA-I [65]	CA-II [66]	CA-III [67]	CA-IV [68]	CA-V [69]	CA-VI [70]	CA-VII [71]	CA-VIII [72]	CA-IX [73]
Image I	0.8237	0.8257	0.8499	1.0957	1.1319	1.1106	0.8396	1.0727	0.7866
Image II	0.6432	0.7818	0.6661	0.7645	0.8516	0.7901	0.6315	0.7671	0.5569
Image III	0.6591	0.8367	0.6712	0.8235	0.9097	0.8938	0.5488	0.8671	0.5734
Image IV	0.6897	0.8226	0.7045	0.8097	0.8398	0.8734	0.6394	0.8199	0.65

Table 6. Benchmarking the SSIM index of the 3D-CT-LSK against existing transform-based HSICA implementations employing set partitioning

BR	CA-I [65]	CA-II [66]	CA-III [67]	CA-IV [68]	CA-V [69]	CA-VI [70]	CA-VII [71]	CA-VIII [72]	CA-IX [73]	3D-CT-LSK
	Image I									
0.001	0.078	0.078	0.077	0.073	0.063	0.075	0.074	0.077	0.076	0.08
0.005	0.195	0.195	0.194	0.186	0.183	0.186	0.187	0.188	0.192	0.196
0.01	0.232	0.232	0.23	0.235	0.218	0.233	0.237	0.238	0.237	0.238
0.05	0.371	0.371	0.369	0.375	0.37	0.376	0.374	0.377	0.375	0.377
0.1	0.422	0.422	0.421	0.436	0.424	0.429	0.428	0.437	0.434	0.44
0.25	0.504	0.504	0.504	0.518	0.521	0.519	0.524	0.519	0.518	0.521
0.5	0.589	0.591	0.591	0.593	0.591	0.592	0.589	0.591	0.592	0.599
	Image II									
0.001	0.27	0.267	0.268	0.266	0.264	0.268	0.267	0.264	0.266	0.271
0.005	0.373	0.365	0.372	0.367	0.362	0.367	0.374	0.364	0.371	0.375
0.01	0.42	0.415	0.419	0.421	0.414	0.418	0.417	0.419	0.421	0.422
0.05	0.608	0.601	0.607	0.611	0.602	0.608	0.611	0.610	0.607	0.61
0.1	0.666	0.661	0.666	0.668	0.663	0.665	0.666	0.665	0.664	0.67
0.25	0.764	0.762	0.764	0.766	0.763	0.764	0.763	0.765	0.765	0.767
0.5	0.824	0.825	0.827	0.828	0.826	0.827	0.83	0.827	0.828	0.83

	Image III									
0.001	0.164	0.169	0.164	0.163	0.164	0.164	0.164	0.164	0.163	0.166
0.005	0.291	0.285	0.291	0.29	0.284	0.285	0.283	0.286	0.285	0.286
0.01	0.338	0.339	0.337	0.331	0.326	0.326	0.334	0.326	0.328	0.33
0.05	0.482	0.477	0.483	0.488	0.478	0.478	0.481	0.479	0.478	0.481
0.1	0.541	0.537	0.541	0.547	0.539	0.539	0.527	0538	0.541	0.542
0.25	0.649	0.647	0.646	0.648	0.647	0.647	0.649	0.647	0.649	0.651
0.5	0.723	0.721	0.723	0.733	0.724	0.724	0.728	0.724	0.724	0.728
	Image IV									
0.001	0.213	0.208	0.212	0.212	0.204	0.207	0.211	0.203	0.211	0.218
0.005	0.316	0.311	0.316	0.315	0.307	0.312	0.315	0.313	0.314	0.32
0.01	0.365	0.366	0.363	0.362	0.366	0.359	0.364	0.359	0.362	0.366
0.05	0.532	0.529	0.533	0.535	0.529	0.531	0.53	0.531	0.533	0.537
0.1	0.598	0.594	0.597	0.604	0.601	0.604	0.603	0.603	0.603	0.608
0.25	0.711	0.708	0.71	0.708	0.712	0.714	0.715	0.712	0.711	0.716
0.5	0.787	0.784	0.787	0.791	0.789	0.788	0.79	0.789	0.79	0.792

Table 7. Comparing the FSIM index of the 3D-CT-LSK with other transform-based set-partitioned HSICA approaches

BR	CA-I [65]	CA-II [66]	CA-III [67]	CA-IV [68]	CA-V [69]	CA-VI [70]	CA-VII [71]	CA-VIII [72]	CA-IX [73]	3D-CT-LSK
	Image I									
0.001	0.366	0.366	0.371	0.371	0.372	0.374	0.37	0.374	0.373	0.374
0.005	0.433	0.433	0.432	0.434	0.436	0.435	0.435	0.436	0.434	0.438
0.01	0.55	0.551	0.552	0.555	0.552	0.554	0.551	0.554	0.554	0.558
0.05	0.685	0.681	0.686	0.687	0.677	0.681	0.684	0.682	0.686	0.69
0.1	0.742	0.742	0.744	0.751	0.748	0.749	0.748	0.75	0.75	0.752
0.25	0.802	0.799	0.803	0.804	0.801	0.802	0.801	0.803	0.804	0.805
0.5	0.888	0.889	0.889	0.886	0.887	0.887	0.888	0.887	0.888	0.89
	Image II									
0.001	0.587	0.577	0.586	0.589	0.583	0.584	0.586	0.584	0.588	0.589
0.005	0.686	0.682	0.688	0.689	0.682	0.692	0.691	0.69	0.691	0.691
0.01	0.699	0.699	0.699	0.702	0.701	0.702	0.701	0.701	0.702	0.703
0.05	0.712	0.711	0.714	0.707	0.708	0.709	0.708	0.708	0.71	0.711
0.1	0.734	0.736	0.74	0.738	0.741	0.742	0.738	0.74	0.741	0.742
0.25	0.765	0.77	0.772	0.771	0.774	0.775	0.771	0.771	0.773	0.774
0.5	0.807	0.805	0.807	0.807	0.806	0.805	0.806	0.806	0.807	0.808
	Image III									
0.001	0.537	0.536	0.538	0.537	0.53	0.529	0.53	0.531	0.535	0.535
0.005	0.661	0.657	0.657	0.657	0.664	0.663	0.659	0.662	0.666	0.667
0.01	0.688	0.691	0.695	0.69	0.694	0.693	0.693	0.692	0.692	0.693
0.05	0.709	0.707	0.71	0.709	0.709	0.709	0.71	0.709	0.711	0.711
0.1	0.744	0.744	0.743	0.743	0.747	0.74	0.742	0.742	0.749	0.75
0.25	0.768	0.771	0.775	0.772	0.771	0.773	0.774	0.772	0.775	0.775
0.5	0.812	0.818	0.808	0.812	0.819	0.804	0.803	0.801	0.811	0.812
	Image IV									
0.001	0.377	0.379	0.381	0.38	0.378	0.381	0.381	0.382	0.383	0.386
0.005	0.579	0.577	0.581	0.582	0.58	0.581	0.58	0.581	0.582	0.582
0.01	0.667	0.67	0.672	0.671	0.669	0.673	0.674	0.674	0.674	0.675
0.05	0.726	0.73	0.731	0.732	0.731	0.729	0.728	0.73	0.733	0.734
0.1	0.744	0.749	0.751	0.749	0.752	0.751	0.75	0.752	0.754	0.755
0.25	0.779	0.784	0.786	0.783	0.788	0.789	0.791	0.789	0.791	0.79
0.5	0.814	0.816	0.806	0.809	0.811	0.812	0.814	0.812	0.816	0.817

Table 8. Coding memory requirement between the 3D-CT-LSK with the other HSICA

BR	CA-I [65]	CA-II [66]	CA-III [67]	CA-IV [68]	CA-V [69]	CA-VI [70]	CA-VII [71]	CA-VIII [72]	CA-IX [73]	3D-CT-LSK
	Image I									
0.001	26.67	37.33	28.08	4096	8192	96	2318	0	4097	1666
0.005	102.3	99.21	89.33	4096	8192	96	2318	0	4097	1666
0.01	232.2	222.7	202.4	4096	8192	96	2318	0	4097	1666
0.05	1084	1041	991.7	4096	8192	96	2318	0	4097	1666
0.1	1846	1931	1756	4096	8192	96	2318	0	4097	1666
0.25	4571	4463	4289	4096	8192	96	2318	0	4097	1666
0.5	8644	8555	8514	4096	8192	96	2318	0	4097	1666
	Image II									
0.001	22.58	21.51	22.69	4096	8192	96	2318	0	4097	1666
0.005	91.12	98.91	91.29	4096	8192	96	2318	0	4097	1666
0.01	265.9	267.8	266.4	4096	8192	96	2318	0	4097	1666
0.05	982.4	1036	985.4	4096	8192	96	2318	0	4097	1666
0.1	2219	2326	2229	4096	8192	96	2318	0	4097	1666
0.25	5450	5611	5464	4096	8192	96	2318	0	4097	1666
0.5	10005	9981	9832	4096	8192	96	2318	0	4097	1666
	Image III									
0.001	25.28	24.94	25.06	4096	8192	96	2318	0	4097	1666
0.005	101.2	105.8	101.5	4096	8192	96	2318	0	4097	1666
0.01	205.1	218.9	208.6	4096	8192	96	2318	0	4097	1666
0.05	1108	1149	1136	4096	8192	96	2318	0	4097	1666
0.1	1855	1808	1854	4096	8192	96	2318	0	4097	1666
0.25	4401	4449	4412	4096	8192	96	2318	0	4097	1666
0.5	7918	7805	7935	4096	8192	96	2318	0	4097	1666
	Image IV									
0.001	24.67	22.41	24.55	4096	8192	96	2318	0	4097	1666
0.005	100.8	105.5	101.1	4096	8192	96	2318	0	4097	1666
0.01	210.9	229.9	214.4	4096	8192	96	2318	0	4097	1666
0.05	1088	1212	1106	4096	8192	96	2318	0	4097	1666
0.1	1970	2083	1980	4096	8192	96	2318	0	4097	1666
0.25	4867	5047	4878	4096	8192	96	2318	0	4097	1666

4.2. Coding Memory

The coding memory of the demand of the listless compression algorithm is fixed depending only on the size of the HS image, while for the listless, the demand of coding memory varies with the bit rate. It has been observed from Table 8 that the proposed compression algorithm has slightly higher coding memory demand than 3D-LMBTC [70], 3D-ZM-SPECK [72] and 3D-BCP-ZM-SPECK [74]. At the low bit rate, list-based compression algorithms have low coding memory demand because the number of coefficients is smaller. Table 9 covers the comparative analysis between the different compression algorithms (listless) for different image sizes.

4.3. Coding Efficiency

Coding efficiency is measured by the time the compression algorithm consumes [78-79]. Every transform-based compression algorithm has two phases in the compression process: encoding and decoding. The encoded embedded bit stream is generated from the transform HS image after the compression in the encoding process. At the same time, decompression of this bit stream is performed during the encoding process. It has been known that the time duration of the encoding process is always greater than the decoding process [70]. This is because, in the encoding process, the significance of the sets or coefficients is always checked for each bit plane, while significance testing of partitioned sets or coefficients is not required in the decoding process [78]. The proposed compression algorithm has less number of markers than 3D-LSK [68] and 3D-NLS [69], which reduces the time requirement for read or write operation. Table 10 represents the encoding time, while Table 11 covers the decoding time. A short comparative analysis between the listless HSICA at bit rate is covered in Table 12.

Table 9. Coding memory requirement of listless HSICAs for different sizes of HS images (KB)

Dimension of HS Image Cube	CA-IV [68]	CA-V [69]	CA-VI [70]	CA-VII [71]	CA-VIII [72]	3D-BCP-ZM-SPECK [74]	CA-IX [73]	3D-CT-LSK
64	64 KB	128 KB	1.5 KB	46.79 KB	0	0	65 KB	27 KB
128	512 KB	1024 KB	12 KB	300.59 KB	0	0	513 KB	209 KB
256	4 MB	8 MB	96 KB	2318 KB	0	0	4097 KB	1666 KB
512	32 MB	64 MB	768 KB	18.02 MB	0	0	32769 KB	14 MB

Table 10. Comparison of encoding time (coding complexity) between 3D-CT-LSK and other HSICA

BR	CA-I [65]	CA-II [66]	CA-III [67]	CA-IV [68]	CA-V [69]	CA-VI [70]	CA-VII [71]	CA-VIII [72]	CA-IX [73]	3D-CT-LSK
	Image I									
0.001	3.99	4.06	5.94	2.67	14.18	5.91	3.17	3.24	3.03	2.97
0.005	9.85	9.73	8.2	2.78	61.33	8.35	3.35	4.83	3.41	3.11
0.01	20.45	29.93	10.99	3.25	73.64	9.26	4.41	5.97	4.08	3.59
0.05	222.2	303.4	94.36	5	90.57	19.45	5.49	12.18	5.57	5.28
0.1	1163	1297	762.6	7.31	102.5	34.74	7.94	19.55	8.04	7.64
0.25	6234	6871	4358	13.35	120.8	68.15	14.02	40.25	14.12	13.89
0.5	17995	18742	19551	24.12	151.3	122.5	26.03	74.87	25.21	24.54
	Image II									
0.001	3.42	4.33	5.94	2.35	15.97	5.73	2.47	2.94	2.91	2.56
0.005	9.84	5.85	8.5	2.71	75.93	7.36	3.87	6.44	3.37	2.94
0.01	22.53	9.41	10.83	2.88	90.43	16.99	4.29	10.28	3.94	3.08
0.05	250.3	134.4	131.5	4.14	106.55	27.4	5.02	16.02	4.82	4.47
0.1	966.7	570.8	632.6	6.04	125.87	36.27	7.21	18.42	6.76	6.23
0.25	4973	3032	4100	10.24	134.4	96.34	12.21	56.67	11.02	10.87
0.5	12007	10112	12975	17.25	154.41	177.73	18.95	67.74	19.23	17.84
	Image III									
0.001	4.08	4.03	5.85	2.07	15.97	5.68	2.76	3.19	2.22	2.54
0.005	9.12	5.96	7.87	2.89	75.93	7.78	3.28	4.74	3.01	3.11
0.01	20.18	9.7	11.64	3.34	90.43	8.55	4.01	7.52	3.92	3.69
0.05	204.3	125.2	89.77	4.57	106.55	19.48	5.31	22.88	5.07	4.97
0.1	1183	775.8	835.9	5.91	125.87	32.46	6.47	30.14	6.24	6.65
0.25	8499	5151	6309	10.41	134.14	70.4	11.91	43.49	11.92	11.21
0.5	29849	18383	23861	16.19	154.41	125.42	17.09	72.62	16.87	17.35
	Image IV									
0.001	4.56	5.6	7.23	2.39	6.03	5.74	2.89	2.82	2.52	2.61
0.005	15.24	6.23	8.15	2.81	11.53	7.53	3.34	4.44	3.01	3.14
0.01	21.67	10.2	12.64	3.18	18.44	8.93	3.98	5.64	3.54	3.52
0.05	269.6	130.4	98.12	4.3	22.64	18.61	4.88	13.02	4.57	4.64
0.1	1336	893.4	882.3	6.11	25.53	32.45	6.41	18.18	6.48	6.55
0.25	8435	5133	5501	10.35	34.5	69.66	11.38	36.3	11.12	10.89
0.5	27917	17945	18818	17.43	65.13	125.19	19.01	66.91	18.05	18.02

Table 11. Comparison of decoding time (coding complexity) between 3D-CT-LSK with the other HSICA

BR	CA-I [65]	CA-II [66]	CA-III [67]	CA-IV [68]	CA-V [69]	CA-VI [70]	CA-VII [71]	CA-VIII [72]	CA-IX [73]	3D-CT-LSK
	Image I									
0.001	1.78	2.92	1.59	2.08	12.79	2.48	2.21	3.02	2.07	2.57
0.005	5.18	5.25	2.41	2.43	48.29	3.86	2.68	4.65	2.38	2.98
0.01	10.78	14.31	4.51	2.68	57.16	4.04	3.08	5.61	2.74	3.16
0.05	172.7	236.2	84.75	4.02	69.23	12.01	4.34	11.79	4.31	4.94
0.1	1081	1078	762.11	6.24	77.57	21.79	6.71	18.36	6.47	7.11
0.25	6012	6305	4703	11.68	90.45	50.91	12.02	37.86	12.79	13.21
0.5	17597	18534	15400	22.65	100.5	96.84	25.07	69.02	24.43	22.95
	Image II									
0.001	1.87	1.52	1.46	1.4	12.18	2.18	1.61	2.79	1.51	2.01
0.005	5.4	2.45	2.77	2.49	66.24	3.21	3.01	6.05	2.78	2.78
0.01	10.01	4.92	3.86	2.71	81.48	6.23	3.27	10.04	2.94	2.97
0.05	207.2	127.8	130.1	3.38	94.49	14.94	3.94	11.35	3.33	3.98
0.1	887.6	717.5	614.3	5.98	106.8	23.01	6.64	17.81	5.94	6.02
0.25	4796	3129	4140	6.74	113.86	58.62	7.18	47.06	6.98	10.21
0.5	11898	9954	12299	14.7	125.56	120.33	15.34	60.13	15.03	16.09
	Image III									
0.001	1.74	1.39	1.32	1.89	8.43	4.1	2.11	3.02	2.01	2.33
0.005	5.13	2.24	2.44	2.47	66.02	6.02	2.74	3.99	2.64	2.84
0.01	12.51	5.18	5.14	2.69	84.96	7.06	3.02	6.33	2.94	2.98
0.05	160.3	114.7	80.01	4.46	92.68	14.84	5.19	18.56	5.02	4.02
0.1	1474	760.5	827.8	5.59	104.98	21.49	6.37	27.82	6.11	5.91
0.25	8587	5832	6549	9.27	115.94	48.95	10.34	39.95	10.02	10.21
0.5	26948	15672	23161	14.97	141.97	114.52	16.68	67.23	16.21	16.35
	Image IV									
0.001	2.41	1.64	1.73	2.02	5.27	2.1	2.24	2.74	2.11	2.49
0.005	9.57	2.33	2.55	2.34	8.26	2.88	2.47	4.28	2.31	3.05
0.01	12.68	5.23	6.11	2.89	14.44	3.91	3.23	5.41	2.82	3.28
0.05	226.5	120.5	89.08	3.74	19.5	11.48	4.29	11.36	4.01	4.22
0.1	1241	829.1	866.3	5.96	21.07	21.02	6.57	17.22	6.22	6.07
0.25	9067	4536	5494	6.62	29.65	48.91	7.08	33.79	6.89	9.74
0.5	25042	17677	18136	12.03	55.03	92.97	12.87	62.31	12.12	13.08

Table 12. Coding complexity (encoding time & decoding time) of listless HS image compression for two HS images at the high bit rate

BR	CA-IV [68]	CA-V [69]	CA-VI [70]	CA-VII [71]	CA-VIII [72]	CA-IX [73]	Proposed Algorithm	CA-IV [68]	CA-V [69]	CA-VI [70]	CA-VII [71]	CA-VIII [72]	CA-IX [73]	Proposed Algorithm
	Encoding Time													
	Hyperspectral Image I							**Hyperspectral Image II**						
1	48.9	247.9	241.7	50.04	150.1	44.19	50.2	31.93	221.66	274.24	33.19	139.07	29.74	33.9
2	113.8	320.9	465.4	116.8	312.1	101.9	116.1	68.14	304.4	480.00	70.84	392.25	60.79	71.2
3	192.1	366.3	666.4	209.2	465.4	174.8	198.3	110.58	341.38	866.77	117.9	568.82	98.17	119.1
4	257.7	446.9	905.1	266.7	617.9	224.9	261.2	154.12	383.59	915.67	187.2	702.01	144.2	165.3
5	327.4	467.8	1119.1	344.2	880.7	287.1	333.1	199.04	411.9	1289.2	209.8	754.85	184.8	208.9
6	340.9	488.1	1165.4	357.9	854.3	304.8	357.3	249.9	446.29	1454.4	269.6	918.16	233.7	264.2
7	356.9	501.2	1179.1	387.2	908.2	314.9	384.2	296.22	480.6	1603.5	308.3	1303.9	277.1	305.8

8	368.2	517.2	1187.0	398.1	960.4	322.8	398.5	346.45	505.28	1718.1	387.9	1718.2	306.8	355.5
	Decoding Time													
	Hyperspectral Image I							**Hyperspectral Image II**						
1	45.86	135.17	189.38	48.9	136.23	39.21	48.2	29.49	197.62	218.00	30.92	120.53	26.41	30.9
2	104.8	294.8	385.4	107.1	269.2	91.98	111.2	54.01	289.05	395.17	63.27	326.39	48.87	67.9
3	187.5	314.4	551.7	198.4	395.2	164.6	189.3	98.69	307.936	703.14	102.8	506.97	84.92	105.2
4	232.4	402.2	741.4	247.6	516.2	204.9	248.2	133.11	330.404	756.75	144.9	690.78	108.95	147.2
5	301.8	427.5	922.7	307.5	632.4	267.4	321.8	168.91	394.926	925.61	181.5	717.44	151.81	199.8
6	328.1	449.5	958.0	334.2	677.9	298.4	344.7	234.92	415.639	1141.9	234.8	846.17	201.84	254.1
7	332.8	461.7	977.3	341.9	777.8	307.2	361.8	268.36	430.549	1330.4	288.4	1207.8	222.31	297.2
8	349.7	491.3	1067.44	366.1	812.4	311.9	389.1	282.52	468.749	1456.7	319.2	1440.3	251.73	314.7

5. Conclusion

In this manuscript, we proposed a novel contourlet transform-based compression algorithm (listless). From the results, it has been clear that the proposed compression algorithm performance has significantly improved in coding efficiency and complexity. The simulation experiment on four different HS images shows that the proposed algorithm has higher PSNR than other compression algorithms under test. Further, the demand for coding memory can be reduced by implementing the contourlet transform with the 3D-ZM-SPECK [72] or 3D-BCP-ZM-SPECK [74]. Apart from the contourlet and wavelet transform, compression performance can be improved by using the radon transform and shearlet transform.

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Authors' Contributions

Tripathi and Bajpai developed the algorithm algorithms simulation and prepared the manuscript.

References

[1] Nitin Tyagi et al., “Nondestructive Identification of Wheat Species Using Deep Convolutional Networks with Oversampling Strategies on Near-Infrared Hyperspectral Imagery,” *Journal of Nondestructive Evaluation*, vol. 44, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[2] D. Chutia et al., “Hyperspectral Remote Sensing Classifications: A Perspective Survey,” *Transactions in GIS*, vol. 20, no. 4, pp. 463-490, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[3] B. Krishna Mohan, and Alok Porwal, “Hyperspectral Image Processing and Analysis,” *Current Science*, vol. 108, no. 5, pp. 833-841, 2015. [Google Scholar] [Publisher Link]

[4] M. Yoshinuma, K. Ida, and Y. Ebihara, “Development of Hyperspectral Camera for Auroral Imaging (HySCAI),” *Earth, Planets and Space*, vol. 76, pp. 1-16, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[5] L. Castellino et al., “Application of Raman Hyperspectral Imaging for Bio-Fluid Spots Segmentation and Characterization on Cotton Supports,” *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*, vol. 334, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[6] Alankar Kotwal et al., “Hyperspectral Imaging in Neurosurgery: A Review of Systems, Computational Methods, and Clinical Applications,” *Journal of Biomedical Optics*, vol. 30, no. 2, pp. 1-54, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[7] Giulia Barzan et al., “Hyperspectral Chemical Imaging of Single Bacterial Cell Structure by Raman Spectroscopy and Machine Learning,” *Applied Sciences*, vol. 11, no. 8, pp. 1-12, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[8] Jaime Zabalza et al., “Hyperspectral Imaging Based Corrosion Detection in Nuclear Packages,” *IEEE Sensors Journal*, vol. 23, no. 21, pp. 25607-25617, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] Manoj Kaushik, Rama Rao Nidamanuri, and B. Aparna, “Hyperspectral Discrimination of Vegetable Crops Grown Under Organic and Conventional Cultivation Practices: A Machine Learning Approach,” *Scientific Reports*, vol. 15, no. 1, pp. 1-12, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[10] Vusal I. Pasha, and Dalila B. Megherbi, “A Deep Learning Approach for Hyperspectral Image Classification with Additive Noise for Remote Sensing and Airborne Surveillance,” *2022 IEEE 9th International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA)*, Chemnitz, Germany, pp. 1-6, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[11] Roozbeh Rajabi et al., “Hyperspectral Imaging in Environmental Monitoring and Analysis,” *Frontiers in Environmental Science*, vol. 11, pp. 1-2, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[12] Ye Ma et al., "A Deep-Learning-Based Tree Species Classification for Natural Secondary Forests Using Unmanned Aerial Vehicle Hyperspectral Images and LiDAR," *Ecological Indicators*, vol. 159, pp. 1-13, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[13] Amal S. Pradeep et al., "Innovations in Forensic Science: Comprehensive Review of Hyperspectral Imaging for Bodily Fluid Analysis," *Forensic Science International*, vol. 364, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[14] Rupsa Chakraborty et al., "A Spectral and Spatial Comparison of Satellite-Based Hyperspectral Data for Geological Mapping," *Remote Sensing*, vol. 16, no. 12, pp. 1-21, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[15] Ajay Nautiyal, "Developing Smart HyperSpectral Imaging Technology to Aid Healthcare Professionals in Sustainable Medical Environments," *2024 3rd International Conference for Innovation in Technology (INOCON)*, Bangalore, India, pp. 1-6, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[16] Narayan Kayet et al., "Detection and Mapping of Vegetation Stress Using AVIRIS-NG Hyperspectral Imagery in Coal Mining Sites," *Advances in Space Research*, vol. 73, no. 2, pp. 1368-1378, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[17] J.L. Garrett et al., "Hyperspectral Image Processing Pipelines on Multiple Platforms for Coordinated Oceanographic Observation," *2021 11th Workshop on Hyperspectral Imaging and Signal Processing: Evolution in Remote Sensing (WHISPERS)*, Amsterdam, Netherlands, pp. 1-5, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[18] Mohammad Al Ktash et al., "Characterization of Pharmaceutical Tablets Using UV Hyperspectral Imaging as a Rapid In-Line Analysis Tool," *Sensors*, vol. 21, no. 13, pp. 1-13, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[19] Nafiseh Ghasemi et al., "Onboard Processing of Hyperspectral Imagery: Deep Learning Advancements, Methodologies, Challenges, and Emerging Trends," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 18, pp. 4780-4790, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[20] A. Nisha, and A. Anitha, "Current Advances in Hyperspectral Remote Sensing in Urban Planning," *2022 Third International Conference on Intelligent Computing Instrumentation and Control Technologies (ICICICT)*, Kannur, India, pp. 94-98, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[21] Garima Jaiswal et al., "Integration of Hyperspectral Imaging and Autoencoders: Benefits, Applications, Hyperparameter Tunning and Challenges," *Computer Science Review*, vol. 50, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[22] Jaime Zabalza et al., "Singular Spectrum Analysis for Effective Feature Extraction in Hyperspectral Imaging," *IEEE Geoscience and Remote Sensing Letters*, vol. 11, no. 11, pp. 1886-1890, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[23] Arati Paul, and Nabendu Chaki, *Dimensionality Reduction of Hyperspectral Imagery*, 1st ed., Springer Charm, pp. 1-116, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[24] Ganji Tejasree, and Loganathan Agilandeeswari, "An Extensive Review of Hyperspectral Image Classification and Prediction: Techniques and Challenges, *Multimedia Tools and Applications*, vol. 83, pp. 80941-81038, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[25] Debasrita Chakraborty et al., "Change Detection in Hyperspectral Images Using Deep Feature Extraction and Active Learning," *Proceedings of the 29th International Conference on Neural Information Processing*, pp. 212-223, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[26] Yaman Dua, Vinod Kumar, and Ravi Shankar Singh, "Comprehensive Review of Hyperspectral Image Compression Algorithms," *Optical Engineering*, vol. 59, no. 9, pp. 1-39, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[27] Tao Zhang, Ying Fu, and Jun Zhang, "Guided Hyperspectral Image Denoising with Realistic Data," *International Journal of Computer Vision*, vol. 130, no. 11, pp. 2885-2901, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[28] Radhesyam Vaddi et al., "Strategies for Dimensionality Reduction in Hyperspectral Remote Sensing: A Comprehensive Overview," *The Egyptian Journal of Remote Sensing and Space Sciences*, vol. 27, no. 1, pp. 82-92, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[29] Pallavi Ranjan, and Ashish Girdhar, "Deep Siamese Network with Handcrafted Feature Extraction for Hyperspectral Image Classification," *Multimedia Tools and Applications*, vol. 83, pp. 2501-2526, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[30] Mohammed Abdulmajeed Moharram, and Divya Meena Sundaram, "Dimensionality Reduction Strategies for Land Use Land Cover Classification Based on Airborne Hyperspectral Imagery: A Survey," *Environmental Science and Pollution Research*, vol. 30, no. 3, pp. 5580-5602, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[31] Dioline Sara et al., "Hyperspectral and Multispectral Image Fusion Techniques for High Resolution Applications: A Review," *Earth Science Informatics*, vol. 14, pp. 1685-1705, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[32] Yinhu Wu, Junping Zhang, and Dongyang Liu, "Predictive Filtering Integrated Generative Remote Sensing Hyperspectral Image Inpainting," *IEEE Geoscience and Remote Sensing Letters*, vol. 22, pp. 1-5, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[33] Debaleena Datta et al., "Hyperspectral Image Classification: Potentials, Challenges, and Future Directions," *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1-36, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[34] Reaya Grewal, Singara Singh Kasana, and Geeta Kasana, "Hyperspectral Iimage Segmentation: A Comprehensive Survey," *Multimedia Tools and Applications*, vol. 82, pp. 20819-20872, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[35] Sneha, and Ajay Kaul, "Hyperspectral Imaging and Target Detection Algorithms: A Review," *Multimedia Tools and Applications*, vol. 81, pp. 44141-44206, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[36] Samiran Das, and Sandip Ghosal, "Unmixing Aware Compression of Hyperspectral Image by Rank Aware Orthogonal Parallel Factorization Decomposition," *Journal of Applied Remote Sensing*, vol. 17, no. 4, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[37] Rui Dusselaar, and Manoranjan Paul, "Hyperspectral Image Compression Approaches: Opportunities, Challenges, and Future Directions: Discussion," *Journal of the Optical Society of America*, vol. 34, no. 12, pp. 2170-2180, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[38] Amal Altamimi, and Belgacem Ben Youssef, "A Systematic Review of Hardware-Accelerated Compression of Remotely Sensed Hyperspectral Images," *Sensors*, vol. 22, no. 1, pp. 1-53, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[39] Amal Altamimi, and Belgacem Ben Youssef, "Hardware Acceleration of Division-Free Quadrature-Based Square Rooting Approach for Near-Lossless Compression of Hyperspectral Images," *Sensors*, vol. 25, no. 4, pp. 1-21, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[40] R. Nagendran et al., "Lossless Hyperspectral Image Compression by Combining the Spectral Decorrelation Techniques with Transform Coding Methods," *International Journal of Remote Sensing*, vol. 45, no. 18, pp. 6226-6248, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[41] Mohd Tausif, and Ekram Khan, "Image Coding of Natural and Light Field Images: A Tutorial," *IETE Journal of Education*, pp. 1-10, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[42] R. Nagendran, and A. Vasuki, "Hyperspectral Image Compression Using Hybrid Transform with Different Wavelet-Based Transform Coding," *International Journal of Wavelets, Multiresolution and Information Processing*, vol. 18, no. 1, pp. 1-21, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[43] Divya Sharma, "Image Quality Assessment Metrics for Hyperspectral Image Compression Algorithms," *2024 Second International Conference Computational and Characterization Techniques in Engineering & Sciences (IC3TES)*, Lucknow, India, pp. 1-5, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[44] Diego Valsesia, Tiziano Bianchi, and Enrico Magli, "Onboard Deep Lossless and Near-Lossless Predictive Coding of Hyperspectral Images with Line-Based Attention," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 62, pp. 1-14, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[45] Rui Li, Zhibin Pan, and Yang Wang, "The Linear Prediction Vector Quantization for Hyperspectral Image Compression," *Multimedia Tools and Applications*, vol. 78, pp. 11701-11718, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[46] Ranganathan Nagendran, and Arumugam Vasuki, "Hyperspectral Image Compression Using Hybrid Transform With Embedded Zero-Tree Wavelet and Set Partitioning In Hierarchical Tree," *International Journal of Scientific & Technology Research*, vol. 9, no. 6, pp. 811-819, 2020. [Google Scholar] [Publisher Link]

[47] K.S. Gunasheela, and H.S. Prasantha, "Compressive Sensing Approach to Satellite Hyperspectral Image Compression," *Proceedings of Information and Communication Technology for Intelligent Systems*, Ahmedabad, India, vol. 1, pp. 495-503, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[48] Samiran Das, "Hyperspectral Image, Video Compression Using Sparse Tucker Tensor Decomposition," *IET Image Processing*, vol. 15, no. 4, pp. 964-973, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[49] Chubo Deng, Yi Cen, and Lifu Zhang, "Learning-Based Hyperspectral Imagery Compression through Generative Neural Networks," *Remote Sensing*, vol. 12, no. 21, pp. 1-19, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[50] Yuanyuan Guo et al., "Edge-Guided Hyperspectral Image Compression with Interactive Dual Attention," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 61, pp. 1-17, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[51] Ranjan Kumar Senapati and Prasanth Mankar, "Improved Listless Embedded Block Partitioning Algorithms for Image Compression," *Improved LisInternational Journal of Image and Graphics*, vol. 14, no. 4, pp. 1163-11187, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[52] M.N. Do, and M. Vetterli, "The Contourlet Transform: An Efficient Directional Multiresolution Image Representation," *IEEE Transactions on Image Processing*, vol. 14, no. 12, pp. 2091-2106, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[53] Zainab N. Abdulhameed Al-Rawi, Haraa R. Hatem, and Israa H. Ali, "Image Compression Using Contourlet Transform," *2018 1st Annual International Conference on Information and Sciences (AiCIS)*, Fallujah, Iraq, pp. 254-258, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[54] R. Eslami, and H. Radha, "Wavelet-Based Contourlet Transform and its Application to Image Coding," *2004 International Conference on Image Processing*, Singapore, vol. 5, pp. 3189-3192, 2004. [CrossRef] [Google Scholar] [Publisher Link]

[55] Navid Khalili Dizaji, and Mustafa Doğan, "A Comprehensive Brain MRI Image Segmentation System Based on Contourlet Transform and Deep Neural Networks," *Algorithms*, vol. 17, no. 3, pp. 1-15, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[56] Rajakumar Krishnan et al., "Web-Based Remote Sensing Image Retrieval Using Multiscale and Multidirectional Analysis Based on Contourlet and Haralick Texture Features," *International Journal of Intelligent Computing and Cybernetics*, vol. 14, no. 4, pp. 533-549, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[57] Sepideh Vafaie, and Eysa Salajegheh, "A Comparative Study of Shearlet, Wavelet, Laplacian Pyramid, Curvelet, and Contourlet Transform to Defect Detection," *Journal of Soft Computing in Civil Engineering*, vol. 7, no. 2, pp. 1-42, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[58] Padma Ganasala, and Vinod Kumar, "CT and MR Image Fusion Scheme in Nonsubsampled Contourlet Transform Domain," *Journal of Digital Imaging*, vol. 27, pp. 407-418, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[59] Vipin Milind Kamble et al., "Performance Evaluation of Wavelet, Ridgelet, Curvelet and Contourlet Transforms Based Techniques for Digital Image Denoising," *Artificial Intelligence Review*, vol. 45, pp. 509-533, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[60] N.G. Chitaliya, and A.I. Trivedi, "An Efficient Method for Face Feature Extraction and Recognition Based on Contourlet Transforms and Principal Component Analysis," *Procedia Computer Science*, vol. 2, pp. 52-61, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[61] H.B. Kekre et al., "Identification of Multi-Spectral Palmprints Using Energy Compaction by Hybrid Wavelet," *2012 5th IAPR International Conference on Biometrics (ICB)*, New Delhi, India, pp. 433-438, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[62] Mohd Tausif, Ekram Khan, and Antonio Pinheiro, "Computationally Efficient Wavelet-Based Low Memory Image Coder for WMSNs/IoT," *Multidimensional Systems and Signal Processing*, vol. 34, pp. 657-680, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[63] Mohd Tausif et al., "Memory-Efficient Architecture for FrWF-Based DWT of High-Resolution Images for IoMT Applications," *Multimedia Tools and Applications*, vol. 80, pp. 11177-11199, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[64] Mohd Tausif, Ekram Khan, and Mohd Hasan, "BFrWF: Block-Based FrWF for Coding of High-Resolution Images with Memory-Complexity Constrained-Devices," *2018 5th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON)*, Gorakhpur, India, pp. 1-5, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[65] Xiaoli Tang, and W.A. Pearlman, "Lossy-to-Lossless Block-Based Compression of Hyperspectral Volumetric Data," *2004 International Conference on Image Processing*, Singapore, vol. 5, pp. 3283-3286, 2004. [CrossRef] [Google Scholar] [Publisher Link]

[66] Xiaoli Tang, and William A. Pearlman, *Three-Dimensional Wavelet-Based Compression of Hyperspectral Images*, 1st ed., Hyperspectral Data Compression Springer, pp. 273-308, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[67] Shrish Bajpai, Naimur Rahman Kidwai, and Harsh Vikram Singh, "3D Wavelet Block Tree Coding for Hyperspectral Images," *International Journal of Innovative Technology and Exploring Engineering*, vol. 8, no. 6C, pp. 64-68, 2019. [Google Scholar] [Publisher Link]

[68] Ruzelita Ngadiran et al., "Efficient Implementation of 3D Listless Speck," *International Conference on Computer and Communication Engineering*, Kuala Lumpur, Malaysia, pp. 1-4, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[69] V.K. Sudha, and R. Sudhakar, "3D Listless Embedded Block Coding Algorithm for Compression of Volumetric Medical Images," *Journal of Scientific and industrial Research*, vol. 72, pp. 735-748, 2013. [Google Scholar]

[70] Shrish Bajpai et al., "Low Memory Block Tree Coding for Hyperspectral Images," *Multimedia Tools and Applications*, vol. 78, pp. 27193-27209, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[71] Shrish Bajpai, "Low Complexity Block Tree Coding for Hyperspectral Image Sensors," *Multimedia Tools and Applications*, vol. 81, pp. 33205-33323, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[72] Shrish Bajpai et al., "A Low Complexity Hyperspectral Image Compression through 3D Set Partitioned Embedded Zero Block Coding," *Multimedia Tools and Applications*, vol. 81, pp. 841-872, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[73] Shrish Bajpai, "3D-Listless Block Cube Set-Partitioning Coding for Resource Constraint Hyperspectral Image Sensors," *Signal, Image and Video Processing*, vol. 18, pp. 3163-3178, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[74] Shrish Bajpai, "Low Complexity Image Coding Technique for Hyperspectral Image Sensors," *Multimedia Tools and Applications*, vol. 82, no. 20, pp. 31233-31258, 2023. doi : 10.1007/s11042-023-14738-x. [CrossRef] [Google Scholar] [Publisher Link]

[75] Divya Sharma, Y.K. Prajapati, and R. Tripathi, "Success Journey of Coherent PM-QPSK Technique with Its Variants: A Survey," *IETE Technical Review*, vol. 37, no. 1, pp. 36-55, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[76] Divya Sharma, Jitendra Bahadur Maurya, and Yogendra Kumar Prajapati, "Effect of Noise on Constellation Diagram of 100 Gbps DP-QPSK Systems under Influence of Different Digital Filters," *International Conference on Microwave and Photonics (ICMAP)*, Dhanbad, India, pp. 1-2, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[77] De Rosal Igantius Moses Setiadi, "PSNR vs SSIM: Imperceptibility Quality Assessment for Image Steganography," *Multimedia Tools and Applications*, vol. 80, pp. 8423-8444, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[78] Mohd Tausif et al., "SMFrWF: Segmented Modified Fractional Wavelet Filter: Fast Low-Memory Discrete Wavelet Transform (DWT)," *IEEE Access*, vol. 7, pp. 84448-84467, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[79] Nadia Zikiou, Mourad Lahdir, and David Helbert, "Support Vector Regression-Based 3D-Wavelet Texture Learning for Hyperspectral Image Compression," *The Visual Computer*, vol. 36, pp. 1473-1490, 2020. [CrossRef] [Google Scholar] [Publisher Link]