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ORIGINAL PAPER

3D-listless block cube set-partitioning coding for resource constraint hyperspectral image sensors

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Abstract
The hyperspectral image provides rich spectral information content, which facilitates multiple applications. With the rapid advancement of the spatial and spectral resolution of optical instruments, the image data size has increased by many folds. For that, it requires a compression algorithm having low coding complexity, low coding memory demand and high coding efficiency. In recent years, many coding algorithms are proposed. The wavelet transform-based set-partitioned hyperspectral compression algorithms have superior coding performance. These algorithms employ linked lists or state tables to track the significant/insignificant of the partitioned sets/coefficients. The proposed algorithm uses the pyramid hierarchy property of wavelet transform. The markers are used to track the significance/insignificance of the pyramid level. A single pyramid level has many sets. An insignificant pyramid level having multiple sets is represented as a single bit in proposed compression algorithm, while a single insignificant set in 3D Set Partition Embedded bloCK (3D-SPECK) and 3D-Listless SPECK (3D-LSK) is represented as a single bit. Through this, the requirement of the bits in the proposed algorithm is less than other wavelet transform compression algorithms at the high bit planes. The simulation result shows that the proposed compression algorithm has high coding efficiency with very less coding complexity and moderate coding memory requirement. The reduced coding complexity improves the performance of the image sensor and lowers the power consumption. Thus, the proposed compression algorithm has great potential in low-resource onboard hyperspectral imaging systems.

Keywords Low complexity · Discrete wavelet transform · Listless embedded block partitioning · Set-partitioning embedded block cube · Transform coding

1 Introduction

The hyperspectral (HS) image from spaceborne spectrometers is a 3D volumetric data that has abundant spatial and spectral information ranging from visible near-infrared (from 400 to 1000 nm) and short wave infrared (from 1000 to 2500 nm) of the electromagnetic (EM) spectrum for a single scene [1, 2]. Due to high spectral resolution, the HS image is used in numerous applications such as precision farming [3], aerospace [4], medical surgery [5], drug sample verification [6], corrosion detection [7], document validation [8], food grain quality [9], mineral detection and exploration [10], urban planning [11], soil quality measurement [12], analysis for land use and land cover [13], meteorological condition monitoring [14], semiconductor device metrology [15], astrionics [16], monsoon monitoring [17], and military surveillance [18]. Remote sensing (RS) [19] is one of the fast-growing fields of HS imaging in which researchers develop algorithms related to the compression process [20], object classification [21], feature extraction [22], target detection [23], band selection [24], denoising [25], change detection estimation [26], feature reduction [27], dimensionality reduction [28], segmentation [29], image unmixing [30], etc. The HS images for the remote sensing applications are acquired from the onboard HS image sensors [31]. The memory required to save one HS image is approximately 150 MB. [32]. Thus, HS image compression becomes a necessary step before the HS image is transmitted to the earth station for further processing to save the memory storage, transmission bandwidth, data transmission time, and processing power [33–36]. Besides the above-mentioned advantages, HyperSpectral Image Compression Algorithm (HSICA) also

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reduces computational complexity, which improves the HS image sensor performance [37].

The classification of different HyperSpectral Image Compression Algorithms (HSICAs) can be performed on the basis of data loss or coding process [38]. Based on data loss, HSICAs can be divided into three sub-categories, named lossless, lossy and near-lossless HS image compression [39]. For the lossless compression, there are no data loss and the reconstructed HS image is as same as the original. The near-lossless compression has loss of some data but the reconstructed HS image is near to same as original HS image (before compression process) [40]. The lossy compression has the loss of image data, but it has a very high compression ratio than the other two types of compression. The lossy compression has low coding efficiency. The peak signal-to-noise ratio (PSNR) should be '∞' for the ideal reconstruction of the HS image after the compression process [41]. On the other hand, human observers are almost unable to detect the HS image degradations that occur when the PSNR is at least 40 dB. [42]. The best lossless HSICA has a compression ratio (CR) of 4, which is insufficient [43]. So, the lossy HSICA is needed for the compression of the HS images.

On the basis of coding process, it can be further divided into the nine sub-categories which follows as transform coding (TC) [44], predicative coding (PC) [45], vector quantization (VQ) [46], compressive sensing (CS) [47, 48], sparse representation (SR) [49, 50], tensor decomposition (TD) [51], neural network (NN)-based HS image compression [52], machine learning (ML)-based [53], and hybrid compression algorithm [54].

The TC-based HSICA uses mathematical transform (Fourier transform, cosine transform, wavelet transform, Karhunen–Loeve transform, 3D dual-tree transform, lapped transform) to convert the HS image from time domain to frequency domain by applying in all three dimensions [55]. Mathematical transform removes the unwanted redundancy (spatial and spectral correlation) in the HS image. The wavelet transform has an excellent performance than other mathematical transforms because it offers a simultaneous localization in time and frequency domain. The TC-based HSICA also works with the other type of compression algorithms to achieve the compression (hybrid type) [38].

The 3D set-partitioned embedded zero block coding, 3D embedded zeroblock coding algorithm, improved AT-3D SPIHT algorithm, JPEG-2000 and spectral decorrelation, distributed source coding, 3D wavelet-fractal coding, adapting SPIHT, lapped transform and Tucker decomposition (LT-TD), spatial-orientation tree wavelet (STW), JPEG-2000 and spectral decorrelation are the state-of-the-art TC-based HSICA [39, 56–63].

Through listless HSICA has low coding complexity and constant coding memory requirement, the 3D-LMBTC [61] and 3D-ZM-SPECK [63] have little coding memory requirements, but they have high coding complexity. The 3D-LSK [59] and 3D-NLS [60] have low coding complexity with high coding memory requirement. The 3D-LCBTC [62] is a special case of 3D-WBTC [58], which uses the two small lists, LCBC & LPBC, and two-state marker tables, BCSM & DSM [62]. The 3D-LCBTC [62] has higher coding memory requirements than 3D-LMBTC [61] and 3D-ZM-SPECK [63]. The proposed HSICA 3D- Listless Block Cube Set Partitioning Coding (3D-LBCSPC) uses the property of wavelet transform and has high coding efficiency with the fixed coding memory. The 3D-LBCSPC follows the same partition rule as 3D-SPECK [56]. It also reduces the coding complexity, which makes it an appropriate choice for the resource constraint HS image sensors.

2 Related work

2.1 Set-partitioned hyperspectral image compression algorithms

The set-partitioned HS image compression algorithms use the set structure to represent a large number of insignificant coefficients. The set-partitioned HS image compression algorithm has several properties such as low coding memory requirement, low coding complexity, high coding efficiency and embeddedness, which make them a perfect choice for the compression of the HS image [40, 64]. The set-partitioned HSICAs can be classified into four types named as list-based set-partitioned HSICA [58], listless set-partitioned HSICA [40], list & state table-based set-partitioned HSICA [62] and array-based set-partitioned HSICA [43].

1. **List-based set-partitioned HSICA**: This type of HSICA uses the linked lists for tracking the partitioned sets or coefficients. The 3D-SPIHT [57], 3D-SPECK [56] and 3D-WBTC [58] are the major compression algorithms under this category. The 3D-SPIHT & 3D-WBTC use three lists, while 3D-SPECK uses the two link lists for the tracking of the sets. As bit rates grow, the size of the lists grows rapidly and it also increases the coding complexity [28]. Thus, these HSICAs are not the best solution at the high bit rates.
2. **Listless set-partitioned HSICA**: This type of HSICA uses the state table or marker for tracking the partitioned sets or coefficients. The 3D-LSK [59], 3D-NLS [60], 3D-LMBTC [61] and 3D-ZM-SPECK [63] are the major compression algorithms under this category. The demand for coding memory is constant and depends only on the dimension of the HS image and does not depend on the bit rate. Due to the state table/markers, it has very less coding complexity [63]. But the reduced coding complexity

and coding memory come at the cost of reduced coding efficiency. This type of algorithm has slightly less coding efficiency if the bit budget is exhausted in between the bit plane [61].

3. **List & state table-based set-partitioned HSICA**: The 3D-LCBTC [62] is a type of compression algorithm that uses the lists (2) and state table (2) to tracking of the partitioned sets or coefficients. 3D-LCBTC is less complex than other state-of-the-art HSICA with at par coding efficiency [62].
4. **Array-Based set-partitioned HSICA**: The 3D-BPEC is a type of HSICA which uses arrays (six) to track the partitioned sets or coefficients. It has slightly lower complexity than list-based HSICA [43].

3 3D-Listless block cube set-partitioning coding (3D-LBCSPC)

The proposed 3D-LBCSPC is a low-weight listless version of 3D-SPECK [56], which has low coding complexity, low coding memory requirement and high coding efficiency at low bit rates. 3D-LBCSPC also outperforms the other wavelet transform-based listless HSICA 3D-LSK [59] and 3D-ZM-SPECK [63], which follows the same partitioned rules as 3D-SPECK [56]. 3D-LBCSPC uses the property of 3D dyadic wavelet transform in which a large number of insignificant coefficients are represented as a single numeric digit '0' at the high bit planes. 3D-LBCSPC uses the property of wavelet transform. 3D-LBCSPC needs less than three to six times bits at the highest bit plane than it's peer compression algorithms. Thus, it outperforms at low bit rates.

3.1 State markers

3D-LBCSPC uses three types of state table markers for the tracking/significance of the partitioned block cube or coefficients. They are two fixed markers ($\alpha[\eta]$ and $\beta[\eta]$) and one variable marker ($\gamma[\eta]$). The numeric value of the fixed markers is fixed during the compression process, while the variable markers change the value according to the partition rule or bit plane. For the fixed markers, η is the leading indices of the wavelet transform level while for the variable marker η is the indices of all wavelet coefficients of the transform HS image.

The numeric value of the marker $\alpha[\eta]$ and $\gamma[\eta]$ depends on the level of the wavelet transform. The HS image of size '$N \times N \times N$' with 'L' level of wavelet transform, the initial value and final value of the markers $\alpha[\eta]$ and $\gamma[\eta]$ are given in Eq. 1 and Eq. 2:

$$\log_2 N - L \tag{1}$$

$$\log_2 N \tag{2}$$

The mathematical value of the $\beta[\eta]$ is the fixed value on the leading indices of each wavelet transform orientation. Alike 3D-LSK [29], each marker in the proposed HSICA holds 0.5 byte per coefficient.

The $\alpha[\eta]$ tracks wavelet pyramid level rather than the partitioned sub-band. It gave a great advantage at the low bit rates where the lots of transform coefficients are insignificant against the current threshold. If any pyramid level is found insignificant against the current threshold, then a single bit '0' is used to represent the whole pyramid. In 3D-LSK [59] and 3D-SPECK [56] seven '0' is used for the LLH, LHL, LHH, HLL, HLH, HHL and HHH sub-band. The $\beta[\eta]$ marker is used to skip the multiple wavelet pyramid level instead of skipping a single pyramid level at the top bit plane. The $\gamma[\eta]$ is used to track the set partitioned with the pyramid-level sub-band.

The 3D-LBCSPC uses three different types of symbols to define the single coefficients, which are as follows.

IC	The coefficient is insignificant to the last bit-plane and not tested for the current bit plane
NC	The coefficient is significant to the current bit-plane
SC	The coefficient is significant to the last bit plane and will be refined in the current bit plane

The working of the static markers (α [η] and β [η]) and dynamic marker (γ [η]) for the wavelet pyramid level 'L' (for static markers) and 'L-1' (for dynamic markers) is described as below. In the same way, it can be generalized for the other working levels of the transform HS image. The markers are defined as in Tables 1, 2, and 3.

3.2 Proposed algorithm

The HS image is transformed (L level) with the dyadic wavelet transform. The transform HS image coefficients are quantized to the nearest integer. The transform HS image cube is converted to the 1D array (linear array) through the Morton mapping. The low-resolution sub-bands are present at the starting of the array, while the high-resolution sub-bands are present at the bottom of the array.

The proposed HSICA consists of two stages: initialization and bit planes pass. Each bit plane pass has three sub-passes named as insignificant coefficient pass (ICP), insignificant set pass (ISP) and refinement pass (RP). Further, ISP can be divided into insignificant bit plane pass (IBPP) and insignificant group of bit plane Pass (IGBPP).

Table 1 Static marker α [η] location in 1D array

α [1]	Coefficient is the first index of the wavelet pyramid level 'L'. This coefficient along with the other associated coefficient of the level 'L' can be skipped
α [4097]	Coefficient is the first index of the wavelet pyramid level 'L-1'. This coefficient along with the other associated coefficient of the level 'L-1' can be skipped
α [32769]	Coefficient is the first index of the wavelet pyramid level 'L-2'. This coefficient along with the other associated coefficient of the level 'L-2' can be skipped
α [262145]	Coefficient is the first index of the wavelet pyramid level 'L-3'. This coefficient along with the other associated coefficient of the level 'L-3' can be skipped
α [2097153]	Coefficient is the first index of the finest pyramid level. This coefficient along with the other associated coefficient of this level can be skipped

Table 2 Static marker β [η] location in 1D array

β [513]	It represents that all pyramid levels except wavelet level 'L' can be skipped
β [4097]	It represents that all pyramid levels except wavelet level 'L' & 'L-1' can be skipped
β [32769]	It represents that all pyramid levels except wavelet level 'L', 'L-1' & 'L-2' can be skipped
β [2097153]	It represents that only finest pyramid level can be skipped

Table 3 Dynamic Marker γ [η] location in 1D array

γ [4097] = α [4097] represents all the coefficients present in the wavelet level 'L-1' can be skipped
γ [4097] = α [4097]–1 represents a sub-band in the wavelet level 'L-1' can be skipped
γ [4097] = α [4097]–2 represents a 1/8th of a sub-band in the wavelet level 'L-1' can be skipped
γ [4097] = 0 the block cube size equal to coefficient size. The coefficient is to be tested for the significance

3.2.1 Initialization pass

The encoding process of the proposed HSICA starts from the upmost bit plane 'n' and move toward the lower bit plane or until the bit budget is available. The initial threshold 'T' is shown in Eq. 3

$$T = 2^n \tag{3}$$

where

$$n = \log_2[\max\{|C_i|\}] \tag{4}$$

The static marker (α [η]) and the dynamic marker (γ [η]) are initialized as follows.

*	α [1, 65, 129, 193, 257, 321, 385,449] = γ [1, 65, 129, 193, 257, 321, 385,449] = 3 for LLL_5 sub-band
*	α [513, 1025, 1537, 2049, 2561, 3073, 3585] = γ [513, 1025, 1537, 2049, 2561, 3073, 3585] = 4 for the staring nodes of LLH_5, LHL_5, LHH_5, HLL_5, HLH_5, HHL_5, and HHH_5 sub-bands
*	α [4097, 8193, 12,289, 16,385, 20,481, 24,577, 28673] = γ [4097, 8193, 12,289, 16,385, 20,481, 24,577, 28673] = 5 for the staring nodes of LLH_4, LHL_4, LHH_4, HLL_4, HLH_4, HHL_4, and HHH_4 sub-bands
*	α [32769, 65,537, 98,305, 131,073, 163,841, 196,609, 229377] = γ [32769, 65,537, 98,305, 131,073, 163,841, 196,609, 229377] = 6 for the staring nodes of LLH_3, LHL_3, LHH_3, HLL_3, HLH_3, HHL_3, and HHH_3 sub-bands
*	α [262145, 524,289, 786,433, 1,048,577, 1,310,721, 1,572,865, 1835009] = γ [262145, 524,289, 786,433, 1,048,577, 1,310,721, 1,572,865, 1835009] = 7 for the staring nodes of LLH_2, LHL_2, LHH_2, HLL_2, HLH_2, HHL_2, and HHH_2 sub-bands
*	α [2097153, 4,194,305, 6,291,457, 8,388,609, 10,485,761, 12,582,913, 14680065] = γ [2097153, 4,194,305, 6,291,457, 8,388,609, 10,485,761, 12,582,913, 14680065] = 8 for the staring nodes of LLH_1, LHL_1, LHH_1, HLL_1, HLH_1, HHL_1, and HHH_1 sub-bands
*	β [513, 4097, 32,769, 262,145, 2097153] = 9
*	γ [η] will be initialized to a higher value more than 8 except for the η = 1, 65, 129, 193,…………………, 12,582,913, 14,680,065

3.2.2 Insignificant coefficient pass (ICP)

The insignificant coefficient pass (ICP) is used to test the insignificant coefficients of the previous bit plane or pass against the threshold of the current bit plane.

3.2.3 Insignificant set pass (ISP)

The insignificant set pass is the combination of two sub-passes, namely insignificant wavelet level (IWL) and insignificant group of wavelet level (IGWL). The IWL pass is used to test the specific wavelet pyramid level for insignificance against the current threshold, while IGWL pass is used to test the multiple wavelet pyramid levels for insignificance against the current threshold. These passes are conducted through the static markers. When the compression algorithm moves from the higher bit plane to the lower bit plane, these passes shall be ignored as maximum transform coefficients are significant at the lower bit planes.

3.2.4 Refinement pass (RP)

The refinement pass is used to send the refinement bits for those coefficients that are significant in any previous bit plane.

The algorithm starts from the top bit plane 'n' with all three types of markers initialized as per coefficient location in the 1D array defined in Tables 1, 2, and 3 for the HS image cube of size '256'. The five-level dyadic wavelet transform is used to transform the HS image. The 3D-LBCSPC follows the same partitioned rule as 3D-SPECK, but the testing of the significance of the coefficients is slightly different from the 3D-SPECK and 3D-LSK. Instead of testing for the block cubes, the 3D-LBCSPC test for the whole wavelet orientation. In the best condition, one insignificant wavelet orientation has maximum seven insignificant block cubes. This way for the top bit planes when there are a lot of insignificant coefficients, 3D-LBCSPC generates one bit to represent the insignificant wavelet orientation, while 3D-SPECK will generate the seven bits for the same set of coefficients. Identification of the wavelet orientation is performed through the markers as the marker is present as the first index of the block cube or wavelet orientations. For the significant wavelet orientation, 3D-LBCSPC executes the same process as 3D-SPECK and generates the same length of bit steam. It is partitioned till it reaches the coefficient level. For any significant block cube, the significance of the block cube is sent and the block cube is partitioned into equal block cubes. For any significant coefficient to the current bit plane, the significance coefficient with the sign bit is sent to the output. Thus, in the top bit plane, 3D-LBCSPC saves a lot of bits and the coding efficiency should be high for the low bit rates and for the high bit rate, it is almost the same as the other zero block cube set-partitioned HSICA. The pseudo-code for the 3D-LBCSPC is covered in Table 4.

4 Results and discussion

The implementation and validation of the proposed HSICA 3D-LBCSPC with the other wavelet transform-based set-partitioned HSICA 3D-SPECK (HSICA 1) [56], 3D-SPIHT (HSICA 2) [57], 3D-WBTC (HSICA 3) [58], 3D-LSK (HSICA 4) [59], 3D-NLS (HSICA 5) [60], 3D-LMBTC (HSICA 6) [61], 3D-LCBTC (HSICA 7) [62] and 3D-ZM-SPECK (HSICA 8) [63] are implemented on the Intel core i3 central processing unit @ 1.6 GHz (64 bit) and RAM of 8 GB. Four HS images are employed in this manuscript to determine the performance of the HSICAs, which include Washington DC Mall (Hyperspectral Image I), Yellowstone Scene 0 (Hyperspectral Image II), Yellowstone Scene 3 (Hyperspectral Image III), and Yellowstone Scene 18 (Hyperspectral Image IV) [65]. The "Yellow Stone" data set (having spatial dimension 512 by 680 and the spectral dimension of 224 with uncalibrated 16 bits/pixel) is captured by the AVIRIS (Airborne Visible/Infrared Imaging Spectrometer) sensor and "Washington DC Mall" (having spatial dimension 1280 by 307 and the spectral dimension of 191 with the pixel depth of 14 bits per pixel) is captured by the HYDICE (Hyperspectral Digital Imagery Collection Experiment) sensor. The Washington DC Mall HS image has made man structure, while Yellow Stone HS images cover natural areas. The HS images are cropped from the left top corner to the size of a cube and zero padding is done if it is required. The five-level dyadic wavelet transform is applied to each HS image, and transform coefficients are quantized to the nearest integer. The 3D transform image cube is converted to the 1D array through the Morton mapping (linear indexing scheme) [62, 66]. The performance of the HSICAs is calculated based on coding efficiency (peak signal-to-noise ratio, mean square error, structural similarity index and feature-similarity index), coding memory and coding complexity (execution time required for the generation of the encoded bitstream and execution time required for the decoding of the received bitstream) [40, 67, 68]. The peak signal-to-noise ratio (PSNR) is calculated in decibel (dB), coding memory in Kilobyte (KB) and Megabyte (MB), encoding time and decoding time is calculated in second. The mean square error, structural similarity (SSIM) index and feature-similarity (FSIM) index are the unitless metrics [38, 69–72].

4.1 Coding efficiency

PSNR is mainly used to quantify the reconstruction quality of HS images affected by lossy compression. PSNR is mathematically shown in Eq. 5 [70]

$$\mathrm{PSNR} = \left[20\log_{10}(\mathrm{MAX}_a) - 10\log_{10}(\mathrm{MSE})\right] \tag{5}$$

The maximum value of the image signal is represented as MAX_a. The mean square error (MSE) is calculated in Eq. 6

$$\mathrm{MSE} = \frac{1}{(N \times N \times N)} \sum_x \sum_y \sum_z [A(x, y, z) - B(x, y, z)]^2 \tag{6}$$

Table 4 Pseudo-code of proposed 3D-LBCSPC encoding algorithm

```
Algorithm : Encoding Process of proposed HSICA 3D-LBCSPC
Input   : Five Level Wavelet Transform HS image is converted to the 1D array 'Ci' through .
Morton mapping
Output : Encoded Embedded Bit Stream
M and N are the spatial dimension & P is the spectral dimension of the HS image
  INITIALIZATION PASS
      Set : n = ⌊log2[max{|Ci|}]⌋
      Magnitude of the threshold : T = 2^n
      Initialize η = 0 ; η ≤ Ci
      Set the fixed markers as per Table 1 & 2
      Set the variable marker as per Table 3
      Set : Starting index of the linear array Ci as zero
  BIT PLANE PASS
    INSIGNIFICANT COEFFICIENT PASS
      if (γ [η] ⟵ IC) then
          output ({λ = val[η]} && T)
      else
          if (λ == 1) then
              output(Sn [η])
              γ [η] ⟵ NC
          else
              Go to next coefficient in line
          end
      Go to insignifiant set pass
      end
    INSIGNIFICANT SET PASS
      if ({α [η] = γ [η]} & {γ[η] ≠ IC }) then
          if (η ∈ topmost wavelet level) then
              S[Wavelet Level]
              output (λ)
              if (λ == 1) then
                  OctaSplit ()
                  if (blocksize == coefficientsize)    then
                      Move to the IC Pass
                  else
                      Move to next wavelet level
                  end
              else
                  Skip to the next combined level
              end
          else (η ∉ top wavelet level) then
              output (λ = Ω (val [λ : Ci]))
              if (λ == 1) then
                  output (λ = Ω (val [λ : end of the LLL_L]))
                  if (λ == 1) then
                      Split the LLL_L to the equal seven sub band
                  else
                      Skip LLL_L sub band
                  end
              else
                  Move to the Refinement Pass
              end
          end
       else ({α [η] ≠ γ [η]} & {γ[η] ≠ IP}) then
          S[Wavelet Subband or block cube]
          output (λ)
          if (λ == 1) then
```

Table 4 (continued)

```
            OctaSplit ()
            if (blocksize == coefficientsize)    then
                Move to the IC Pass
            else
                Skip and move  to the next combined subbandlevel or block cube
            end
        else
            Skip to the next combined subbandlevel or block cube
        end
    end
REFINEMENT PASS
    if (γ [η] ⟵ SC) then
        output ({λ = val[η]}  && T)
        Go to next coefficient in line
    else
        if (γ [η] ⟵ NC) then
            γ [η] ⟵ SC
            Go to next coefficient in line
        else
            Skip the block cube or set
        end
    Skip the coefficient
    end

OctaSplit ()
{
    γ [η] = γ [η] − 1
    for δ = 1:7
        γ [η + {δ × 2^(3 × γ[η])}] = γ[η]
    end
}
```

The A(x,y,z) is the original (uncompressed) HS image and B(x,y,z) is the reconstructed (compressed) HS image. The 'N' is a dimension (each) of the HS image. The compression ratio (CR) is a parameter (unitless) that defines the ratio between the bits required to represent the original image to the bits required to represent the reconstructed image. Mathematically, it defines as in Eq. 7

$$\mathrm{CR} = \frac{\sum_x \sum_y \sum_z [A(x,\ y,\ z)]}{\sum_x \sum_y \sum_z [B(x,\ y,\ z)]} \tag{7}$$

Bit rate associated with the compression process is defined as in Eq. 8

$$\text{Bit Rate}\,(bpppb) = \frac{\text{Bits required to represent a pixel in the reconstrcuted HS image}}{\text{Bits required to represent a pixel in the original HS image}} \tag{8}$$

The 3D-LBCSPC has the same partition rule as 3D-LSK [59] and 3D-SPECK [56] (zero block cube-based set-partitioned HSICA). We observed from Table 5 (PSNR) that 3D-LBCSPC outperformers in the low bit rates (equal to 0.1 or less than 0.1) with the other HSICA. It has been also observed from Table 6 that 3D-LBCSPC has more significant bits than the other HSICA, which increases the PSNR of the proposed HSICA. 3D-LBCSPC uses the wavelet orientation property in which a single bit is used to define the seven insignificant sub-bands present in the same wavelet orientation plane while for the 3D-LSK [59], 3D-ZM-SPECK [63] and 3D-SPECK [56], each insignificant sub-band is defined by the bit at the high bit planes. So, a large number of bits are saved at the high bit plane level and for the high bit rate the performance of 3D-LBCSPC is almost better to its peer's algorithms. It has been noticed from Table 5 that variation between the PNSR of proposed 3D-LBCSPC and 3D-SPECK [56] exists in the range of − 0.28 dB to 0.14 dB for Hyperspectral Image I, − 0.01 dB to 0.11 dB for Hyperspectral Image II, − 0.19 dB to 0.18 dB for Hyperspectral Image III, and − 0.27 dB to 0.14 dB for Hyperspectral Image IV. Similarly, the variation between the 3D-LBCSPC and 3D-LSK [59] exists in the range of 0.15 dB to 0.73 dB for Hyperspectral Image I, 0.03 dB to 0.36 dB for Hyperspectral Image II, 0.13 dB to 0.39 dB for Hyperspectral Image III, and − 0.1 dB to 0.28 dB for Hyperspectral Image IV. In the

Table 5 Comparison of the 3D-LBCSPC with other state-of-the-art HSICA on coding efficiency (PSNR)

Bit rate	Compression ratio	HSICA 1 [56]	HSICA 2 [57]	HSICA 3 [58]	HSICA 4 [59]	HAICA 5 [60]	HAICA 6 [61]	HSICA 7 [62]	HAICA 8 [63]	3D-LBCSPC
Hyperspectral image I										
0.001	14,000	26.28	26.28	26.25	26.14	25.90	26.26	26.41	26.32	26.39
0.005	2800	28.95	28.95	28.93	28.71	28.71	28.70	28.66	28.73	29.01
0.01	1400	30.08	30.08	30.04	29.99	29.83	29.98	30.01	29.99	30.14
0.05	280	34.23	34.23	34.21	34.04	33.81	33.99	34.29	34.06	34.37
0.1	140	37.22	37.22	37.20	36.96	37.00	36.83	37.34	36.87	37.29
0.25	56	42.17	42.17	42.16	41.62	41.69	41.34	42.28	41.37	42.01
0.5	28	48.02	47.99	47.97	47.01	47.79	47.51	48.11	47.55	47.74
Hyperspectral image II										
0.001	16,000	27.11	26.75	27.09	26.83	26.61	26.75	26.87	26.82	27.19
0.005	3200	29.45	29.31	29.43	29.27	29.25	29.24	29.41	29.25	29.55
0.01	1600	30.28	30.19	30.27	30.27	30.15	30.31	30.53	30.33	30.38
0.05	320	33.76	33.61	33.73	33.56	33.59	33.51	33.69	33.54	33.87
0.1	160	35.57	35.44	35.56	35.49	35.41	35.45	35.55	35.46	35.67
0.25	64	39.30	39.19	39.29	39.26	39.17	39.22	39.37	39.23	39.29
0.5	32	43.62	43.65	43.51	43.57	43.26	43.55	43.62	43.58	43.68
Hyperspectral image III										
0.001	16,000	27.82	27.49	27.8	27.78	27.28	27.88	28.07	27.92	27.97
0.005	3200	30.24	30.09	30.22	30.03	30.03	30.01	30.44	30.02	30.38
0.01	1600	31.27	31.14	31.25	31.17	31.1	31.13	31.42	31.14	31.37
0.05	320	34.57	34.39	34.55	34.58	34.27	34.44	34.67	34.51	34.71
0.1	160	36.63	36.49	36.64	36.42	36.49	36.35	36.74	36.37	36.81
0.25	64	40.83	40.63	40.84	40.46	40.59	40.29	40.81	40.31	40.65
0.5	32	45.88	45.66	45.87	45.39	45.57	45.13	45.58	45.15	45.69
Hyperspectral image IV										
0.001	16,000	28.11	27.94	28.06	28.08	27.88	28.07	28.14	28.16	28.21
0.005	3200	30.44	30.32	30.43	30.27	30.03	30.26	30.22	30.28	30.51
0.01	1600	31.41	31.29	31.39	31.32	31.1	31.29	31.57	31.43	31.55
0.05	320	34.46	34.3	34.45	34.41	34.27	34.25	34.62	34.28	34.54
0.1	160	36.43	36.29	36.43	36.25	36.49	36.19	36.51	36.2	36.53
0.25	64	40.08	39.93	40.07	39.92	40.59	39.8	40.19	39.84	39.82
0.5	32	44.51	44.47	44.5	44.31	44.46	44.22	44.63	44.22	44.24

same way, the variation between the 3D-LBCSPC and 3D-ZM-SPECK [63] exists in the range of 0.07 dB to 0.64 dB for Hyperspectral Image I, 0.05 dB to 0.37 dB for Hyperspectral Image II, 0.05 dB to 0.54 dB for Hyperspectral Image III, and − 0.02 dB to 0.33 dB for Hyperspectral Image IV. For the ideal HS image reconstructed after the compression, the numeric value of MSE should be ‘0’ and PSNR numeric should be ‘∞’ [38, 42]. Table 6 throws the detailed view of the HS image quality (HSIQ) as coding efficiency (PSNR) with the refinement coefficients (RC) and newly significant coefficients (NSC) for that bit rate.

Bjontegaard metric calculation or BD-PSNR is used to compare the rate-distortion performance of two different HSICA of the same HS image over a range of different bit rates (bpppb) [40]. Table 7 gives the numeric value of the BD-PSNR over the seven different bit rates.

4.2 Coding memory

The 3D-LBCSPC uses the markers to track the significance of coefficients or partitioned block cube sets. The memory required by the dynamic marker γ [η] is ‘RCW’ when each marker is the size of one byte (‘R’, ‘C’ and ‘W’ represents the

Table 6 Image quality of 3D-SPECK [56], 3D-LSK [59], 3D-ZM-SPECK [63] and proposed 3D-LBCSPC for two HS images

Bit rate	Hyperspectral image I											
	HSICA 1 [56]			HSICA 4 [59]			HSICA 8 [63]			3D-LBCSPC		
	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
0.005	28.95	16,563	4134	28.71	14,905	4134	28.73	14,297	4174	29.01	16,821	4194
0.01	30.08	29,621	12,018	29.99	27,742	12,018	29.99	27,034	17,916	30.14	30,817	12,918
0.05	34.23	159,915	36,960	34.04	154,678	36,960	34.06	144,247	107,342	34.37	161,495	95,823
0.1	37.22	330,216	112,621	36.96	314,919	112,621	36.87	291,818	231,642	37.29	337,414	123,568
Bit rate	Hyperspectral image II											
	HSICA 1 [56]			HSICA 4 [59]			HSICA 8 [63]			3D-LBCSPC		
	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
0.005	29.45	17,212	7129	29.27	15,469	7129	29.25	14,481	9433	29.55	18,002	8154
0.01	30.28	29,247	12,415	30.27	29,196	12,415	30.33	27,583	13,814	30.38	30,017	12,989
0.05	33.76	170,267	47,234	33.56	158,703	47,234	33.54	148,700	46,602	33.87	165,268	47,008
0.1	35.57	314,698	142,703	35.49	302,729	142,703	35.46	290,236	142,472	35.67	310,523	143,651

Table 7 Comparison of the 3D-LBCSPC with other state-of-the-art HSICA on Bjøntegaard Delta PSNR gain

HS Image	HSICA 1 [56]	HSICA 2 [57]	HSICA 3 [58]	HSICA 4 [59]	HAICA 5 [60]	HAICA 6 [61]	HSICA 7 [62]	HAICA 8 [63]
Hyperspectral Image I	0.0372	0.0391	0.0634	0.3092	0.3454	0.3241	0.0530	0.2861
Hyperspectral Image II	0.0863	0.2249	0.1093	0.2076	0.2947	0.5225	0.0746	0.4994
Hyperspectral Image III	0.0857	0.2632	0.0978	0.2501	0.3363	0.3203	- 0.0246	0.2937
Hyperspectral Image IV	0.0397	0.1726	0.0545	0.1597	0.1898	0.2234	- 0.0107	0.1698

three dimensions of the transformed HS image). In the same way, the static markers α [η] and β [η] require the memory of '7L + 8' and 'L'. The coding memory required by the sub-band coefficients is defined as '$I\mathcal{P}$' ('P' is the size of the coefficient of sub-band and 'I' is the length of sub-band).

Thus, the total memory is required by the coding (encoding and decoding) process.

$$\begin{aligned} \mathrm{MEM}_{3D-\mathrm{LBCSPC}} &= [I\mathcal{P} + \mathrm{RCW} + (7L + 8) + L] \\ &= [I\mathcal{P} + RCW + 8\,(L + 1)] \end{aligned} \tag{9}$$

It has been noted that the static marker does not get updated. They use it as the reference for the dynamic marker to determine the significance of the wavelet transform level or new sub-band. The numeric value of the coding memory is calculated with the help of Eq. 9

The coding memory required by 3D-LSK is given as in Eq. 10

$$\mathrm{MEM}_{3D-\mathrm{LSK}} = [I\mathcal{P} + \mathrm{RCW}] \tag{10}$$

So, it is clear that the memory requirement of the 3D-LBCSPC is slightly higher than the 3D-LSK, which is equal to the '8(L + 1)'. For the five levels of the wavelet transform, only 48 bytes of extra memory is required (less than 1 KB coding memory). It has been clear from Table 8 that 3D-LBCSPC requires more coding memory than 3D-LCBTC, 3D-LMBTC and 3D-ZM-SPECK [61–63], but it outperformed the 3D-NLS [60]. It also requires less coding memory for the high bit rates (greater than 0.25 bpppb) than its list-based HSICA 3D-SPECK, 3D-SPIHT and 3D-WBTC [56–58].

4.3 Coding complexity

The coding complexity is the time required by the HSICA to encode the input HS image and decode the received bitstream to reconstruct the HS image [62]. It has been noticed in Tables 9, 10 that encoding time is greater than the decoding time. From Tables 9, 10, the proposed HSICA outperforms the other HSICA and it has the lowest coding time requirement for all bit rates. The complexity is reduced because the proposed HSICA uses the markers to define the wavelet level. If the whole wavelet level is insignificant, it saves the coding memory requirement and also it reduces the number of computation operations (logical and numeric).

For an insignificant wavelet level, the proposed HSICA requires only one significance test while for the other compression algorithms at least seven significance tests are required for the testing of the whole wavelet level. Thus, it has very low complexity at the low bit rates and moderate performance at the high bit rate.

5 Conclusion

The coding complexity is a big issue with the HS image sensors. The high coding complexity minimizes the performance of the sensor and more power is consumed by the sensor due to a lot of computations. Hence, for the resource constraint HS image sensors, compression algorithms have low coding complexity with low coding memory requirement and at par coding efficiency. The proposed HSICA 3D-LBCSPC is the low complexity compression algorithm that utilizes the property of the wavelet orientation. It also required a low fixed coding memory. 3D-LBCSPC gives the best coding efficiency performance at the low bit rate, but for the high bit rates, it performs at par with the other compression algorithms. It also works with both lossy and lossless compression. Thus, 3D-LBCSPC is an optimum choice for the low-resource HS image sensors.

Table 8 Evaluation of coding memory of 3D-LBCSPC with other state-of-the-art HSICA

Bit rate	HSICA 1 [56]	HSICA 2 [57]	HSICA 3 [58]	HSICA 4 [59]	HAICA 5 [60]	HAICA 6 [61]	HSICA 7 [62]	HAICA 8 [63]	3D-LBCSPC
Hyperspectral image I									
0.001	26.67	37.33	28.08	4096	8192	96	2318	0	4097
0.005	102.3	99.21	89.33	4096	8192	96	2318	0	4097
0.01	232.2	222.7	202.4	4096	8192	96	2318	0	4097
0.05	1084	1041	991.7	4096	8192	96	2318	0	4097
0.1	1846	1931	1756	4096	8192	96	2318	0	4097
0.25	4571	4463	4289	4096	8192	96	2318	0	4097
0.5	8644	8555	8514	4096	8192	96	2318	0	4097
Hyperspectral image II									
0.001	22.58	21.51	22.69	4096	8192	96	2318	0	4097
0.005	91.12	98.91	91.29	4096	8192	96	2318	0	4097
0.01	265.9	267.8	266.4	4096	8192	96	2318	0	4097
0.05	982.4	1036	985.4	4096	8192	96	2318	0	4097
0.1	2219	2326	2229	4096	8192	96	2318	0	4097
0.25	5450	5611	5464	4096	8192	96	2318	0	4097
0.5	10,005	9981	9832	4096	8192	96	2318	0	4097
Hyperspectral image III									
0.001	25.28	24.94	25.06	4096	8192	96	2318	0	4097
0.005	101.2	105.8	101.5	4096	8192	96	2318	0	4097
0.01	205.1	218.9	208.6	4096	8192	96	2318	0	4097
0.05	1108	1149	1136	4096	8192	96	2318	0	4097
0.1	1855	1808	1854	4096	8192	96	2318	0	4097
0.25	4401	4449	4412	4096	8192	96	2318	0	4097
0.5	7918	7805	7935	4096	8192	96	2318	0	4097
Hyperspectral image IV									
0.001	24.67	22.41	24.55	4096	8192	96	2318	0	4097
0.005	100.8	105.5	101.1	4096	8192	96	2318	0	4097
0.01	210.9	229.9	214.4	4096	8192	96	2318	0	4097
0.05	1088	1212	1106	4096	8192	96	2318	0	4097
0.1	1970	2083	1980	4096	8192	96	2318	0	4097
0.25	4867	5047	4878	4096	8192	96	2318	0	4097
0.5	9078	8488	9093	4096	8192	96	2318	0	4097

Table 9 Evaluation of encoding time of 3D-LBCSPC with other state-of-the-art HSICA

Bit rate	HSICA 1 [56]	HSICA 2 [57]	HSICA 3 [58]	HSICA 4 [59]	HAICA 5 [60]	HAICA 6 [61]	HSICA 7 [62]	HAICA 8 [63]	3D-LBCSPC
Hyperspectral image I									
0.001	3.99	4.06	5.94	2.67	14.18	5.91	3.17	3.24	3.03
0.005	9.85	9.73	8.2	2.78	61.33	8.35	3.35	4.83	3.41
0.01	20.45	29.93	10.99	3.25	73.64	9.26	4.41	5.97	4.08
0.05	222.2	303.4	94.36	5	90.57	19.45	5.49	12.18	5.57
0.1	1163	1297	762.6	7.31	102.5	34.74	7.94	19.55	8.04
0.25	6234	6871	4358	13.35	120.8	68.15	14.02	40.25	14.12
0.5	17,995	18,742	19,551	24.12	151.3	122.5	26.03	74.87	25.21
Hyperspectral image II									
0.001	3.42	4.33	5.94	2.35	15.97	5.73	2.47	2.94	2.91
0.005	9.84	5.85	8.5	2.71	75.93	7.36	3.87	6.44	3.37
0.01	22.53	9.41	10.83	2.88	90.43	16.99	4.29	10.28	3.94
0.05	250.3	134.4	131.5	4.14	106.55	27.4	5.02	16.02	4.82
0.1	966.7	570.8	632.6	6.04	125.87	36.27	7.21	18.42	6.76
0.25	4973	3032	4100	10.24	134.4	96.34	12.21	56.67	11.02
0.5	12,007	10,112	12,975	17.25	154.41	177.73	18.95	67.74	19.23
Hyperspectral image III									
0.001	4.08	4.03	5.85	2.07	15.97	5.68	2.76	3.19	2.22
0.005	9.12	5.96	7.87	2.89	75.93	7.78	3.28	4.74	3.01
0.01	20.18	9.7	11.64	3.34	90.43	8.55	4.01	7.52	3.92
0.05	204.3	125.2	89.77	4.57	106.55	19.48	5.31	22.88	5.07
0.1	1183	775.8	835.9	5.91	125.87	32.46	6.47	30.14	6.24
0.25	8499	5151	6309	10.41	134.14	70.4	11.91	43.49	11.92
0.5	29,849	18,383	23,861	16.19	154.41	125.42	17.09	72.62	16.87
Hyperspectral image IV									
0.001	4.56	5.6	7.23	2.39	6.03	5.74	2.89	2.82	2.52
0.005	15.24	6.23	8.15	2.81	11.53	7.53	3.34	4.44	3.01
0.01	21.67	10.2	12.64	3.18	18.44	8.93	3.98	5.64	3.54
0.05	269.6	130.4	98.12	4.3	22.64	18.61	4.88	13.02	4.57
0.1	1336	893.4	882.3	6.11	25.53	32.45	6.41	18.18	6.48
0.25	8435	5133	5501	10.35	34.5	69.66	11.38	36.3	11.12
0.5	27,917	17,945	18,818	17.43	65.13	125.19	19.01	66.91	18.05

Table 10 Evaluation of decoding time of 3D-LBCSPC with other state-of-the-art HSICA

Bit rate	HSICA 1 [56]	HSICA 2 [57]	HSICA 3 [58]	HSICA 4 [59]	HAICA 5 [60]	HAICA 6 [61]	HSICA 7 [62]	HAICA 8 [63]	3D-LBCSPC
Hyperspectral image I									
0.001	1.78	2.92	1.59	2.08	12.79	2.48	2.21	3.02	2.07
0.005	5.18	5.25	2.41	2.43	48.29	3.86	2.68	4.65	2.38
0.01	10.78	14.31	4.51	2.68	57.16	4.04	3.08	5.61	2.74
0.05	172.7	236.2	84.75	4.02	69.23	12.01	4.34	11.79	4.31
0.1	1081	1078	762.11	6.24	77.57	21.79	6.71	18.36	6.47
0.25	6012	6305	4703	11.68	90.45	50.91	12.02	37.86	12.79
0.5	17,597	18,534	15,400	22.65	100.5	96.84	25.07	69.02	24.43
Hyperspectral image II									
0.001	1.87	1.52	1.46	1.4	12.18	2.18	1.61	2.79	1.51
0.005	5.4	2.45	2.77	2.49	66.24	3.21	3.01	6.05	2.78
0.01	10.01	4.92	3.86	2.71	81.48	6.23	3.27	10.04	2.94
0.05	207.2	127.8	130.1	3.38	94.49	14.94	3.94	11.35	3.33
0.1	887.6	717.5	614.3	5.98	106.8	23.01	6.64	17.81	5.94
0.25	4796	3129	4140	6.74	113.86	58.62	7.18	47.06	6.98
0.5	11,898	9954	12,299	14.7	125.56	120.33	15.34	60.13	15.03
Hyperspectral image III									
0.001	1.74	1.39	1.32	1.89	8.43	4.1	2.11	3.02	2.01
0.005	5.13	2.24	2.44	2.47	66.02	6.02	2.74	3.99	2.64
0.01	12.51	5.18	5.14	2.69	84.96	7.06	3.02	6.33	2.94
0.05	160.3	114.7	80.01	4.46	92.68	14.84	5.19	18.56	5.02
0.1	1474	760.5	827.8	5.59	104.98	21.49	6.37	27.82	6.11
0.25	8587	5832	6549	9.27	115.94	48.95	10.34	39.95	10.02
0.5	26,948	15,672	23,161	14.97	141.97	114.52	16.68	67.23	16.21
Hyperspectral image IV									
0.001	2.41	1.64	1.73	2.02	5.27	2.1	2.24	2.74	2.11
0.005	9.57	2.33	2.55	2.34	8.26	2.88	2.47	4.28	2.31
0.01	12.68	5.23	6.11	2.89	14.44	3.91	3.23	5.41	2.82
0.05	226.5	120.5	89.08	3.74	19.5	11.48	4.29	11.36	4.01
0.1	1241	829.1	866.3	5.96	21.07	21.02	6.57	17.22	6.22
0.25	9067	4536	5494	6.62	29.65	48.91	7.08	33.79	6.89
0.5	25,042	17,677	18,136	12.03	55.03	92.97	12.87	62.31	12.12

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