FPGA Based Hyperspectral Image Compression Using DWT and DCT

S. Kala and Dr. S. Vasuki

1Associate Professor, Department of Electronics and Communication Engineering, Sri Subramanya College of Engineering and Technology, Palani, Tamil Nadu, India.
2Professor and head of the Department of Electronics and Communication Engineering, Velammal College of Engineering and Technology, Madurai, Tamil Nadu, India.

ABSTRACT

Background: Hyperspectral imaging (HSI) is typically defined as a spectral sensing technique which takes hundreds of contiguous narrow waveband images in the visible and infrared regions of the electro-magnetic spectrum. HSI compression is an important issue in remote sensing application. In this paper, an efficient technique for compressing the hyperspectral image is introduced. The proposed HSI compression is based on Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT). DWT has multi-resolution transformation and DCT has high energy compaction property and requires less computational resources. The idea behind the proposed approach is to apply the DCT to the DWT coefficients of the Hyperspectral images to utilize the advantages of both spatial and spectral redundancies. JPEG is used to perform quantization and encoding of core tensors. The proposed approach has been implemented on Xilinx 14.2 FPGA and tested on real hyperspectral image. The experiments are conducted with HSI compression based on DWT, DCT and JPEG. Compression ratio and PSNR values are compared with the existing M-CALIC and the proposed DWT-DCT-JPEG. The result shows that the DWT-DCT-JPEG performs good in terms of compression ratio, PSNR, MSE and memory consumption. Objective: In this paper, an efficient technique for compressing the hyperspectral image is introduced. Results: The HSI-1 compression steps of Paris image use the HSI compression method based on DWT-DCT-JPEG and are shown in Fig.3. The input HSI-1 is loaded and it is split into 7 spectral bands. There are 5 HSI images which are compressed using the proposed technique. The HSI images include Landsat images (.lan) of Paris, Little Colorado River, Mississippi River, Montana state and Rio city. Fig.3 shows the compression steps performed on the landsat image of Paris.

Conclusion: The proposed compression method DWT-DCT-JPEG reduces the size of the 3D tensors, which are calculated from the 4 sub-images of the spectral bands of HSI. The simulation experiments are tested on 5 HSI images such as Paris city, Little Colorado River, Mississippi River, Montana State and Rio City with the HSI compression based on DWT, DCT and JPEG. The proposed method is compared with some of the existing compression algorithms like JPEG-LS, M-CALIC, JPEG2000, MJPEG2000, OB-SPECK and DWT-TD (ALS) -RLE. Our proposed work results good in terms of compression ratio, PSNR, MSE and memory consumption. Our future plan is to perform hyperspectral image compression using various encoding techniques with DWT features.

INTRODUCTION

Hyperspectral images has been broadly used in remote sensing for different purposes like agriculture, resource management, environmental monitoring and mineral exploration. In agriculture it is helpful to monitor the development and health control of crops, detection of chemical composition of plants and control of water quality. In oil and mining industries, HSI is used to identify and search different minerals and oil fields. It uses an array of sensors to gather a set of images across the spectrum. HSI sensors are leading digital color cameras with advanced spectral resolution at a specific illumination wavelength. These sensors are generally used to measure the radiation reflected by each pixel a large number of visible or invisible frequency bands.

HSIs are considered as 3D data in compression strategies known as third-order tensor, composing of two spatial dimensions and a spectral dimension. HSI applications are adapted toward classifying or grouping the...
similar pixels. The compression of HSI can be implemented by detecting the spatial and spectral redundancies. Several compression methods have been proposed recently, which can be classified into two major types: lossless compression and lossy compression methods. A lossless compression technique that decompresses data back to its original form without any loss. Redundant data is removed during compression and added during decompression. It basically rewrites the data of the original file in a more efficient way. Lossless methods are used in legal and medical documents, computer programs etc. Lossless compression methods are recommended in hyperspectral images due to the huge quantity of data and the data loss must be small. But the demerit of this compression is that the resulting file will be larger than if the lossy compression format had used. Lossy compression methods are used to compress the image and video files. These methods are cheaper and consume less time and space. The disadvantage of lossy compression is that they suffer a lot from generation loss, which means that after repeatedly compressing and decomposing the file will cause it to gradually lose its quality.

Wavelets play an important role in image processing applications. Wavelet based compression are more robust under transmission and decoding errors, provides good frequency resolution at lower frequencies, good time resolution at higher frequencies and also it avoids blocking artifacts. The main advantage of wavelets over DCT are absence of blocking artifacts and the multiscale nature of the DWT which allows near-optimal compression of features with a variety of different scales or sizes. The DWT is based on sub-band coding, found to yield a fat computation of Wavelet Transform. DWT is simple to implement and reduces the computation time and resources required. The advantage of DWT is the temporal resolution in both frequency and time. The decomposition into sub-bands are highly flexible in terms of resolution scalability. But DWT results low compression rates, it cannot individually decompose the HSI with good compression ratio, so it integrates the DCT technique to decompose the HSI into one more level for better compression ratio. The DCT has special advantages such as flexibility at the block-by-block level, Parallel processing, low memory cost etc. DCT is a real-valued and provides a better approximation of a signal with fewer coefficients.

In this paper, hyperspectral images are represented as a 3D tensor with 2D in spatial and 1D in the spectral domain. The proposed method utilizes both the properties of spatial and spectral dimensions. This hybrid technique is based on DWT and DCT. The idea behind this approach is to apply the DCT to the DWT coefficients of the Hyperspectral images to utilize the advantages of spatial and spectral redundancies. The experiments were conducted for 5 HSI with the Hyperspectral image compression based on DWT, DCT and JPEG.

The remaining part of the paper is organized as follows: Section II involves the works related to HSI compression techniques. Section III involves the detailed description of modeling of 3D-HSI. Section IV involves the description of proposed compression technique. Section V involves design issues. Section VI involves the performance analysis and comparison of the proposed DWD-DCT-JPEG and existing compression techniques. The paper is concluded in Section VII.

Related Work:

This section deals with the works related to recent HSI compression techniques. Karami, et al proposed a method for Hyperspectral image compression based on Tucker Decomposition (TD) and the Three Dimensional Discrete Cosine Transform (3D-DCT). In this paper, TD was applied to the 3D-DCT coefficients of Hyperspectral image in order to exploit redundancies between bands and also to use spatial correlations of each image band. The result was applied to real Hyperspectral images and it results good compression ratio with improved quality (2010). Pan, et al proposed a low-complexity discrete cosine transform (DCT) - based distributed source coding (DSC) scheme for hyperspectral images. First, the DCT was applied to the hyperspectral images. Then, set-partitioning-based approach was utilized to recognize DCT coefficients into wavelet like tree structure. Third, low-density parity check based Slepian-Wolf (SW) coder was adopted to implement the DSC strategy. In last an auxiliary reconstruction method was employed to improve the reconstruction quality (2012).

Karami, et al proposed a method based on three dimensional discrete cosine transform (3D-DCT) and support vector machine (SVM). In this paper, SVM was applied on the 3D-DCT coefficients of hyperspectral images in order to determine which coefficients are more critical to preserve (2012). Abrardo, et al presented an overview the state of art of lossless and near-lossless compression of hyperspectral images. This paper also focused on approaches that complied with the requirements of real world mission, in terms of how complexity and memory usage, error resilience and hardware friendliness. The lossless compression algorithm was based on a block-by-block prediction. Adaptive Golomb coding was used to exploit optimal band order and can be extended to near-lossless compression (2011). Kusuma and Widodo proposed a combined technique of VHDL design of the 2-D DCT with quantization and zig-zag arrangement. The architecture was used in JPEG image compression. DCT calculation is based on using scaled DCT. The output of DCT module was multiplied with the post - scalar value to get the real DCT coefficients. The post - scaling process is done together with quantization process. 2-D DCT was computed by combining two 1-D DCT that connected by a transpose buffer. This design was implemented in Spartan-3E XC3S500 FPGA (2010).
Chang, et al formulated an approach composed of two algorithms, which are clustered signal subspace projection (CSSP) and the maximum correlation band clustering (MCBC). The CSSP divided the image into proper regions by transforming the high dimensional image data into one dimensional projection length. The MCBC partitions the spectral bands into several groups based on their associated band correlation for each image region. The image data with high degree correlations in spatial/spectral domains were gathered in groups. Then that grouped data were further compressed by Principal Component Analysis (PCA) based spectral/spatial hyper-spectral image compression techniques. To accelerate the computing efficiency, a parallel cluster computing technique was proposed (2011). Karami, et al proposed an algorithm based on Discrete Wavelet Transform and Tucker Decomposition (DWT-TD). It exploits both the spectral and spatial information in the images. The idea behind (DWT-TD) was applied TD to DWT images and TD to efficiently compact the energy of sub-images (2012).

Cheng and Dill proposed a compression method which includes an integer Karhunen-Leove Transform (KLT) and integer Discrete Wavelet Transform (DWT). The integer KLT was employed to eliminate the presence of correlations among the bands of the hyperspectral image. The integer 2-D DWT was applied to eliminate the correlations in the spatial dimensions and produce wavelet coefficients. These coefficients are then coded by a proposed binary EZW algorithm. The binary EZW algorithm has the combined merits of EZW and SPHT algorithms (2013). Sriraam and Shyamsunder presented a compression of 3-D medical images using 3-D wavelet encoders. Experiments were performed using medical test images such as magnetic resonance images (MRI) and x-ray angiograms (XA). Mean Structural Similarity (MSSIM) index was introduced to evaluate the structural similarity between the original and reconstructed images (2011). Hou and Li proposed a hyperspectral image lossy-to-lossless compression using three-dimensional Embedded ZeroBlack Coding (3D EZBC) algorithm based on Karhunen-Leove transform (KLT) and Wavelet Transform (WT). An improved Hao’s matrix factorization method for integer KLT were presented, which can reduce the computational complexity and memory requirements (2012).

Dutra, et al proposed an algorithm Set Partitioned Embedded Block Coder (SPECK). SPECK incorporated a lattice vector quantizer codebook. It can process multiple samples at one time. The LVQ-SPECK and DWP-SPECK algorithms were proposed in this paper. LVQ-SPECK uses a lattice vector quantizer-based codebook in the spectral direction to encode a number of consecutive bands that is equal to the codeword dimension. DWP-SPECK incorporates the 1-D discrete wavelet transform in the spectral direction, producing a discrete wavelet packet decomposition and simultaneously a large number of spectral bands are encoded (2011). Hwang, et al proposed a lossless compression system for hyperspectral images on a processor-plus-field-programmable gate array (FPGA) based embedded platform. Software execution time of compression algorithm was profiled to conclude the decision of accelerating the most time consuming intervened prediction module by hardware realization. A set of optimization techniques was applied systematically to enhance the overall system performance (2011).

Zhao and Jing proposed a vector quantization algorithm which is applied to hyperspectral image compression. First the three dimensional hyperspectral images were converted into two dimensional pixel vectors and then the vector quantization was applied to the transformed pixel vectors (2013). Singh and Goswami presented a novel scheme that composed a combination of two techniques for hyperspectral image compression, Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) (2012). Song, et al proposed an Optimized Combination Coding (OCC) as a different prediction-based (DP-based) lossless compression scheme. The main modules of OCC scheme consist of two predictors and Huffman code. The prediction errors between predicted and real pixel grey value is encoded ultimately in variable-length code words attached to the binary code stream by Huffman codebook (2011).

Garci, et al quantified the impact of lossy compression on two standard approaches for hyperspectral data exploration: spectral unmixing and supervised classification using support vector machines (2011). Liang, et al proposed an algorithm for lossless compression of hyperspectral images using hybrid context prediction. The lossless compression algorithm divides into two stages: decorrelation stage and a coding stage. The decorrelation stage supports both intraband and interband predictions. The hybrid context prediction is the combination of linear prediction (LP) and a context prediction(2012). Gao, et al designed an improved inter-spectral prediction algorithm.(2011). Mat Noor and Vladimirrova reviewed hyperspectral spaceborne missions and compression techniques for hyperspectral images used on board satellites. Clustering and tiling strategies are employed to reduce the computational complexity of the algorithm (2013).

Qian, et al proposed an operational approach to determine the approximately optimal bitrate to be used to preserve both the majority of the information in the dataset as well as the anomalous pixels (2012). Wang, et al proposed an algorithm for lossless compression of hyperspectral images. The spectral redundancy in hyperspectral image was exploited using a context-match method. The proposed method results lower complexity (2007).
3D Modeling of Hyperspectral Images:

Hyperspectral images are the images which are originated by the image spectrometer by simultaneously gathering the image data in hundreds of spectral bands or frequencies. The huge amount of bands increases complexity and time of processing. HSI can be denoted as a 3-D data \( \mathbb{R} \in X_{G_1} \times X_{G_2} \times X_{G_3} \).

\( G_1 \times G_2 \times G_3 \) is the dimensional real vector space and \( G_1 \times G_2 \times G_3 \) is the length of the HSI. HSI simultaneously consist of two types of correlation. They are spatial correlation within images and the spectral correlation between spectral bands. The spectral correlation is usually stronger than the spatial correlation. The average correlation coefficient is denoted as \( \bar{\rho} \) and it is measured between two spectral bands of 3D-data cube as follows:

For \( g_1 = 1 \) to \( G_1 - 1 \)

\[
\bar{\rho}(g_1) = \frac{\text{cov} (\bar{E}(\cdot, g_1), \bar{E}(\cdot, g_1 + 1))}{\sqrt{\text{var}(\bar{E}(\cdot, g_1)) \text{var}(\bar{E}(\cdot, g_1 + 1))}}
\]

End \( \bar{\rho} = \frac{1}{G_1-1} \sum_{g_1=1}^{G_1-1} \rho(g_1) \) (1)

Handling both of spectral and spatial correlations is the key for the success of a compression algorithm. In this paper, a new hybrid scheme based on Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) for compressing the hyperspectral images is introduced. DWT and DCT are briefly explained in the following sections.

Discrete Wavelet Transform:

The DWT has been profitably applied in many of the image processing applications. DWT can efficiently reduce the noise present in the images, edge detection, compressing normal and hyperspectral images etc. DWT is capable to decompose the signals into lower resolution with finer details. DWT can be noticed as consecutive low-pass and high-pass filtering of the discrete time-domain signal. At each level, the high pass filter generates complete information given about the horizontal (H), vertical (V), and diagonal (D) of the HSI; whereas the low pass filter correlated with the scaling function results the approximate (A) information.

![3D HSI Decomposition](image)

Fig.1: 3D HSI Decomposition.

The two dimensional DWT is applied to each band of HSI. The 3D HSI has \( G_1 \) rows and \( G_2 \) columns; after applying the 2DWT to the HSI, it results four sub-band images such as A, H, V, D. Each sub-band images consists of \( G_1/2 \) rows and \( G_2/2 \) columns. The sub-band image A has a maximum energy when compared with the other 3 sub-band images. The 2DWT of function \( \rho(x, y) \) can be presented as

\[
W_x(g_1, g_2) = \frac{1}{\sqrt{G_1 G_2}} \sum_{x=0}^{G_1-1} \sum_{y=0}^{G_2-1} \rho(x, y) \varphi_{g_1, g_2}(x, y)
\]

\[
W_y(g_1, g_2) = \frac{1}{\sqrt{G_1 G_2}} \sum_{x=0}^{G_1-1} \sum_{y=0}^{G_2-1} \rho(x, y) \psi_{g_1, g_2}(x, y)
\]

\( s = \{H, D, V\} \)

\[
\varphi_{g_1, g_2}(x, y) = \varphi(x - g_1, y - g_2)
\]

\( \psi_{g_1, g_2}(x, y) = \varphi(x - g_1, y - g_2) \)
\[ \psi_{m+1,2}^{(5)}(x, y) = 2^m \psi_{m}^{(2^m x - g_1, 2^m y - g_2)} = 2^m \sum_j h_{m+1} (j - 2g_2) \sqrt{2} \psi (2^{m+1} x - j) \]

\[ \psi_{m+1,2}^{(6)}(x, y) = 2^m \sum_j h_{m+1} (j - 2g_2) \sqrt{2} \psi (2^{m+1} x - j) \]

\( \varphi \) is called scaling factor. \( \psi_{m}^{(2^m x - g_1, 2^m y - g_2)} \) Coefficients define an approximation of \( p(x, y) \). \( \phi_{m}^{(2^m x - g_1, 2^m y - g_2)} \) Coefficients add horizontal, vertical and diagonal details. Usually \( g_1 = g_2 = 2^m \) is selected such that \( m = 0, 1, 2, 3, \ldots M-1 \). \( h_{\varphi} \) and \( h_{\psi} \) are called wavelet filters.

The inverse 2DWT is calculated as

\[ p(x, y) = \frac{1}{\sqrt{2g_2}} \sum_{i=0}^{g_1-1} \sum_{j=0}^{g_2-1} \sum_k \sum_l \psi_{m}^{(i, j)} \phi_{m}^{(i, j)} \psi_{m}^{(l, k)} \phi_{m}^{(l, k)} \]

In order to obtain a better compression ratio the images are undergone one more level of decomposition.

3D-Discrete Cosine Transform of third-order Tensor:

The Discrete Cosine Transform (DCT) helps to partition the image into spectral sub-bands with respect to the image quality. DCT is similar to the Discrete Fourier Transform (DFT). It performs transformation from the spatial domain to the frequency domain. DCT pointed an arrangement of data points in terms of sum of cosine functions.

The third order tensor \( T_{3} \in \mathbb{X}^{G_1 \times G_2 \times G_3} \) is decomposed by 3D-DCT into an unknown core tensor \( \mathbb{C} \in \mathbb{X}^{Q_1 \times Q_2 \times Q_3} \). In 3D-DCT, ID-DCT is performed three times, each on every dimension. The representation of the 3D-DCT for an input image \( L \) (size \( G_1 \times G_2 \times G_3 \)) and output image \( M \) is:

\[ M_{3D} = d_1 \cdot d_2 \cdot d_3 \cdot L_{3D} \]

\[ d_1 = \cos \frac{n_{2a} \pi (x + 1)}{2G_1} \]

\[ d_2 = \cos \frac{n_{2a} \pi (y + 1)}{2G_2} \]

\[ d_3 = \cos \frac{n_{2a} \pi (z + 1)}{2G_3} \]

The \( M_{3D} \) values are called the DCT coefficients of \( L \). The inverse DCT is given by:

\[ L_{3D} = \frac{1}{2G_1 \cdot 2G_2 \cdot 2G_3} \sum_{x=0}^{G_1-1} \sum_{y=0}^{G_2-1} \sum_{z=0}^{G_3-1} d_1 \cdot d_2 \cdot d_3 \cdot M_{3D} \]

Most of the DCT coefficients have values close to zero for hyperspectral images. These coefficients are not affecting the quality of the reconstructed image.

Proposed Compression Technique:

The flow of the proposed HSI compression technique based on DWT and DCT is shown in Fig.2. The compression is performed using the following steps:

1. For each spectral band of HSI, 2DWT is applied to obtain four sub-images such as approximate, diagonal, vertical and horizontal components.
2. 3D-DCT is applied to the four tensors. For each tensor the size of core tensor \( \mathbb{C} \) that is \( Q_1, Q_2, Q_3 \) is manually selected. The approximate tensor has the lowest frequency components, so the values of \( Q_{1A}, Q_{2A}, Q_{3A} \) has higher coefficient energy than the other 3 tensors. The values of the diagonal tensors \( Q_{1D}, Q_{2D}, Q_{3D} \) composed of diagonal information was also set higher than the values of horizontal and vertical tensors \( (Q_{1H}, Q_{2H}, Q_{3H}) \) and \( (Q_{1V}, Q_{2V}, Q_{3V}) \).
3. JPEG performs quantization of the DCT coefficients with the core tensors. Then encoding of core tensors \( \mathcal{X} \) is performed. Each core tensor is scanned based on the repetition among the pixel value and the repetition of frequency. If a pixel value is located only once, then the frequency value is not replaced which may cause overhead in compression. Let us consider the following example:

\[
\text{Input Stream} : 88 \ 88 \ 33 \ 33 \ 33 \ 90 \ 10 \ 10 \\
\text{Output Stream} : 288 \ 3 \ 33 \ 90 \ 210
\]

4. The transmitted compression data is decoded using JPEG.

5. Inverse 2DWT is applied to the compressed data to obtain the reconstructed HSI.

**Fig. 2:** Flow Diagram for DWT-DCT-JPEG.

**Design Issues:**

To visually simulate the experimented results of the proposed method rely on Field Programmable Gate Arrays (FPGAs). FPGAs are non-conventional processors built primarily out of logic blocks connected by programmable wires. Each and every logic block has one or more lookup tables (LUTs) and several bits of memory. The FPGA provides many advantages over conventional implementations like long time availability, extremely short time to market, fast and efficient systems, performance gain for software applications, real time applications, massively parallel data processing, less power consumption etc. FPGAs may be reprogrammed within milliseconds for no cost other than the designer’s time, while ASICs require a completely new fabrication run lasting a month or two and costing hundreds of thousands of dollars.

**Low cost:**

The cost of the FPGA is quite affordable and hence it makes them very designer friendly. Also the power requirement is less since the architecture is based on LUTs.

**Parallel processing:**

FPGAs especially find applications in any area or algorithm that can make use of the massive parallelism offered by their architecture. The implicit parallelism of the logic resources on an FPGA allows for considerable computational throughput even at a low MHz clock rate. The flexibility of the FPGA allows for even higher performance by trading off precision and range in the number format for an increased number of parallel arithmetic units.

**High Speed:**

Since the FPGA technology is based on look-up tables, the time taken to execute is less than that in ASIC technology. This high speed is used in making various multipliers today, which had traditionally been the sole reserve of DSP processors.
The FPGA tested with real image shows that the reconstruction of the images maintains a high accuracy and the running time of the program is shorter. The FPGA designed with high computational power and compact size makes this reconfigurable device very appealing for on-board and real time data processing. In our proposed work, DWT-DCT-JPEG is implemented on Xilinx 14.2 FPGA. The result shows good performance than the existing compression techniques.

**Performance Analysis:**

The proposed system is implemented on Xilinx 14.2 FPGA. The performance of the compression techniques is analyzed and compared in terms of compression ratio, PSNR, MSE and memory consumption. The main advantage of using FPGA, which results less memory consumption for compressing the HSI and normal images.

**Experimental Results:**

The HSI-1 compression steps of Paris image use the HSI compression method based on DWT-DCT-JPEG and are shown in Fig.3. The input HSI-1 is loaded and it is split into 7 spectral bands. There are 5 HSI images which are compressed using the proposed technique. The HSI images include Landsat images (.lan) of Paris, Little Colorado River, Mississippi River, Montana state and Rio city. Fig.3 shows the compression steps performed on the landsat image of Paris.

![Compression steps](image1)

**Fig. 3:** Compression steps for a HSI-1 of Paris City: (a) Band 1 (b) Band 2 (c) Band 4 (d) Band 7.

![Input HSI image](image2)

**Fig. 4:** Input HSI image (Little colorado river) (a) Band 1 (b) Band 6.
**Fig. 5:** Output HSI image (Little colorado river) (a) Band 1 (b) Band 6.

Fig.4 and Fig.5 are the input and output HSI’s of Little Colorado river for Band 1 and Band 6.

**Compression Ratio:**

Compression ratio is the ratio between the bit stream lengths of the original with the compressed image/data. Fig.6. shows the result comparison between the existing M-CALIC (Modified 3D Context-based Adaptive Lossless Image Coding) based compressions with the proposed DWT-DCT-JPEG compression. The compression is calculated as

\[
CR = \frac{L_o}{L_c}
\]  

(13)

Here \(L_o\) is the bitstream length of the original source and \(L_c\) is the length of the compound source.

The proposed system yields compression ratio revising from 3.8 to 4.2, which is greater than the existing method M-CALIC. M-CALIC results compression ratio ranges between 3.23 to 3.4. the difference in CR compared to M-CALIC is 0.62.

**Fig. 6:** Compression ratios of M-CALIC and DWT-DCT-JPEG.

**Table I:** Comparison Of Compression Ratio.

<table>
<thead>
<tr>
<th>Image/Data</th>
<th>Method/Application</th>
<th>Main focus</th>
<th>CR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lena</td>
<td>Wireless Image Sensor</td>
<td>JPEG-LS</td>
<td>3.30</td>
</tr>
<tr>
<td>Cuprite</td>
<td>Context Match</td>
<td>M-CALIC</td>
<td>3.21</td>
</tr>
<tr>
<td>Jasper Ridge</td>
<td>Context Match</td>
<td>M-CALIC</td>
<td>3.16</td>
</tr>
<tr>
<td>CASIA V1</td>
<td>Polar Iris</td>
<td>JPEG2000</td>
<td>2.42</td>
</tr>
<tr>
<td>Party Scene</td>
<td>Lossless intra coding</td>
<td>JPEG-LS</td>
<td>1.79</td>
</tr>
<tr>
<td>Traffic</td>
<td>Lossless intra coding</td>
<td>MJPEG2000</td>
<td>2.45</td>
</tr>
<tr>
<td>Little Colorado River</td>
<td>Our Previous Work-Avg.</td>
<td>DWT-TD (ALS) – RLE</td>
<td>3.38</td>
</tr>
<tr>
<td>Little Colorado River</td>
<td>Our Proposed Work-Avg.</td>
<td>DWT-DCT-JPEG</td>
<td>3.86</td>
</tr>
</tbody>
</table>

Table I shows the comparison result of some of the compression techniques such as Context match [21], Wireless image sensor (Renyan, Z., et al., 2010), DWT-TD(ALS) – RLE (Kala S. and S.Vasuki, 2013), Polar Iris (Horvath, K., et al., 2011), Lossless intra coding (Cai, Q., et al., 2012) and the proposed method DWT-
DCT-JPEG. It shows that the proposed method results better compression ratio than the existing compression algorithms.

**Peak Signal to Noise Ratio:**

![Fig. 7: PSNR of M-CALIC and DWT-DCT-RLE.](image)

Peak Signal to Noise Ratio (PSNR) is estimated from the ratio between the maximum possible power and the power of corrupting noise. MSE is used to estimate the noise/error present on the image. PSNR is a measure of peak error. The proposed system DWT-DCT-JPEG results 40.2 to 45.3 dB, which is greater than the existing system PSNR values. M-CALIC results 24.3 to 35.4 dB. The average PSNR difference between these two techniques are noted as 11.926 dB.

**Table II: Comparison of PSNR.**

<table>
<thead>
<tr>
<th>Method/Application</th>
<th>Main focus</th>
<th>Image/Data</th>
<th>PSNR (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neural representation</td>
<td>3D DCT+TD</td>
<td>Natural scenes</td>
<td>25.9</td>
</tr>
<tr>
<td>OB-SPECK</td>
<td>SA-DWT</td>
<td>Shelter Island-ROI</td>
<td>32.99</td>
</tr>
<tr>
<td>OB-SPECK</td>
<td>SA-DWT</td>
<td>Shelter Island – BG</td>
<td>27.12</td>
</tr>
<tr>
<td>OB-SPECK</td>
<td>SA-RDCT</td>
<td>San Francisco – ROI</td>
<td>39.28</td>
</tr>
<tr>
<td>OB-SPECK</td>
<td>JPEG2000</td>
<td>North Island NAS-ROI</td>
<td>28.98</td>
</tr>
<tr>
<td>Our Previous Work – Avg.</td>
<td>DWT-TD (ALS) – RLE</td>
<td>Little Colorado River</td>
<td>34.59</td>
</tr>
<tr>
<td>Our Proposed Work -Avg.</td>
<td>DWT-DCT-JPEG</td>
<td>Little Colorado River</td>
<td>42.906</td>
</tr>
</tbody>
</table>

**Table II** shows the comparison result for some of the existing compression algorithms such as Neural representation (Karami, A., et al., 2010), OB-SPECK, JPEG 2000 (Licheng, J., et al., 2011), DWT-TD(ALS)-RLE (Kala S. and S.Vasuki, 2013) and our proposed work DWT-DCT-JPEG. It shows that the proposed method results better PSNR than the existing compression algorithms.

**Mean Square Error:**

![Fig. 8: MSE of M-CALIC and DWT-DCT-JPEG.](image)
Mean Square Error (MSE) is the cumulative squared error between the compressed and the original image. The result shows that the MSE for the proposed method DWT-DCT-JPEG is lesser than the existing method M-CALIC. The average MSE for DWT-DCT-JPEG is 12.58dB and for M-CALIC is 38.34dB. The difference between DWT-DCT-JPEG and M-CALIC is 25.76dB.

**Memory Consumption:**

![Graph showing Memory Consumption of M-CALIC and DWT-DCT-JPEG](image)

**Fig. 9:** Memory Consumption of M-CALIC and DWT-DCT-JPEG.

Memory consumption of the proposed and existing method is shown in Fig.9. The result shows that the proposed work results lesser memory consumption than the existing method.

**Conclusion and Future Work:**

The proposed compression method DWT-DCT-JPEG reduces the size of the 3D tensors, which are calculated from the 4 sub-images of the spectral bands of HSI. The simulation experiments are tested on 5 HSI images such as Paris city, Little Colorado River, Mississippi River, Montana State and Rio City with the HSI compression based on DWT, DCT and JPEG. The proposed method is compared with some of the existing compression algorithms like JPEG-LS, M-CALIC, JPEG2000, MJPEG2000, OB-SPECK and DWT-TD(ALS)-RLE. Our proposed work results good in terms of compression ratio, PSNR, MSE and memory consumption.

Our future plan is to perform hyperspectral image compression using various encoding techniques with DWT features.

**REFERENCES**


