

Effective compression of hyperspectral imagery using an improved 3D DCT approach for land cover analysis in remote sensing applications

Tong Qiao^a, Jinchang Ren^{b,*}, Meijun Sun^{c,*},
Jiangbin Zheng^d, Stephen Marshall^e

^a *Centre for Excellence in Signal and Image Processing (CeSIP), Department of Electronic and Electrical Engineering, University of Strathclyde, Glasgow, UK. Tel: +44(0)141 548 3535. Email: t.qiao@strath.ac.uk.*

^b *Centre for Excellence in Signal and Image Processing (CeSIP), Department of Electronic and Electrical Engineering, University of Strathclyde, Glasgow, UK. Tel: +44 (0) 141 548 2384. Email: jinchang.ren@strath.ac.uk.*

^c *School of Computer Science and Technology, Tianjin University, Tianjin, China. Tel: +86(0)22 2740 6538. Email: sunmeijun@tju.edu.cn.*

^d *School of Computer Software and Microelectronics, Northwestern Polytechnical University, Xi'an, China. Tel: +86(0)29 8846 0323. Email: Zhengjb@nwpu.edu.cn.*

^e *Centre for Excellence in Signal and Image Processing (CeSIP), Department of Electronic and Electrical Engineering, University of Strathclyde, Glasgow, UK. Tel: +44 (0) 141 548 2199. Email: stephen.marshall@strath.ac.uk.*

*Corresponding author(s).

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Although hyperspectral imagery (HSI), which has been applied in a wide range of applications, suffers from very large volumes of data, its uncompressed representation is still preferred to avoid compression loss for accurate data analysis. In this paper, we focus on quality-assured lossy compression of HSI, where the accuracy of analysis from decoded data is taken as a key criterion to assess the efficacy of coding. An improved 3D Discrete Cosine Transform (DCT) based approach is proposed, where a Support Vector Machine (SVM) is applied to optimally determine the weighting of inter-band correlation within the quantisation matrix. In addition to the conventional quantitative metrics Signal-to-Noise Ratio (SNR) and Structural Similarity (SSIM) for performance assessment, the classification accuracy on decoded data from the SVM is adopted for quality-assured evaluation, where the Set Partitioning in Hierarchical Trees (SPIHT) method with 3D Discrete Wavelet Transform (DWT) is used for benchmarking. Results on four publically available HSI datasets have indicated that our approach outperforms SPIHT in both subjective (qualitative) and objective (quantitative) assessments for land cover analysis in remote sensing applications. Moreover, our approach is more efficient and generates much reduced degradation for subsequent data classification hence provides a more efficient and quality-assured solution in effective compression of HSI.

Keywords: HSI; coding and compression; 3D DCT; SVM; SPIHT; land cover analysis; remote sensing.

1. Introduction

Hyperspectral imagery (HSI), through capturing hundreds of bands in a broad spectral range covering visible, near-infrared and beyond, has proved successful in many areas (Christophe, Mailhes, and Duhamel 2008). Typical examples include traditional applications in remote sensing and military surveillance (Zhao et al. 2013) as well as newly emerging platforms for food quality analysis (Sun 2010; Kelman, Ren, and Marshall 2013), pharmaceutical (Roggo et al. 2005) and forensics/security (Payne et al.

2007; Brewer et al. 2008; Gill et al. 2011). However, a major problem associated with HSI is the huge volumes of data, leading to not only high cost and large data for storage but also greater analysing/processing time and difficulty in data transmission, especially the one from satellites to ground (Christophe, Léger, and Mailhes 2005). As a result, compression and coding of HSI is highly desired in this context.

According to different requirements in various applications, compression techniques in HSI can be divided into two categories, i.e. lossless (Magli, Olmo, and Quacchio 2004) and lossy compression (Du, Zhu, and Fowler 2008; Penna et al. 2007; Wang, Rucker, and Fowler 2004). For lossless compression, images are encoded without loss of information thus the original images can be fully recovered when decoded. Consequently, redundancy reduction within the data is achieved purely by examining its spatial (and spectral) distributions. Some widely used approaches for lossless compression include run-length encoding, predictive coding and entropy encoding (Magli 2009). Since it does not lose information, lossless compression can only achieve a very limited compression ratio of about 3:1 (Liang, Li, and Guo 2012). Lossy compression, on the other hand, allows loss of information when images are compressed hence it achieves a much higher compression ratio of 50:1 or more (Marpe et al. 2000).

Since redundancies within the hyper-cube can be more effectively removed, lossy compression has been widely used by many researchers, using typical approaches including vector quantisation (VQ) (Mendenhall and Merenyi 2008; Qian et al. 2001; Qian 2006; Li et al. 2014), principal component analysis (PCA) (Du and Fowler 2007; Zabalza, Ren, Wang, Zhang, et al. 2014; Zabalza, Ren, Ren, et al. 2014; Ren et al. 2014) and transform-domain approaches (Kim, Xiong, and Pearlman 2000; Pearlman et al. 2004; Said and Pearlman 1996). In Chen's work (Chen 1998), it was found that

although it is simple, the VQ approach is inappropriate for low bit rate compression. Consequently, a new method based on Kronecker-product gain-shape vector quantisation (Canta and Poggi 1998) was proposed for very low bit rate encoding of multispectral and hyperspectral images. For transform-domain compression, discrete cosine transforms (DCT) and discrete wavelet transforms (DWT) are two commonly used techniques, which have been adopted in the Joint Photographic Experts Group (JPEG) and JPEG2000 standards, respectively. Basically, these transforms help to remove correlation (redundancy) in both spatial and spectral domains, followed by a quantiser and an entropy encoder. Usually, these approaches are employed to compress individual bands of HSI and are taken as baseline techniques for benchmarking (Taubman, Marcellin, and Rabbani 2002). A compression algorithm based on 3D DCT was proposed by Abousleman et al. (Abousleman, Marcellin, and Hunt 1995), employing the trellis coded quantisation (TCQ) scheme. It was shown that the 3D DCT system achieved much higher compression ratio than systems using DPCM (differential pulse code modulation), block truncation coding and various VQ schemes.

As mentioned above, entropy coding should be applied to the transformed coefficients. According to different entropy coding methods, compression algorithms based on DWT can be divided into two groups, which are zero-tree coding and context-based coding (Pickering and Ryan 2006). The most famous approach for zero-tree coding is the set partitioning in hierarchical trees (SPIHT) (Said and Pearlman 1996), some extensions include 3D SPIHT (Kim, Xiong, and Pearlman 2000) and 3D set partitioning embedded block (SPECK) (Pearlman et al. 2004). For context-based coding, JPEG2000 standard has adopted it for the core entropy encoder. Annex N of Part 2 of JPEG2000 standard supports multi-component imagery compression which can be used for hyperspectral imagery compression. Even though Part 10 of JPEG2000

standard was designed for 3D images, it is not suitable for hyperspectral images because it requires the image as isotropic as possible. Many researchers have compared performances between 3D SPIHT and JPEG2000 multi-component. Fowler and Rucker has shown that JPEG2000 multi-component achieved SNR of 0.1 to 0.3dB higher than 3D SPIHT for several remote sensing images (Fowler and Rucker 2007). However, Tang and Pearlman have proved that 3D SPIHT yielded higher SNRs, e.g. 1.5 to 3.5 dB, than JPEG2000 multi-component at various compression bit rates (Tang and Pearlman 2006b). Nevertheless, 3D SPIHT provided comparable results to JPEG2000 multi-component as shown by Christophe et al. (Christophe, Mailhes, and Duhamel 2008). Therefore, 3D SPIHT is chosen as the representation of 3D DWT based approach in this paper.

Although lossy compression can significantly reduce the amount of data for HSI, in most practical situations, lossless compression, which has high computational cost, is desired to avoid loss of information as it may severely affect the accuracy for subsequent data analysis i.e. land cover analysis (Christophe, Léger, and Mailhes 2005; Fowler and Rucker 2007). As a result, lossless compression techniques were also reviewed. Distributed source coding (Abrardo et al. 2010) was used for error-resilient lossless compression, with a compression ratio of 2:1 reported. Through prediction using optimal multibands, a more efficient scheme for lossless compression was presented by Huo et al. (Huo, Zhang, and Peng 2009), with a higher compression ratio of 3.3:1 achieved. In addition, there are also some other approaches introduced, using techniques such as clustered DPCM (differential pulse code modulation) coding (Mielikainen and Toivanen 2003), lookup tables (LUT) (Mielikainen and Toivanen 2008), crisp and fuzzy adaptive spectral predictions (Aiazzi et al. 2007), context-based adaptive classified arithmetic coding in wavelet domain (Zhang and Liu 2007b) and

reordering prediction (Zhang and Liu 2007a). Although higher compression ratios can be reached by such approaches, the cost of complex computations they require seems unaffordable for real-time applications.

It is our aim to propose a solution for quality-assured, low-cost, lossy compression of HSI, where a high compression ratio is achieved under very limited degradation on the accuracy for subsequent analysis and application. We are going to investigate whether it is feasible for quality-assured lossy compression of HSI. As despite the suggestions for lossless compression to preserve the quality of HSI (Christophe, Léger, and Mailhes 2005; Fowler and Rucker 2007), it is suggested that a moderate amount of data loss does not affect the image quality in many applications (Qian et al. 2001; Tang and Pearlman 2006a). In the paper, both DCT and DWT based 3D approaches are investigated, where a modified 3D DCT based approach is proposed and compared with 3D SPIHT algorithm. Although it was found DWT usually outperforms DCT in this context (Penna et al. 2007; Xiong et al. 1999), better results from DCT were reported by others (Pan, Liu, and Lv 2012). Therefore, we also aim to evaluate these two approaches in terms of the compression performance and any side-effects on subsequent data analysis. Using four publically available remote sensing datasets, interesting results are produced to fully validate the efficacy and efficiency of our proposed approach for quality-assured compression of HSI.

The remaining part of this paper is organised as follows. In Section 2, technical details of our proposed 3D DCT based approach are presented. Section 3 discusses the datasets and evaluation criteria used. Experimental results and evaluations on land cover analysis are given in Section 4. Finally, some concluding remarks are drawn in Section 5.

2. Improved 3D DCT based approach

By combining the 2D spatial DCT and the 2D spectral DCT together (Pickering and Ryan 2001), 3D DCT is formed for more effective compression of hyperspectral imagery as it can fully exploit the correlation in the hypercube (Taubman, Marcellin, and Rabbani 2002). On the other hand, it allows fast access to each band image by partially decoding the compressed image, in band groups. An improved 3D DCT approach with learning based determination of optimal quantisation table is presented.

2.1 From 2D DCT to 3D DCT

For 2D DCT in JPEG standard, a block size of 8×8 is chosen for block-based compression. For 3D DCT used for hypercube compression, similarly, an $8 \times 8 \times 8$ sub-cube is applied. As a result, every 8 bands is grouped when they are compressed, which enables each band to be accessed by decoding the grouped 8 bands, i.e. partially decoding the whole compressed hypercube.

Let $f(x, y, \lambda)$ denote a hypercube, the 3D forward DCT is defined as follows (Adjeroh and Sawant 2009):

$$\begin{cases} F(u, v, w) = \frac{c(u)c(v)c(w)}{(N/2)^{3/2}} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} \sum_{\lambda=0}^{N-1} f(x, y, \lambda) \\ \cos\left(\frac{2x+1}{2N}u\pi\right) \cos\left(\frac{2y+1}{2N}v\pi\right) \cos\left(\frac{2\lambda+1}{2N}w\pi\right) \end{cases} \quad (1)$$

where $u, v, w = 0, 1, \dots, N - 1$ and $c(\cdot)$ satisfies

$$c(k) = \begin{cases} \frac{1}{\sqrt{2}} & \text{for } k = 0 \\ 1 & \text{otherwise.} \end{cases}$$

In order to acquire lossy compression, the 3D transformed coefficients must be quantised. The step of quantisation is the main source of loss in the DCT-based coding, thus the quantiser should make the entropy of those quantised coefficients smaller. The

quantisation process is defined in Equation (2), where Q is the 3D quantisation table and C is the quantised result.

$$C(u, v, w) = \text{round} \left(\frac{F(u, v, w)}{Q(u, v, w)} \right) \quad (2)$$

The 3D DCT quantisation table is formed with 512 quantitative values. Low frequency components locate near the coordinate (0, 0, 0) and high frequency components locate near the coordinate (7, 7, 7). High frequency components can be discarded after the quantisation stage since human vision systems are more sensitive to low frequency components (Sun and Pao 1998). However, JPEG standard has only defined the standard quantisation matrix for 2D DCT. Thus, the 3D DCT quantisation matrix can be designed on one's own choice, as long as values in the matrix are small at low frequency while large at high frequency.

In general, the quantisation matrix is the key for DCT-based compression as it affects the performance of coding. The multiplication (Lee, Chan, and Adjero 1997) and the sum of the three coordinates (Yeo and Liu 1995), uvw and $u + v + w$, were used by some researchers to determine the quantisation matrix, respectively. In our experiments, however, the quantisation matrix below (Tang et al. 2012) is used, where the spectral component, w , is nonlinearly weighted to reflect the inter-band correlation. In fact, inter-band correlation decreases when the bands are further apart, similar to correlation between video frames. As a result, the matrix from video compression can be used for coding of HSI, shown in Equation (3),

$$Q(u, v, w) = \text{round}(u + v + kw + 3), u, v, w \in [0, 7] \quad (3)$$

where k stands for an inter-band correlation coefficient between spectral bands, which has 26 values of choice: 0.1, 0.15, 0.2, 0.25, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5, 5.5, 6, 6.5, 7, 7.5 and 8. Therefore, in total there are 26 quantisation

tables, denoted from No.1 to No.26, where No.1 is used for weak inter-band correlation and No.27 for strong inter-band correlation.

2.2 Proposed learning based approach

As mentioned before, every 8 bands forms a group to be compressed. Therefore, the value of k for each group should not be the same considering the inter-band correlation for each group could be different. Thus, the quantisation table from Tang et al. (Tang et al. 2012) with only a fixed k may not be an optimal solution. In the paper, we have proposed to use a support vector machine (SVM) to predict k for each group. In each group containing eight spectral bands, if the correlation coefficient between every two bands is calculated, a vector containing 28 correlation coefficients can be obtained. In order to train the prediction model, a few spectral band groups from a hyperspectral image will be selected. The next thing is to determine optimal values of k for selected groups. 26 quantisation tables with values of k shown in Section 2.1 have been applied to compress every group at a bit rate of 0.5bpppb (bits per pixel per band) respectively. Therefore, for each group, we have 26 reconstructed images at the same compression bit rate. The lowest MSE (mean squared error) of 26 reconstructed images indicates the best compression performance, where the corresponding k is the optimal value of the quantisation table for that particular group. Thus, in the training set for the SVM, for every instance, it contains one ‘target value’ k and 28 ‘attributes’ (correlation coefficients). The goal is to construct a regression model to predict ‘target value’ k for remaining band groups given their correlation coefficients only. The performance of the above mentioned three quantisation matrices in Section 2.1 and the proposed SVM prediction based quantisation matrix is compared in Section 3.3.

For a trade-off between the quality of the reconstructed image and the compression bit rate achieved, a quality level ranging from 1 to 99 is decided, where a smaller number refers to poorer quality of the compressed image hence a higher compression ratio and a lower bit rate. By adjusting the quality level, the desired compression bit rate can be achieved.

The quality level of the quantisation matrix specified in Equation (3) is defined as 50 and Q_{50} is denoted as the standard quantisation matrix. For a quality level higher than 50 and lower than 50, the quantisation matrices are different as shown in Equation (4) (Wallace 1991):

$$Q = \begin{cases} \frac{100 - \text{Quality level}}{50} \times Q_{50} \\ \frac{50}{\text{Quality level}} \times Q_{50} \end{cases} \quad (4)$$

Entropy coding is completed after the quantisation, where coefficients at (0, 0, 0) in each $8 \times 8 \times 8$ cube are referred to as DC coefficients whilst all others are AC coefficients. For the Huffman encoder, DC coefficients and AC coefficients are separately coded. Let DC_i and DC_{i-1} represent DC coefficients for block i and block $i - 1$, respectively. Considering a high correlation of DC coefficients in adjacent blocks, differential coding can be employed to encode the DC values for improved efficacy, where only the difference of DC_i and DC_{i-1} needs to be Huffman coded (Wallace 1991).

For AC coefficients, the scanning order is from low frequency to high frequency items, in the connection order with the 3D zigzag shape. Please note that the scanning order here is fixed, enabling fast access to designated items in a look-up table. On the contrary, DWT relies on SPIHT tree to determine the connection between coefficients, thus it is unfixed and time-consuming though it is expected to produce better results of coding.

Except for DC and AC coefficients, the inter-band correlation coefficients k for each compression group need to be coded as well. Similar to DC coefficients, values of k are differential coded.

At the decoding stage, the Huffman codes are decoded (Hashemian 2003), followed by the de-quantisation step and the inverse DCT transform. Then, the reconstructed image is achieved. Similar to other block-based coding techniques, one of the most noticeable degradations of 3D DCT are the block artefacts, which is a regular pattern of visible block boundaries (Luo and Ward 2003). However, such artefacts do not necessarily degrade the performance of subsequent image analysis, as demonstrated in next two sections.

3. Datasets and experimental setup

In total four publically available datasets are used for performance evaluation, the datasets, experimental setup and quantitative criteria are discussed in detail below.

3.1 Datasets preparation

The four hyperspectral datasets used in our experiments include ‘Moffett field’ scene 1, ‘92AV3C’, ‘SalinasB’ and ‘PaviaUA’, which are all publically available and widely used in this context. The first three datasets were taken by the Airborne Visible Infra-Red Imaging Spectrometer (AVIRIS) at NASA’s Jet Propulsion Laboratory and the last dataset was acquired by the Reflective Optical System Imaging Spectrometer (ROSIS) (Chakrabarty et al. 2012).

The first dataset, ‘Moffett field’ scene 1, was taken above the Moffett Field area in California at the southern end of San Francisco Bay in 1997. In the image, there are a hilly ridge and an urban area (Griffin and Burke 2003). ‘Moffett field’ scene 1 dataset has 224 contiguous bands ranging from 400nm to 2500nm that covers the complete

VIS-NIR-SWIR spectrum. The original size of the hypercube is $512 \times 614 \times 224$. For simplicity, the hypercube was cropped from the top-left corner and 16 noise bands were removed to form a cube with dimensions of $512 \times 512 \times 208$. This cropped hypercube was then binned to a smaller size of $128 \times 128 \times 208$ by using the average spectrum to represent each 4×4 block in the spatial domain. Therefore, the image size was dramatically reduced for easy processing using the 3D SPIHT algorithm.

The second dataset, '92AV3C', was collected over the Indian Pines test site in North-western Indiana, USA in the early 1990s (Chakrabarty et al. 2012; Pal and Foody 2010). The spatial size of this hypercube contains 145×145 pixels of an agriculture area, with a spatial resolution of 20m (Chakrabarty et al. 2012). This dataset also has 224 spectral reflectance bands within the same wavelength range as used for the first dataset, with a nominal spectral resolution of 10nm and a radiometric resolution of 16 bits. After discarding 20 bands affected by water absorption and noise (Chakrabarty et al. 2012), additional 19 bands were removed so that 185 bands remained as suggested in Pal and Foody's work (Pal and Foody 2010). Finally, the hypercube had a new size of $144 \times 144 \times 184$, by cropping the image to allow each dimension to be divided by 8 with no remainder, for the easy implementation of DCT in block-based compression.

The third dataset, 'SalinasB', was gathered at Salinas Valley, California at low altitude, leading to a high spatial resolution of 3.7m per pixel (Chakrabarty et al. 2012). The image is made up of 512 lines of 217 samples. Similar to '92AV3C' dataset, only 184 of 224 bands were used for testing. Also the image was cropped in spatial dimension, forming a new hypercube sized of $144 \times 144 \times 184$, i.e. same as the second dataset.

The last dataset, 'PaviaUA', was collected using the ROSIS sensor during a flight campaign over Pavia district in north Italy (Benediktsson, Palmason, and

Sveinsson 2005). After removing 12 noisy bands, the original hypercube was resized to $610 \times 340 \times 103$. This was further cropped to $144 \times 144 \times 96$ in our experiments for easy implementation of the coding algorithms.

As the 3D DCT based compression in this paper is adapted from video compression whose maximum pixel value is 255, the hyperspectral images need to be normalised to the range of 0 to 255 first. Therefore, the normalised hyperspectral images are used both for 3D DCT based compression and 3D SPIHT based compression. Although the images are transformed from 16 bits to 8 bits per pixel, subsequent image analysis are not influenced as shown in Section 4. Another thing needs to be addressed is that considering the test image size, the decomposition level of 3D DWT in this experiment is set as three.

To illustrate the contents of the four datasets after essential cropping, pseudo colour images of each dataset are shown in Figure 1. Actually, these images contain different natural scenes, which correspond to various regions of interest. More importantly, there are ground truth maps available for the last three datasets, as shown in Figure 2, which enables classification of pixels for quality-assured performance evaluation of the compression approaches.

Figure 1. Pseudo colour images from the four datasets, from left to right: ‘Moffett Field’ (after cropping and binning), ‘92AV3C’ (after cropping), ‘SalinasB’ (cropping), and ‘PaviaUA’ (after cropping).

Figure 2. Ground truth maps for the last three datasets including ‘92AV3C’ (left), ‘SalinasB’ (middle) and ‘PaviaUA’ (right).

In Figure 2, the ground truth for the '92AV3C' dataset contains 16 classes, corresponding to Alfalfa, Corn-notill, Corn-min, Corn, Grass-pasture, Grass-trees, Grass-pasture-mowed, Hay-windrowed, Oats, Soybean-notill, Soybean-mintill, Soybean-clean, Wheat, woods, Building-Grass-Trees-Drives and Stone-Steel-Towers (Chakrabarty et al. 2012). For the 'SalinasB' dataset, the ground truth has 9 classes, corresponding to broccoli, lettuce and grapes et al (Chakrabarty et al. 2012). Finally, the 'PaviaUA' dataset has 8 classes defined in the ground truth, including meadows, asphalt, base soil and trees, et al (Chakrabarty et al. 2012). How these ground truth maps are used for classification and quality-assured performance evaluation is discussed below.

3.2 Evaluation criteria

For performance evaluation of the compression algorithms, several commonly used criteria are summarised. The first one is the compression bit rate, which is determined through dividing the compressed bit stream size by the original image size and its unit is bits per pixel per band (bpppb).

Although a lower bit rate means a smaller number of data needed for the compressed hypercube, the degradation of the image quality is high. Therefore, a good compromise between the compression rate and the image quality is desired (Pal and Foody 2010). For quality assessment of the reconstructed images, subjective and objective criteria are usually used as summarised below.

For subjective evaluation, it mainly relies on the judgment from some selected observers. First, the visual capabilities of the candidate observers are tested, and those qualified are chosen to assess the quality of the resulted images by giving different ranks. Since human visual systems are highly adapted to extract structural information from the viewing area, subjective assessment is considered as the best way to evaluate

images to be viewed by human beings. However, in practice, subjective evaluation is less preferable than objective approaches because the solution tends to be inconsistent, inconvenient and time consuming (Chen et al. 2003), especially for hypercube that contains hundreds of band images. Besides, it is meaningless to compare a single band of the hyperspectral imagery because it is not typically observed by human viewers. Therefore, in this paper, subjective assessment was completed by visually comparing two accumulated difference images between the reconstructed image and the original image under the same compression bit rate, thus a straightforward evaluation is achieved. The accumulated difference image I_{diff} for a B-band HSI is calculated as shown in Equation (5),

$$I_{diff}(i, j, k) = \sum_{k=1}^B |X(i, j, k) - Y(i, j, k)| \quad (5)$$

where X and Y represent the original image and the reconstructed image respectively.

Ideally objective evaluation approaches also prove good subjective tests, and they are easier to apply as images could be automatically analysed for quality assessment without human involvement. Often, a full-reference approach is used for objective quality assessment, where a complete reference is supplied for comparison (Erickson 2002). A simple statistical error metric called the Signal-to-Noise Ratio (SNR) is adopted for this purpose. Under a given compression bit rate, SNR can be used to assess the rate-distortion performance in terms of reconstruction fidelity as detailed below.

Regarding the SNR, it is defined as the energy ratio between the original image and the noise, which is widely used for quality assessment. As SNR increases, the reconstructed image quality improves. However, it only has an approximate relationship with the human visual image quality because it compares the data pixel by pixel without

taking the global contents represented into consideration (Winkler and Mohandas 2008).

The SNR is represented in decibels (dB) and its definition is given by:

$$SNR = 10 \log_{10} \frac{\sum_{i=1}^M \sum_{j=1}^N \sum_{k=1}^K X(i,j,k)^2}{\sum_{i=1}^M \sum_{j=1}^N \sum_{k=1}^K (X(i,j,k) - Y(i,j,k))^2} \quad (6)$$

Despite the fact that SNR is simple to calculate, it is not perfectly matched to perceived visual quality (Wang and Bovik 2002). Another metric called structural similarity (SSIM) (Wang et al. 2004) was also applied to measure the similarity between two spectral bands. The formula for calculating SSIM is given in Equation (7),

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (7)$$

where μ is the mean intensity, σ is the standard deviation, and C_1, C_2 are two constants.

The mean SSIM of the whole spectra will be used to compare the distortion.

To fully compare the similarity of the original and compressed hyperspectral images, not only spatial difference should be addressed, but also the spectral integrity need be considered. Therefore, a spectral angle map (SAM) between original and reconstructed images is shown to illustrate it. The spectral angle of a single pixel is calculated as:

$$\alpha(i, j) = \arccos\left(\frac{\sum_{k=1}^B \lambda_x(i, j, k)\lambda_y(i, j, k)}{\sqrt{\sum_{k=1}^B \lambda_x^2(i, j, k)}\sqrt{\sum_{k=1}^B \lambda_y^2(i, j, k)}}\right) \quad (8)$$

where λ is the selected spectra.

Although distortion measures shown above can give a general concept of how the reconstructed is distorted, they have little or even no correlation to the degradation in accuracy of subsequent image analysis (Pickering and Ryan 2006). Instead of looking at the rate-distortion performance, quality-assured assessment, such as HSI classification (Zabalza, Ren, Wang, Marshall, et al. 2014), can be adopted. The results

from the original image and the reconstructed image are collected and compared to show how the compression and coding have affected the performance of data analysis. Since rate-distortion performance is not always a good indicator (Penna, Tillo, Magli, and Ohmo 2006), quality-assured evaluation is particularly important for quality assessment in coding of hypercube.

With the ground truth available, the SVM is employed for pixel classification. The SVM is applied to images compressed using 3D SPIHT and 3D DCT techniques, respectively. By comparing the classification results from the two reconstructed images, a higher accuracy reflects better quality preserved from the quality-assured assessment point of view.

For SVM based multi-class classification, a publicly available library BSVM (Hsu and Lin 2012) was used. In our implementation, 50% of the pixel samples in each class were used for training and the remaining 50% for testing. The spectral data was linearly scaled to the range [0, 1] for normalisation required before applying SVM for classification. As the most commonly used kernel function (Cherkassky and Ma 2004), the RBF (radial basis function) kernel was selected as it also generated better classification results in our experiments. The two important parameters, the penalty C and gamma γ , were optimally determined by cross validation. A ‘grid-search’ was employed to look for the optimal values of C and γ by trying exponentially growing sequences. For instance, $C = 2^{-10}, 2^{-9}, \dots, 2^{14}, 2^{15}$ and $\gamma = 2^{-15}, 2^{-14}, \dots, 2^9, 2^{10}$. Finally, the optimised model was obtained from SVM for testing, and relevant results are reported in the next section.

3.3 Comparison of different quantisation matrices

The first five groups (40 bands) of dataset ‘Moffett field’ scene 1 are selected to train the SVM regression model. Optimal values of k are calculated for each group, which

are 3, 5, 5, 5.5 and 3.5. The performance of the mentioned three quantisation matrices and the proposed SVM prediction based quantisation matrix is compared, using the second dataset '92AV3C'. Under the same compression bit rates from 0.1 to 1bpppb, the rate-distortion curve with SNR is illustrated in Figure 3. As can be seen, thanks to the weighting of inter-band correlation, the quantisation matrix 3 (Tang et al. 2012) consistently outperforms the other two quantisation matrices (Lee, Chan, and Adjero 1997; Yeo and Liu 1995) as introduced above. Meanwhile, with the help of SVM, the precise prediction of inter-band correlation coefficient k improves the SNR further than the quantisation matrix 3 which only has a fixed k .

Figure 3. Rate-distortion curves for four quantisation matrices on '92AV3C'.

4. Results and discussion

Using the four datasets as described in the previous section, results from both subjective and objective assessment are analysed and compared in detail as follows.

4.1 Results of subjective assessment

For the four datasets, firstly we set a compression rate of 0.1bpppb and the accumulated difference images from 3D SPIHT and 3D DCT are compared in Figure 4, along with the average values of the difference. Contrast of difference images has been adjusted using histogram equalisation, in order to be seen more clearly. The corresponding original images can be found in Figure 4 for reference.

Figure 4. The difference images between reconstructed and original images based on 3D SPIHT (top) and 3D DCT (bottom) at 0.1bpppb. From left to right, the four columns correspond to ‘Moffett Field’, ‘92AV3C’, ‘SalinasB’ and ‘PaviaUA’, respectively.

As can be seen, the difference images show some details at 0.1bpppb, yet the results from 3D SPIHT using DWT seem to show more high frequency components than those from 3D DCT approach, which can be proved by higher average difference values as well. Specifically, 3D SPIHT has over-smoothed the high-frequency details of the image, whilst 3D DCT helps to preserve such details even under the same compression bit rate, though the block-effect can be observed. In addition, those slight block artefacts with 3D DCT approach are due to the accumulated difference images, which can hardly be noticed in reconstructed images.

When the compression bit rate increases, due to limited space, only the ‘Moffett Field’ dataset is compared. For other datasets, they are further evaluated using quality-assured measurement as discussed in Section 4.3. Under various bit rates ranging within 0.2, 0.5, 0.8, 1bpppb, the contrast-adjusted difference images are shown in Figure 5 for comparisons. Again, we can see that our approach produces better results at various bit rates. In addition, block-effect caused artefacts are degraded at higher bit rates, and more detailed evaluations can be observed via quantitative results as given below.

Figure 5. Difference images of ‘Moffett Field’ scene 1 based on 3D SPIHT (top) and 3D DCT (bottom) algorithm, at different bit rates of 0.2, 0.5, 0.8 and 1bpppb, respectively (from left to right).

4.2 Results of objective assessment

At a specific compression bit rate, the rate-distortion related metrics SNR and SSIM, were employed for objective assessment. A better compression approach is expected to produce higher values of SNR and SSIM in comparison with others. With the

compression bit rate varies between 0.02 and 1bpppb, the results from the four datasets are illustrated in Figure 6 and Figure 7 for evaluations.

Figure 6. SNR (dB) comparison between 3D SPIHT and 3D DCT compression performance for four datasets.

Figure 7. SSIM comparison between 3D SPIHT and 3D DCT compression performance for the four datasets.

For the four datasets, the proposed 3D DCT approach consistently outperforms 3D SPIHT approach at various compression bit rates from 0.02 to 1bpppb, and an average gain of 5-8 dB in SNR is achieved. Regarding the SSIM which is closer to human perception, 3D DCT also gives a more similar structure than 3D SPIHT.

The spectral angle maps of four datasets at compression rates of 0.1, 0.2, 0.5, 0.8 and 1bpppb are shown in Figures 8-11 and an average spectral angle is shown above each map. It is noticed that for increased bit rate, average spectral angles of both 3D SPIHT and 3D DCT approach 0, while those of 3D DCT are much lower, which means the spectral distortion from 3D DCT approach is less than that from 3D SPIHT based compression.

Figure 8. Spectral angle maps of ‘Moffett Field’ scene 1 based on 3D SPIHT (top) and 3D DCT (bottom) algorithm, at different bit rates of 0.1, 0.2, 0.5, 0.8 and 1bpppb, respectively (from left to right).

Figure 9. Spectral angle maps of ‘92AV3C’ based on 3D SPIHT (top) and 3D DCT (bottom) algorithms, at different bit rates of 0.1, 0.2, 0.5, 0.8 and 1bpppb, respectively (from left to right).

Figure 10. Spectral angle maps of ‘SalinasB’ based on 3D SPIHT (top) and 3D DCT (bottom) algorithms, at different bit rates of 0.1, 0.2, 0.5, 0.8 and 1bpppb, respectively (from left to right).

Figure 11. Spectral angle maps of ‘PaviaUA’ based on 3D SPIHT (top) and 3D DCT (bottom) algorithms, at different bit rates of 0.1, 0.2, 0.5, 0.8 and 1bpppb, respectively (from left to right).

4.3 Results of quality-assured assessment in classification

Since there is no ground truth for the ‘Moffett Field’ dataset, only the other three datasets, ‘92AV3C’, ‘SalinasB’ and ‘PaviaUA’, were used for quality-assured assessment, where SVM-based classification was employed to measure the quality of subsequent data analysis.

For these three datasets, the optimal parameters determined by grid-search based cross validation are summarised in Table 1. Using these optimal parameters, the classification accuracy achieved from the uncompressed image is also presented. Actually, the accuracy reported is an average one from 10 random tests, where 50% of the pixel samples in each class were used for training and the other 50% for testing.

Table 1. Optimal classification parameters and classification accuracy for original datasets ‘92AV3C’, ‘SalinasB’ and ‘PaviaUA’.

After the optimal SVM model was learnt from the original hyper-cube, it was applied to the reconstructed hyper-cube for testing. A higher accuracy here indicates a better preservation of the data quality. Again, the testing was carried out 10 times on randomly selected samples and the average accuracy was then determined. For the three datasets at various bit rates, the achieved classification accuracy from the two compression approaches is plotted in Figure 12 for comparisons.

Figure 12. Comparison of the classification accuracy with 3D SPIHT and 3D DCT compression for the three datasets with available ground truth including ‘92AV3C’ (top), ‘SalinasB’ (middle) and ‘PaviaUA’ (bottom).

As can be seen, the classification accuracy for images from our 3D DCT compression is consistently higher than those for images from 3D SPIHT approach, especially at low compression bit rates of 0.02 to 0.5bpppb. When the bit rate becomes higher than 0.5bpppb, the classification accuracy on reconstructed images from our approach is almost the same as the one from the original images. This means that the hyper-cube can be compressed at a moderate bit rate without degrading the quality of

data analysis. However, this has to be done using the proposed approach rather than the 3D SPIHT one, as the latter generates much worse results in two images even at a high bit rate of 1bpppb.

In comparison with objective assessments, results from quality-assured assessment are more consistent with subjective assessments. For bit rate lower than 0.2bpppb, where reconstructed images are fuzzy, the classification accuracy for both compression techniques is lower. Also, for images with poorer subjective evaluation, i.e., with 3D SPIHT compression method, the classification error is higher. Besides, it is worth noting that it seems the block artefacts mentioned in Section 3 have little impact on the classification results.

4.4 Complexity

For transform domain coding using 3D DCT and 3D SPIHT approaches, the complexity contains two parts, i.e. the transform itself and the following on sorting, quantisation and coding of coefficients. According to the analysis in (Penna, Tillo, Magli, and Olmo 2006), the computation complexity of 3D DWT is estimated as:

$$C_{DWT} = \frac{M}{2} LPB \frac{2^4}{7} (1 - 8^{-x}) \quad (9)$$

where L is number of lines in the hyperspectral image, P is number of pixels per line, B is number of bands and x is the number of wavelet decomposition levels. M represents the length of the longest filter for biorthogonal decomposition. For the CDF 9/7 filter used in our experiments, M equals to 9.

The complexity of fast 2D DCT is given as $O(N^2 \log_2 N^2)$ for an $N \times N$ block (Boussakta and Alshibami 2004). Similarly, the fast 3D DCT complexity will be $O(N^3 \log_2 N^3)$ for an $N \times N \times N$ block and N is 8 in the paper. Therefore, for a

hyperspectral image with L lines, P pixels per line and B bands, the complexity for 3D DCT transform is determined as

$$C_{DCT} = O(3LPB \log_2 N) \quad (10)$$

Comparing Equation (9) and (10), it is noticed that 3D DWT requires about 71% more operations than 3D DCT. In addition, 3D DCT approach becomes more efficient in the second stage. This is because the sorting order in 3D DCT is fixed and can be easily implemented using a look-up-table for fast access and manipulation. On the contrary, the sorting order in 3D SPIHT is determined by conditional comparisons hence requires much more additional operations.

For the four test datasets, the running time for coding at 0.2bpppb and 0.5bpppb is summarised in Table 2 for comparisons. These experiments were carried out on a personal computer with an Intel Core i5-2400 CPU at 3.10 GHz. As can be seen, our approach requires much less time than 3D SPIHT approach, given the better quality of compressed image generated.

Table 2. Encoding time for ‘Moffett field’ scene 1, ‘92AV3C’, ‘SalinasB’ and ‘PaviaUA’ datasets using 3D SPIHT and 3D DCT for compression.

5. Conclusions

An improved 3D DCT based approach is proposed, which appears to be a low-cost and quality-preserved solution for lossy compression of hyperspectral imagery. With the quantisation matrix optimally determined using the SVM via optimally weighting of inter-band correlation, the compression efficacy of 3D DCT approach is further improved. In general, it generates a lower compression rate whilst successfully

maintaining the quality of the image. The comparison between our approach and 3D SPIHT method has suggested that 3D DCT has great potential to produce better compression as it preserves more high-frequency details. Consequently, the classification accuracy using SVM for land cover analysis is also higher than those from 3D SPIHT. Besides, the classification based quality assured assessment is found to be consistent with visual inspections and distortion based measurements, though it is difficult to gain a straightforward concept of image quality from the latter. Finally, it is suggested that, using our proposed approach, lossy compression of HSI at a bit rate of no less than 0.8bpppb is feasible as the degradation on image quality for analysis is negligible.

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Table 1. Optimal classification parameters and classification accuracy for original datasets ‘92AV3C’, ‘SalinasB’ and ‘PaviaUA’.

Dataset	Parameters		Classification accuracy
	C	γ	
‘92AV3C’	2^7	2^{-1}	93.68%
‘SalinasB’	2^9	2^{-1}	99.02%
‘PaviaUA’	2^{10}	2^{-2}	98.56%

Table 2. Encoding time for ‘Moffett field’ scene 1, ‘92AV3C’, ‘SalinasB’ and ‘PaviaUA’ datasets using 3D SPIHT and 3D DCT for compression.

Dataset	Coding scheme	Compression bit rate	
		0.2bpppb	0.5bpppb
‘Moffett field’ 1	3D SPIHT	74.13 s	938.59 s
	3D DCT	4.04 s	10.74 s
‘92AV3C’	3D SPIHT	75.74 s	1093.23 s
	3D DCT	4.37 s	10.62 s
‘SalinasB’	3D SPIHT	44.99 s	898.49 s
	3D DCT	3.19 s	9.18 s
‘PaviaUA’	3D SPIHT	23.66 s	272.17 s
	3D DCT	2.91 s	6.90 s