Chapter 8
Lookup-Table Based Hyperspectral Data Compression

Jarno Mielikainen

Abstract This chapter gives an overview of the lookup table (LUT) based lossless compression methods for hyperspectral images. The LUT method searches the previous band for a pixel of equal value to the pixel co-located to the one to be coded. The pixel in the same position as the obtained pixel in the current band is used as the predictor. Lookup tables are used to speed up the search. Variants of the LUT method include predictor guided LUT method and multiband lookup tables.

1 Introduction

Hyperspectral imagers produce enormous data volumes. Thus, a lot of effort has been spent to research more efficient ways to compress hyperspectral images. Three different types of compression modalities for hyperspectral images can be defined. Lossy compression achieves the lowest bit rate among the three modalities. It does not bind the difference between each reconstructed pixel and the original pixel. Instead, the reconstructed image is required to be similar to the original image on mean-squared error sense. Near lossless compression bounds the absolute difference between each reconstructed pixel and the original pixel by a predefined constant. Lossless compression requires the exact original image to be reconstructed from the compressed data. Since lossless compression techniques involve no loss of information they are used for applications that cannot tolerate any difference between the original and reconstructed data.

In hyperspectral images the interband correlation is much stronger than the intraband correlation. Thus, interband correlation must be utilized for maximal compression performance. Transform-based and vector-quantization-based methods have not been able to achieve state-of-the-art lossless compression results

J. Mielikainen (✉)
School of Electrical and Electronic Engineering, Yonsei University, Seoul, South Korea
e-mail: mielikai@gmail.com

B. Huang (ed.), *Satellite Data Compression*, DOI 10.1007/978-1-4614-1183-3_8,

for hyperspectral images. Therefore, lossless compression of hyperspectral data is performed by using prediction-based approaches. However, there have been some studies on transform-based [1–3] and vector-quantization based [4–6] methods. Vector quantization is an asymmetric compression method; compression is much more computationally intensive than decompression. On the other hand, transform-based methods have been more successful in lossy compression than lossless compression.

Prediction based methods for lossless compression of hyperspectral images can be seen as consisting of three steps:

1. Band ordering.
2. Modeling extracting information on the redundancy of the data and describing this redundancy in the form of a model.
3. Coding describes the model and how it differs from the data using a binary alphabet.

The problem of optimal band ordering for hyperspectral image compression has been solved in [7]. Optimal band reordering is achieved by computing a minimum spanning tree for a directed graph containing the sizes of the encoded residual bands. A correlation-based heuristic for estimating the optimal order was proposed in [8]. Another prediction method based on reordering was introduced in [9]. However, in this chapter, all the experiments are performed using natural ordering of the bands to facilitate comparisons to the other methods in the literature.

In this chapter, we concentrate on lookup table (LUT) based approaches to modeling and we are will gives an overview of LUT based lossless compression methods for hyperspectral images.

This chapter is organized as follows. In Sect. 2 we will present a short review of previous work in lossless compression of hyperspectral images. Section 3 presents basic LUT method. In Sect. 4 predictor guided LUT is described. Use of a quantized index in LUT method is discussed in Sect. 5. Multiband generalization of LUT method is presented in Sect. 6. Experiments results are shown in Sect. 7. Finally, conclusions are drawn in Sect. 8.

2 Lossless Compression of Hyperspectral Images

Previous approaches to lossless compression of hyperspectral images include A1, which is one of three distributed source coding algorithms proposed in [10]. It focuses on coding efficiency and the other two algorithms proposed in [10] are more focused on error-resiliency. The A1 algorithm independently encodes non-overlapped blocks of 16×16 samples in each band. This independency makes it easy to parallelize the algorithm. The first block of each band is transmitted uncompressed. The pixel values are predicted by a linear prediction that utilizes pixel value in previous bans, the average pixel values of both the current block and the co-located block in the previous band. Instead of sending prediction parameters to decoder they are guessed by the decoder. For each guess the pixels of the block are reconstructed and the Cyclic Redundancy Check (CRC) is computed. Once CRC matches the one included in the compressed file, the process terminates.

The FL algorithm [11] employs the previous band for prediction and adapts the predictor coefficients using recursive estimation. The BG block-based compression algorithm [12] employs a simple block-based predictor followed by an adaptive Golomb code. IP3 (third-order interband predictor) [13] method takes advantage of spatial data correlation and derives spectral domain predictor using Wiener filtering. They also employed a special backward pixel search (BPS) module for calibrated image data.

Clustered differential pulse code modulation (C-DPCM) [14] method partitions spectral vectors into clusters and then applies a separate least-squares optimized linear predictor to each cluster of each band. The method can be seen as an extension of the vector quantization method in [5]. However, the quantization step of [5] is omitted. In [15], another approach using clustering was presented. The causal neighborhoods of each pixel are clustered using fuzzy-c-means clustering. For each of the clusters, an optimal linear predictor is computed from the values, the membership degrees of which exceed a threshold. The final estimate is computed as a weighted sum of the predictors, where the weights are the membership degrees. The Spectral Fuzzy Matching Pursuits (S-FMP) method exploits a purely spectral prediction. In the same paper, a method called Spectral Relaxation-Labeled Prediction (S-RLP) was also proposed. The method partitions image bands into blocks, and a predictor, out of a set of predictors, is selected for prediction.

A method based on Context-Adaptive Lossless Image Coding (CALIC), which is called 3-D CALIC [28], switches between intra- and interband prediction modes based on the strength of the correlation between the consecutive bands. In multiband CALIC (M-CALIC) method [16], the prediction estimate is performed using two pixels in the previous bands in the same spatial position as the current pixel. The prediction coefficients are computed using an offline procedure on training data. An adaptive least squares optimized prediction technique called Spectrum-oriented Least SQuares (SLSQ) was presented in [17]. The prediction technique used is the same as the one in [18], but a more advanced entropy coder was used. The predictor is optimized for each pixel and each band in a causal neighborhood of the current pixel. SLSQ-HEU uses a heuristic to select between the intra- and interband compression modes. Also, an optimal method for inter-/intracoding mode selection called SLSQ-OPT was presented.

Selecting between a Correlation-based Conditional Average Prediction (CCAP) and a lossless JPEG was proposed in [19]. The selection is based on a correlation coefficient for contexts. The CCAP estimate is a sample mean of pixels corresponding to the current pixel in contexts that match the current pixel context. BH [20] is a block-based compressor. Each band of the input image is divided into square blocks. Next, the blocks are predicted based on the corresponding block in the previous band. Nonlinear Prediction for Hyperspectral Images (NPHI) [21] predicts the pixel in the current band based on the information in the causal context in the current band and pixels colocated in the reference band. NPHI was also extended into an edge-based technique, called the Edge-based Prediction for Hyperspectral Images, which classifies the pixels into edge and nonedge pixels. Each pixel is then predicted using information from pixels in the same pixel class within the context. In [23], a method called KSP, which employs a Kalman filter in the prediction stage, was proposed.

3 LUT Method

The LUT method [22] makes a prediction of the current pixel $p_{x,y,z}$ (*x*th row, *y*th column, and *z*th band) using all the causal pixels in the current and previous band. LUT method is based on the idea of Nearest Neighbor (NN) search. The NN procedure searches for the nearest neighbor in the previous band that has the same pixel value as the pixel located in the same spatial position as the current pixel in the previous band $p_{x,y,z-1}$. The search is performed in reverse raster-scan order. First, a pixel value equal to $p_{x,y,z-1}$ is searched. If an equal valued pixel is found at position $(x',y',z-1)$, then estimated pixel is predicted to have the same value as the pixel in the same position as obtained pixel in the current band $p_{x',y',z}$. Otherwise, the estimated pixel value is equal to the pixel value in the previous band $p_{x,y,z-1}$.

LUT method accelerates NN method by replacing time consuming search procedure with a lookup table operation, which uses the pixel co-located in the previous band as an index in the lookup table. The lookup table returns the nearest matching pixel.

An example illustrating the search process is shown in Figs. 8.1–8.3. The example uses two consecutive image bands, which have 3×8 pixels each. The previous band (band number 1) and current band (band number 2) are shown in Figs. 8.1 and 8.2, respectively. The corresponding lookup table is shown in Fig. 8.3. In the example, pixel $p_{3,8,2} = 325$ is the current pixel to be predicted in the current band. The causal pixels in the previous band are searched to find a match for the co-located pixel $p_{3,8,1} = 315$. Both current pixel and its co-located pixel have yellow background in Figs. 8.2 and 8.1, respectively. Three matches (green background) are returned. The pixel value in the current band that is present at the nearest matching location, $p_{2,6,1} = 315$, is used as the predictor for $p'_{3,8,2} = p_{2,6,2} = 332$. A time-consuming search was avoided because the lookup table directly returned the predictor value.

4 Predictor Guided LUT Method

In the LUT method the nearest matching pixel value might be not be as good of a match as many other matching pixels. In the previous example the pixels in the current band corresponding to the other two matching locations are closer to

Fig. 8.1 Previous image band. Co-located pixel has *yellow background*. Matching pixels have *green background*

336	335	314	335	314	335	319	327
316	315	317	315	328	315	325	319
322	334	329	314	329	324	317	315

Fig. 8.2 Current image band. Current pixel has *yellow background*. Pixels corresponding to the matching pixel have *green backgrounds*

328	339	323	339	328	332	331	335
335	324	325	327	320	332	327	335
330	350	339	324	333	325	333	325

Fig. 8.3 Lookup table

Index	Value
314	328
315	332
316	335
317	333

the actual pixel value 325 than the nearest matching pixel value 332. This type of behavior of LUT method motivated the development of Locally Averaged Interband Scaling (LAIS)-LUT method [29], which uses a predictor to guide the selection between two LUTs.

LAIS-LUT method works by first computing a LAIS estimate by scaling pixel co-located in the previous band. The LAIS scaling factor is an average of ratios between three neighboring causal pixels in the current and previous band:

$$\frac{1}{3}\left(\frac{p_{x-1,y,z}}{p_{x-1,y,z-1}}+\frac{p_{x,y-1,z}}{p_{x,y-1,z-1}}+\frac{p_{x-1,y-1,z}}{p_{x-1,y-1,z-1}}\right) \tag{8.1}$$

LAIS scaling factor in (8.1) is used to compute an estimate for the current pixel:

$$p''_{x,y,z}=\frac{1}{3}\left(\frac{p_{x-1,y,z}}{p_{x-1,y,z-1}}+\frac{p_{x,y-1,z}}{p_{x,y-1,z-1}}+\frac{p_{x-1,y-1,z}}{p_{x-1,y-1,z-1}}\right)p_{x,y,z-1} \tag{8.2}$$

Fig. 8.4 LAIS estimates for LAIS-LUT

Pixel Position	Pixel Value	LAIS Estimate
(2,3)	324	320.1
(2,5)	327	321.9
(2,7)	332	316.2

Fig. 8.5 Two lookup tables for LAIS-LUT

index	1st LUT	2nd LUT
314	328	324
315	332	327
316	335	-
317	333	325

LAIS-LUT uses two LUTs, which are similar to the one used in the LUT method. The second LUT is updated with the past entries of the first LUT. The predictor returned by the LUT that is the closest one to the LAIS estimate is chosen as the predictor for the current pixel. If the LUTs return no match then the LAIS estimate is used as the estimated pixel value.

We use the LUT example to illustrate the search process in LAIS-LUT. LAIS estimates for the three matching pixels in the previous example are shown in Fig. 8.4. Two LUTs corresponding to bands in Figs. 8.1 and 8.2 are shown in Fig. 8.5. Recall that the current pixel is $p_{3,8,2} = 325$ and the causal pixels in the previous band are searched to find a match for the co-located pixel $p_{3,8,1} = 315$. Out of the three matching pixels two are in LUTs (green background in Fig. 8.5). LAIS estimate (321.9) for 2nd LUT value 327 is closer than LAIS estimate (316.2) for the first LUT value 332. Therefore, pixel value from second LUT is used as the predictor for $p'_{3,8,2} = p_{2,5,2} = 327$.

5 Uniform Quantization of Co-Located Pixels

In [24], a quantization of indices in LUT method was proposed. In LAIS-QLUT method a uniform quantization of the co-located pixels is performed before using them for indexing the LUTs. The use of quantization reduces the size of the LUTs by an order of magnitude A quantized interband predictor is formed by uniformly quantizing the colocated pixel $p_{x,y,z-1}$ before using it as an index to the LUT. Naturally, this reduces the size of the LUTs by the factor that is used in the uniform quantization.

Except for a slightly simpler LAIS from [25] LAIS and an additional quantization step, LAIS-QLUT is the same algorithm as LAIS-LUT.

The LAIS scaling factor in LAIS-QLUT is an average of ratios between three neighboring causal pixels in current and previous band:

$$\frac{1}{3}\left(\frac{p_{x-1,y,z}+p_{x,y-1,z}+p_{x-1,y-1,z}}{p_{x-1,y,z-1}+p_{x,y-1,z-1}+p_{x-1,y-1,z-1}}\right) \tag{8.3}$$

Thus, the corresponding LAIS estimate the current pixel is the following:

$$p''_{x,y,z}=\frac{1}{3}\left(\frac{p_{x-1,y,z}+p_{x,y-1,z}+p_{x-1,y-1,z}}{p_{x-1,y,z-1}+p_{x,y-1,z-1}+p_{x-1,y-1,z-1}}\right)p_{x,y,z-1} \tag{8.4}$$

LAIS in LAIS-QLUT requires a division operation and four addition operations compared to the three division, one multiplication, and two addition operations required by LAIS in LAIS-LUT.

The search process in LAIS-QLUT will be illustrated using the same image bands are in the previous example. Quantized version of the previous image band is shown in Fig. 8.6 for a quantization factor 10. LAIS-Q estimates for two matching pixels are shown in Fig. 8.7. Two LUTs for LAIS-QLUT are shown in Fig. 8.8 for a quantization factor 10. The current pixel is $p_{3,8,2}$ = 325 and the causal pixels in the previous band are searched to find a match for quantized co-located pixel $p_{3,8,1}$ / 10 = 32. Two of matching pixels, which are in LUTs have LAIS-Q estimates of 328.2 for first LUT value 333 and 328.3 for second LUT value 325. The second LUT value is closer to the corresponding LAIS-Q estimate than the other one. Therefore, pixel value from the first LUT is used as the predictor for $p'_{3,8,2} = p_{3,6,2}$ = 324.

34	34	31	34	31	34	32	33
32	32	32	32	33	32	33	32
32	33	33	31	33	32	32	32

Fig. 8.6 Quantized previous image band. Co-located pixel has *yellow background*. Matching pixels have *green background*

Fig. 8.7 LAIS estimates for LAIS-QLUT

Pixel Position	Pixel Value	LAIS Estimate
(3,6)	325	328.3
(3,7)	333	328.2

Fig. 8.8 Two lookup table for LAIS-QLUT

index	1st LUT	2nd LUT
31	324	328
32	333	325
33	339	350
34	332	339

There are two separate variants of LAIS-QLUT. The first variant, The LAIS-QLUT-OPT method selects the optimal uniform quantization factor for each band. In order to find the optimal quantization factor, an exhaustive search of all possible quantization values is performed. Thus, the quantization factor selection is based on which quantization factor achieves the best compression efficiency for that specific band. The excessive time complexity of the LAIS-QLUT-OPT method could be decreased slightly by computing entropy of the residual image instead of actually encoding residuals for the determination of the optimal quantization factor.

The second variant of LAIS-QLUT is called LAIS-QLUT-HEU and it uses constant quantization factors. The constant quantization factors are selected using a heuristic. The heuristic selects the constant quantization factors to be the bandwise mean values of the optimal quantization factors of an image set. A division operation required by the quantization represents the only increase in the time complexity of LAIS-QLUT-HEU compared to LAIS-LUT.

6 Multiband LUT

In [26], LUT and LAIS-LUT method have been generalized to a multiband and multi-LUT method. In the extended method, the prediction of the current band relies on N previous bands. LUTs are defined on each of the previous bands and each band contains *M* LUTs. Thus, there are *NM* different predictors to choose from. The decision among one of the possible prediction values is based on the closeness of the values contained in the LUTs to a reference prediction.

Two different types of purely spectral multiband prediction estimates were proposed for. One of the reference predictors is crisp and the other one is fuzzy. The first method is S-RLP [15]. The method partitions image bands into blocks, and a predictor, out of a set of predictors, is selected for prediction. In the S-FMP method [15] the causal neighborhoods of each pixel are clustered using fuzzy-c-means clustering. For each of the clusters, an optimal linear predictor is computed from the values, the membership degrees of which exceed a threshold. The final estimate is computed as a weighted sum of the predictors, where the weights are the membership degrees. The LUT based compression methods based on S-RLP and S-FMP are denoted as S-RLP-LUT and S-FMP-LUT, respectively.

7 Experimental Results

Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) is an airborne hyperspectral system collecting spectral radiance in 224 contiguous spectral bands with wavelengths from 370 to 2,500 nm. The AVIRIS instrument consists of four spectrometers that view a *20-m*^{2} spot on the ground from a flight altitude of *20 km*. This spot is simultaneously viewed in all the spectral bands. A spatial image is formed by moving the spectrometers perpendicular to the direction of the aircraft [27].

Experimental results are shown for two different AVIRIS data sets. The first data set consists of four calibrated radiance images from 1997 AVIRIS sample data product. The AVIRIS images are from the following four different areas: Cuprite, NV; Jasper Ridge, CA; Lunar Lake, NV; and Moffett Field, CA. They are the most widely used data for benchmarking hyperspectral image compression algorithms. Image features and the number of lines are listed in Table 8.1. Each image contains 614 samples/line and they are stored as 16-bit signed integers. A gray scale image of Moffett Field image can be seen in Fig. 8.9.

Newer data set was acquired on 2006. A new AVIRIS data set consists of five calibrated and uncalibrated 16-bit images from Yellowstone, WY and two 12-bit uncalibrated images one from Hawaii and one from Maine. Summary of the new Consultative Committee for Space Data Systems (CCSDS) AVIRIS data is given in Table 8.2. Each image is a 512-line scene containing 224 spectral bands. An example of a scene can be seen in Fig. 8.10 in the form of a false color image of calibrated Yellowstone scene 11.

Table 8.1 The standard 1997 AVIRIS images [11]

Site	Features	Lines
Cuprite	Geological features	2,206
Jasper Ridge	Vegetation	2,586
Lunar Lake	Calibration	1,431
Moffett Field	Vegetation, urbar, water	2,031

Fig. 8.9 Gray scale image of Moffett Field image from AVIRIS 1997 image set

This AVIRIS data is a part of the CCSDS data set, which is used to assess the performance of hyperspectral compression algorithms.

Table 8.3 shows results for the NN method. The first column depicts the length of the search window; 0 lines means that only the current line is searched. The following columns are bit rates in bits/pixel for the four test images and the average, respectively. When the search window's length is equal to the length of image, the method naturally predicts the same values as the LUT method. These results show

Table 8.2 AVIRIS images included in the CCSDS test set [11]

Site	Scene numbers	Year	Samples/line	Bit depth	Type
Yellowstone	0,3,10,11,18	2006	677	16	Calibrated
Yellowstone	0,3,10,11,18	2006	680	16	Uncalibrated
Hawaii	1	2001	614	12	Uncalibrated
Maine	10	2003	680	12	Uncalibrated

Fig. 8.10 False color image of calibrated Yellow stone 11 from CCSDS AVIRIS data set

Table 8.3 Compression results in bits/pixel for calibrated AVIRIS 1997 test images in bits per pixel

# of lines	Cuprite	Jasper ridge	Lunar lake	Moffett field
0	5.69	5.84	5.78	6.02
1	5.41	5.63	5.50	5.80
2	5.29	5.50	5.33	5.65
4	5.05	5.35	5.14	5.48
8	4.89	5.21	4.98	5.32
16	4.79	5.10	4.88	5.21
32	4.72	5.03	4.79	5.14
64	4.69	5.00	4.75	5.10
128	4.68	4.98	4.73	5.08
256	4.66	4.97	4.72	5.06
512	4.66	4.97	4.72	5.05
1,024	4.65	4.95	4.71	5.05

Table 8.4 Compression results in bits/pixel for calibrated AVIRIS 1997 test images in bits per pixel

	Cuprite	Jasper ridge	Lunar lake	Moffett field	Average
JPEG-LS	7.66	8.38	7.48	8.04	7.89
Diff. JPEG-LS	5.50	5.69	5.46	5.63	5.57
3D-CALIC	5.23/5.39	5.19/5.37	5.18/5.32	4.92/5.05	5.19/5.28
BH	–/5.11	–/5.23	–/5.11	–/5.26	–/5.18
M-CALIC	4.97/5.10	5.05/5.23	4.88/5.02	4.72/4.89	4.98/5.06
SLSQ-OPT	4.94/5.08	4.95/5.08	4.95/5.08	4.98/5.10	4.96/5.09
CCAP	–/4.92	–/4.95	–/4.97	–	–
KSP	–/4.88	–/4.95	–/4.89	–/4.92	–/4.91
FL#	4.82	4.87	4.82	4.93	4.86
NPHI	4.79	4.89	4.97	4.79	4.86
C-DPCM	–/4.68	–/4.62	–/4.75	–/4.62	–/4.67
S-RLP	4.69	4.65	4.69	4.67	4.67
S-FMP	4.66	4.63	4.66	4.63	4.64
LUT	4.66	4.95	4.71	5.05	4.84
LAIS-LUT	4.47	4.68	4.53	4.76	4.61
LAIS-QLUT-HEU	4.30	4.62	4.36	4.64	4.48
LAIS-QLUT-OPT	4.29	4.61	4.34	4.63	4.47
S-RLP-LUT	3.92	4.05	3.95	4.09	4.00
S-FMP-LUT	3.89	4.03	3.92	4.05	3.97
IP3-BPS	3.76	4.06	3.79	4.06	3.92

that limiting the search window size significantly affects the performance of the NN method compared to the full search. Thus, a large search window is necessary in order to achieve good compression ratios.

Table 8.4 shows compression results for AVIRIS 1997 data. The results are reported for the band-interleaved-by-line (BIL) and band-sequential (BSQ) formats. In the BIL format, the current line, along with the two previous lines, is available. For BSQ data, the current band and several previous bands are available for processing. The LUT family does not benefit from the BSQ data format. This is due to two factors. First, LUT and LAIS-LUT methods only utilize one previous band. Second, LAIS-LUT methods need only the data from the current and previous image lines. Those lines were already provided by the BIL data format. Most compression method exhibit identical compression results for both BIL and BSQ data. Only one bits/pixel value is shown for those methods. For the other methods both BIL and BSQ results are provided. The results for the two different data formats are separated by a forward-slash and dash denotes unavailable results. Differential JPEG-LS computes the difference between each band and the previous band before running JPEG-LS on residual data.

Experimental results show that LUT based algorithms work extremely well for calibrated AVIRIS 1997 data. Even the low time complexity LAIS-LUT and QLAIS-LUT variants have close to the state-of-the-art compression ratios. IP3-BPS method takes ten times longer than LUT and five times longer than LAIS-LUT or LAIS-QLUT-HEU to compress AVIRIS image [13].

Table 8.5 Compression results in bits/pixel for 16-bit raw CCSDS AVIRIS test images in bits per pixel

Algorithm	Scene 0	Scene 3	Scene 10	Scene 11	Scene 18	Average
JPEG-LS	9.18	8.87	7.32	8.50	9.30	8.63
BG	6.46	6.31	5.65	6.05	6.40	6.17
A1	6.92	6.78	6.10	6.53	6.92	6.65
LUT	7.13	6.91	6.25	6.69	7.20	6.84
LAIS-LUT	6.78	6.60	6.00	6.30	6.82	6.50
FL#	6.20	6.07	5.60	5.81	6.26	5.99
IP3	6.20	6.08	5.56	5.81	6.25	5.98
C-DPCM-20	5.88	5.71	5.20	5.52	5.75	5.61
C-DPCM-80	5.82	5.65	5.17	5.47	5.69	5.56

Table 8.6 Compression results in bits/pixel for 12-bit raw CCSDS AVIRIS test images in bits per pixel

Algorithm	Hawaii	Maine	Average
JPEG-LS	4.58	4.50	4.54
A1	3.49	3.65	3.57
LUT	3.27	3.44	3.36
LAIS-LUT	3.05	3.19	3.12
BG	3.03	3.17	3.10
IP3	2.55	2.68	2.62
FL#	2.58	2.63	2.61
C-DPCM-20	2.43	2.57	2.50
C-DPCM-80	2.38	2.52	2.45

The LUT method requires a full LUT for each band. Assuming 16-bit LUTs, each LUT's memory requirements are roughly equivalent to 107 lines of an AVIRIS image data. The LUT's memory requirements are independent of the spatial size of the image. Therefore, the relative size of the LUTs compared to the image gets smaller as the spatial size of the image gets larger. For our test images, the amount of the memory required by LUTs is 4–7% of the memory used by the image. The average quantization factor for LAIS-QLUT-HEU was 28. Thus, the average LUT memory requirement is roughly equivalent to four lines of AVIRIS image data compared to 107 lines of data in the original LUT method. We have also experimented with the optimization of the quantization factors for each image instead of for each band. That procedure gave a quantization factor of ten for all the test images. The average bit rate was 4.60 bits/pixel. This compares unfavorably to the 4.47 bits/pixel average bit rate of LAIS-QLUT-HEU. Therefore, separate bandwise quantization factors are worthwhile.

Tables 8.5–8.7 depict compression results for new AVIRIS data in bits per pixel for various different compression methods. C-DPCM-20 and C-DPCM-80 refer to the prediction length 20 and 80 for C-DPCM, respectively. A modified C-DPCM method uniformly quantizes coefficients to 12 bits instead of 16 bits in the original C-DPCM.

Table 8.7 Compression results in bits/pixel for calibrated CCSDS AVIRIS test images in bits per pixel

Algorithm	Scene 0	Scene 3	Scene 10	Scene 11	Scene 18	Average
JPEG-LS	6.95	6.68	5.19	6.24	7.02	6.42
A1	4.81	4.69	4.01	4.41	4.77	4.54
LUT	4.81	4.62	3.95	4.34	4.84	4.51
LAIS-LUT	4.48	4.31	3.71	4.02	4.48	4.20
BG	4.29	4.16	3.49	3.90	4.23	4.01
FL#	3.91	3.79	3.37	3.59	3.90	3.71
IP3	3.81	3.66	3.13	3.45	3.75	3.56
C-DPCM-20	3.61	3.43	2.97	3.28	3.49	3.36
C-DPCM-80	3.53	3.36	2.93	3.22	3.43	3.29

The results for uncalibrated CCSDS AVIRIS test data in Tables 8.5 and 8.6 show that LUT-based methods lose their performance advantage when applied to uncalibrated data. Moreover, the results in Table 8.7 show that LUT-based algorithms that exploit calibration artifacts in AVIRIS 1997 images have no performance advantage on the calibrated CCSDS AVIRIS images.

8 Conclusions

An overview of the lookup table (LUT) based lossless compression methods for hyperspectral images have been presented in this chapter. Experimental results on AVIRIS data showed that the LUT based algorithms work extremely well for old calibrated AVIRIS data. Even the low-complexity LAIS-LUT and QLAIS-LUT variants have close to the state-of-the-art compression ratios.

LUT-based methods exploit artificial regularities that are introduced by the conversion of raw data values to radiance units [11]. The calibration-induced artifacts are not present in the newer AVIRIS images in Consultative Committee for Space Data Systems (CCSDS) test set. Thus, LUT based method do not work as well on raw or the newer AVIRIS images in 2006, which use new calibration measures.

Acknowledgement This work was supported by the Academy of Finland.

References

1. A. Bilgin, G. Zweig, and M. Marcellin, “Three-dimensional image compression with integer wavelet transforms,” Appl. Opt., vol. 39, no. 11, pp. 1799–1814, Apr. 2000.
2. B. Baizert, M. Pickering, and M. Ryan, “Compression of hyperspectral data by spatial/spectral discrete cosine transform,” in Proc. Int. Geosci. Remote Sens. Symp., 2001, vol. 4, pp. 1859–1861, doi: 10.1109/IGARSS.2001.977096.

3. J. Mielikainen and A. Kaarna, “Improved back end for integer PCA and wavelet transforms for lossless compression of multispectral images,” in Proc. 16th Int. Conf. Pattern Recog., Quebec City, QC, Canada, 2002, pp. 257–260, doi: 10.1109/ICPR.2002.1048287.
4. M. Ryan and J. Arnold, “The lossless compression of AVIRIS images vector quantization,” IEEE Trans. Geosci. Remote Sens., vol. 35, no. 3, pp. 546–550, May 1997, doi: 10.1109/36.581964.
5. J. Mielikainen and P. Toivanen, “Improved vector quantization for lossless compression of AVIRIS images,” in Proc. XI Eur. Signal Process. Conf., Toulouse, France, Sep. 2002, pp. 495–497.
6. G. Motta, F. Rizzo, and J. Storer, “Partitioned vector quantization application to lossless compression of hyperspectral images,” in Proc. IEEE Int. Conf. Acoust., Speech, Signal Process., Jul. 2003, vol. 1, pp. 553–556, doi: 10.1109/ICME.2003.1220977.
7. S. Tate, “Band ordering in lossless compression of multispectral images,” IEEE Trans. Comput., vol. 46, no. 4, pp. 477–483, Apr. 1997, doi: 10.1109/12.588062.
8. P. Toivanen, O. Kubasova, and J. Mielikainen, “Correlation-based bandordering heuristic for lossless compression of hyperspectral sounder data,” IEEE Geosci. Remote Sens. Lett., vol. 2, no. 1, pp. 50–54, Jan. 2005, doi: 10.1109/LGRS.2004.838410.
9. J. Zhang and G. Liu, “An efficient reordering prediction based lossless compression algorithm for hyperspectral images,” IEEE Geosci. Remote Sens. Lett., vol. 4, no. 2, pp. 283–287, Apr. 2007, doi: 10.1109/LGRS.2007.890546.
10. A. Abrardo, M. Barni, E. Magli, F. Nencini, “Error-Resilient and Low-Complexity On-board Lossless Compression of Hyperspectral Images by Means of Distributed Source Coding,” IEEE Trans. Geosci. Remote Sens., vol. 48, no. 4, pp. 1892–1904, 2010, doi:10.1109/TGRS.2009.2033470.
11. A. B. Kiely, M. A. Klimesh, “Exploiting Calibration-Induced Artifacts in Lossless Compression of Hyperspectral Imagery,” IEEE Trans. Geosci. Remote Sens., vol. 47, no. 8, pp. 2672–2678, 2009, doi:10.1109/TGRS.2009.2015291.
12. M. Slyz, L. Zhang, “A block-based inter-band lossless hyperspectral image compressor,” in Proc. of IEEE Data Compression Conference, pp. 427–436, 2005, doi: 10.1109/DCC.2005.1.
13. C.-C. Lin, Y.-T. Hwang., “An Efficient Lossless Compression Scheme for Hyperspectral Images Using Two-Stage Prediction”, vol. 7, no. 3, pp. 558–562, 2010, doi:10.1109/LGRS.2010.2041630.
14. J. Mielikainen, P. Toivanen, “Clustered DPCM for the Lossless Compression of Hyperspectral Images”, IEEE Trans. Geosci. Remote Sens., vol. 41, no. 12, pp. 2943–2946, 2003 doi:10.1109/TGRS.2003.820885.
15. B. Aiazzi, L. Alparone, S. Baronti, and C. Lastri, “Crisp and fuzzy adaptive spectral predictions for lossless and near-lossless compression of hyperspectral imagery,” IEEE Geosci. Remote Sens. Lett., vol. 4, no. 4, pp. 532–536, Oct. 2007, 10.1109/LGRS.2007.900695.
16. E. Magli, G. Olmo, and E. Quacchio, “Optimized onboard lossless and near-lossless compression of hyperspectral data using CALIC,” IEEE Geosci. Remote Sens. Lett., vol. 1, no. 1, pp. 21–25, Jan. 2004, doi:10.1109/LGRS.2003.822312.
17. F. Rizzo, B. Carpentieri, G. Motta, and J. Storer, “Low-complexity lossless compression o hyperspectral imagery via linear prediction,” IEEE Signal Process. Lett., vol. 12, no. 2, pp. 138–141, Feb. 2005, doi:10.1109/LSP.2004.840907.
18. J. Mielikainen and P. Toivanen, “Parallel implementation of linear prediction model for lossless compression of hyperspectral airborne visible infrared imaging spectrometer images,” J. Electron. Imaging, vol. 14, no. 1, pp. 013010-1–013010-7, Jan.–Mar. 2005, doi:10.1117/1.1867998.
19. H. Wang, S. Babacan, and K. Sayood, “Lossless Hyperspectral-Image Compression Using Context-Based Conditional Average,” IEEE Transactions on Geoscience and Remote Sensing, vol. 45, no. 12, pp. 4187–8193, Dec. 2007, doi:0.1109/TGRS.2007.906085.

20. M. Slyz and L. Zhang, “A block-based inter-band lossless hyperspectral image compressor,” in Proc. Data Compression Conf., Snowbird, UT, 2005, pp. 427–436, doi:10.1109/DCC.2005.1.
21. S. Jain and D. Adjeroh, “Edge-based prediction for lossless compression of hyperspectral images,” in Proc. Data Compression Conf., Snowbird, UT, 2007, pp. 153–162, doi:10.1109/DCC.2007.36.
22. J. Mielikainen, “Lossless compression of hyperspectral images using lookup tables,” IEEE Sig. Proc. Lett., vol. 13, no. 3, pp. 157–160, 2006, doi:10.1109/LSP.2005.862604.
23. E. Magli, “Multiband lossless compression of hyperspectral images,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 47, no. 4, pp. 1168–1178, Apr. 2009, doi:10.1109/TGRS.2008.2009316.
24. J. Mielikainen, P. Toivanen, “Lossless Compression of Hyperspectral Images Using a Quantized Index to Lookup Tables,” vol. 5, no. 3, pp. 474–477, doi:10.1109/LGRS.2008.917598.
25. J. Mielikainen, P. Toivanen, and A. Kaarna, “Linear prediction in lossless compression of hyperspectral images,” Opt. Eng., vol. 42, no. 4, pp. 1013–1017, Apr. 2003, doi:10.1117/1.1557174.
26. B. Aiazzi, S. Baronti, S., L. Alparone, “Lossless Compression of Hyperspectral Images Using Multiband Lookup Tables,” IEEE Signal Processing Letters, vol. 16, no. 6, pp. 481–484. Jun. 2009, doi:10.1109/LSP.2009.2016834, 0.1109/LSP.2009.2016834.
27. W. Porter and H. Enmark, “A system overview of the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS),” Proc. SPIE, vol. 834, pp. 22–31, 1997
28. X. Wu and N. Memon, “Context-based lossless interband compression—Extending CALIC,” IEEE Trans. Image Process., vol. 9, no. 6, pp. 994–1001, Jun. 2000, doi:10.1109/83.846242.
29. B. Huang, Y. Sriraja, “Lossless compression of hyperspectral imagery via lookup tables with predictor selection,” in Proc. SPIE, vol. 6365, pp. 63650L.1–63650L.8, 2006, doi:10.1117/12.690659.