N95- 14588

Radiometric Resolution Enhancement by Lossy Compression as compared to Truncation Followed by Lossless Compression

J. C. Tilton
Code 935
Goddard Space Flight Center
Greenbelt, MD 20771

M. Manohar
Hughes STX, Code 935
Goddard Space Flight Center
Greenbelt, MD 20771

Abstract

Recent advances in imaging technology make it possible to obtain imagery data of the Earth at high spatial, spectral and radiometric resolutions from Earth orbiting satellites. The rate at which the data is collected from these satellites can far exceed the channel capacity of the data downlink. Reducing the data rate to within the channel capacity can often require painful trade-offs in which certain scientific returns are sacrificed for the sake of others. In this paper we model the radiometric version of this form of lossy compression by dropping a specified number of least significant bits from each data pixel and compressing the remaining bits using an appropriate lossless compression technigue. We call this approach "truncation followed by lossless compression" or TLLC. We compare the TLLC approach with applying a lossy compression technique to the data for reducing the data rate to the channel capacity, and demonstrate that each of three different lossy compression techniques (JPEG/DCT, VQ and and Model-Based VQ) give a better effective radiometric resolution than TLLC for a given channel rate.

1 Introduction

The imaging sensors onboard satellites are capable of scanning the Earth at very high spatial, spectral and radiometric resolutions. Downlink channel capacity is often a major limiting factor for the resolution at which the data is collected. Image compression techniques can be used to reduce the data rate from the imaging sensor to within the downlink channel capacity.

Ideally, decompression of the downlinked data should result in the full lossless recovery of the image data as sensed onboard the satellite. However, the amount of compression possible from lossless techniques is bounded by the entropy of the source. This entropy bound limits the amount of compression that can be obtained to the range of 2 to 3 for most NASA image data sources. This is most often insufficient to reduce the sensor data rate to within the channel capacity.

Large amounts of compression can, instead, be obtained with lossy compression techniques. In fact, a crude form of lossy compression is most often used in these cases, i.e. the temporal, spatial, spectral, and/or radiometric resolutions are limited to produce a data rate that can be handled by the channel capacity. Establishing these limits often requires painful trade-offs in which certain scientific returns are sacrificed for the sake of others. In this paper we model the radiometric version of this form of lossy compression by truncating a specified number of least significant bits followed by lossless compression of the remaining higher order bits. We call this approach "Truncation followed by Lossless Compression" (TLLC). Using the TLLC approach, the data rate can be set to within the channel capacity by selecting the appropriate number of least significant bits dropped. We have found that this method produces reasonable rate distortion values for compression ratios less than 5 or 6. However, for larger compression ratios, the rate distortions increase exponentially as the amount of truncation increases.

Much better rate distortion behavior can be obtained by using other lossy compression approaches. For the lossy compression approaches we have studied, the rate distortion performance is either linear or sublinear. These lossy compression approaches are the JPEG/DCT (Joint Photographic Experts Group/Discrete Cosine Transform [1]), VQ (Vector Quantization [2], and the more recently developed MVQ (Model-based VQ [3]) approach. For a given data rate, this improved distortion behavior over TLLC can be looked upon as a gain in radiometric resolution.

We first describe the TLLC approach in more detail, and give summary descriptions of the JPEG/DCT, VQ and MVQ lossy compression approaches. We then derive our measure of gain in radiometric resolution of a particular lossy compression approach over TLLC. Finally we demonstrate the gain in radiometric resolution provided by the JPEG/DCT, VQ and MVQ appproaches over the TLLC approach with imagery data from three remote sensing instruments: the Landsat Thematic Mapper (TM), the Advanced Solid-state Array Spectroradiometer (ASAS), and the Advanced Very High Resolution Radiometer (AVHRR). Of these, TM imagery data is at 8-bit resolution, while imagery data from the other two are at 12-bit pixel resolution with at most 10 significant bits.

2 Lossy Image Compression Techniques

Lossy compression can produce relatively high compression ratios or low data rates (bit rates) at a cost of losing some information. Here we define the compression ratio (CR) to be the ratio of the number of bits in the original image to the number of bits in the compressed image. The bit rate in bits/pixel can be represented as n/CR, where n is the radiometric resolution (in bits/pixel) of the original image. A common measure of information loss or distortion is the mean squared error between the original image and the image reconstructed from the compressed data. The mean squared error is defined formally as

$$MSE = \frac{1}{N} \sum_{k=0}^{N-1} (f_1(k) - f_2(k))^2 \tag{1}$$

where $f_1(k)$ and $f_2(k)$ are the k^{th} pixels from the original and reconstructed images, respectively, and N is number of pixels in the image. The performance of a lossy compression technique can be characterized by a rate-distortion curve, which is simply a plot of bit rate (n/CR) versus distortion (MSE).

In the following subsections we describe the TLLC approach and other lossy compression techniques that we have used in our tests.

2.1 Truncation followed by Lossless Compression (TLLC)

Truncation followed by Lossless Compression (TLLC) is not a compression approach that one would use directly. However, as mentioned in the introduction, it is a model for the design practice of setting the radiometric resolution to a lower value than sensor technology would allow, so as to keep the data rate produced by the sensor within the limits of channel capacity for bringing the data from the sensor to Earth.

Let the radiometric resolution of the image data collected at the instrument be n bits/pixel and the channel capacity be m bits/pixel ($m < n$). The TLLC approach reduces the bit rate from n to no more than m by dropping a number of lower order bits b. Here b is chosen such that the lossless compression of remaining n-b bits results in an output bit rate of no more than m bits/pixel. The lossless compression approach that consistently performed best in the cases we tested utilizes the coding model for lossless encoding specified in the JPEG still image compression standard [1] combined with the Witten-Neal-Cleary version of arithmetic coding [9].

2.2 JPEG/DCT

JPEG/DCT([1]) lossy compression algorithm consists of three successive stages: Discrete Cosine Transform (DCT) transformation, coefficient quantization and lossless compression. The original image is partitioned into nonoverlapping 8x8 pixel blocks. Each block is independently transformed using the DCT. The DCT coefficients are then quantized using a quantization table that is designed using the Human Visual System (HVS) contrast sensivity function. The first coeffient of DCT transformation is DC coefficient and is proportional to average brightness of the block. The quantized DC coefficient along with other DC coefficients is compressed using DPCM (Differential Pulse Code Modulation) using 1-D causal prediction. The quantized AC coefficients are zig-zag scanned to covert 2-D array into 1-D array and then are lossless compressed by using Huffman table that is transmitted to the decoder as a part of the header information.

The baseline JPEG/DCT does not include standards for pixel resolutions higher than 8-bits. Since some of the images tested here have 12 bit resolution, we truncated the image pixels such that the pixel resolution after truncation was 8-bits. After JPEG/DCT compression was applied and the image was reconstructed from the compressed data, each pixel value was multiplied by the truncation scale factor to scale the pixels values properly for MSE measurements.

Spectral correlations are not easy to exploit in JPEG/DCT, as there are no standards for decorrelating the bands of multispectral image data (JPEG/DCT does however, allow red, green and blue decorrelations by converting them to luminance and chrominance components. ([1], pp.18-20, p.503). Therefore, we compressed each band of the multispectral images independently in our tests.

2.3 Vector Quantization

Vector Quantization (VQ) is the vector extension of scalar quantization which is found to be very useful for multispectral image compression ([4] [5]). The VQ vectors are obtained from image data by systematically extracting nonoverlapping blocks (typically 4x4) and arranging the pixels in each block in raster scan order. Such vectors allow VQ to exploit two dimenstional correlations in the image data. If the image is multispectral, nonoverlapping cubes (typically 4x2x3) may be used. VQ builds up a dictionary of a few representative vectors, called codevectors, and then codes the image with the index value of the closest codevector from the dictionary, called the codebook, in place of of each vector. Each codevector is represented by an address containing $log_2 M$ bits, where M is number of codevectors in the codebook. Assume vectors of size k are drawn from the input image and matched with those in the codebook. Using the indices of the matched codevectors to represent the input image vectors results in a decreased rate of $(log_2 M)/k$ bits/pixel or a compression ration of

$(k * n)/log_2M$, where n is the radiometric resolution of the image. In all practical situations the codebook size, M, is much smaller than the number of vectors that make up the input image.

The most important phase of VQ is the training process in which an optimal codebook (by some criterion such as least MSE) is learned from the input samples. The most widely used algorithm is Linde-Buzo-Gray (LBG) algorithm ([6]). Both the training and coding phases of VQ require finding the codevector which is closest match to a given vector. Computing this closest match requires computations proportional to the size of the codebook. Computational cost can be reduced by employing a suboptimal approaches such as Tree Search Vector Quantization (TVSVQ) and Pruned Tree VQ (PTVQ) ([7]). The computational problems can also be solved by using a special architectures ([4]). While the codebook training and data encoding steps of VQ are computationally intensive, the decoding step is not, because it is a table lookup process that can be performed quickly on a conventional sequential computers. Obvious drawbacks of VQ are computationally intensive training process for generating codebooks for a given class of images and the maintainance of these codebooks at coding and decoding ends. At the encoding end a codebook has to be selected for the given data and a pointer to this codebook may be provided as a part of the header record in the compressed file for the decoder to use the same codebook for decoding purposes. This is one practical difficulty of using VQ for image compression. This problem is solved with the Model-based Vector Quantization (MVQ) approach, described in the next section, in which codebooks are generated using statistical models and input image covariance matrix.

2.4 MVQ

In the MVQ. the codebook is generated using a statistical model of mean removed residual of the vectors. The mean removed vector elements are characterized either Gaussian or Laplacian error models. For small vectors sizes of 2 or 4, the mean removed vector elements can be simulated by a uniform random number generator producing independent and identically distributed (i.i.d) random numbers and then passing them through a Laplacian filter with mean λ. This is a reasonable model of generating mean removed residuals for these small vector sizes . However, as the vector size increases, the mean removed vector elements cannot be treated as independent and so a covariance structure of the source is imposed on Laplacian i.i.d process. For k-element vectors, the covariance matrix, Σ, of the input image is a kxk matrix. The diagonal elements of Σ are approximately equal and correspond to the variance of the normalized pixel values in the image. The square root of Σ_{00} $(= \lambda)$ is used to generate independent and identically distributed (i.i.d) Laplacian random variables. The consecutive Laplacian i.i.d random numbers are grouped into vectors of size $k = (k1 \times k2)$ to form a vector W_i (i^{th} vector). The covariance matrix, Σ, of the source is then factorized into L and U, where L and U are upper and lower triangular matrices, respectively. The factorization is performed by using the Cholesky decomposition algorithm. When the Laplacian vectors are mapped onto L, the resulting vectors will have same multivariate distribution as Σ. The vectors thus generated are independent of other vectors. However, the vector elements have the correlations given by Σ. Let W_i be the k-element vector generated by Laplacian i.i.d process. Let the L be the lower triangular matrix obtained by Cholesky's decomposition of Σ. Now the codevector X_i (which is i^{th} codebook entry) is given by

$$X_i = L * W_i$$

These vectors are used as the code vectors for the source mean removed residual vectors. In the second pass input image is coded using the model codebook. The codebook is completely specified by a seed point of uniform random number generator, λ, and the lower triangular matrix, L. The lower triangular matrix will have at most (k2 + k)/2 nonzero real numbers, where k is the size of the vector. Thus, by transmitting seed point of the uniform random number generator, λ, and L in the header of coded file, the decoder can generate the codebook to decode the VQ coded image.

3 Radiometric Resolution Gain of Lossy Compression Algorithms

In the TLLC approach, the radiometric resolution of the input image is explicitly reduced by b bits by the truncation process. We show here that the MSE distortion resulting from the truncation varies exponentially with b, the loss in radiometric resolution. The relation between MSE distortion and loss of radiometric resolution can be derived as follows:

When b lower order bits are dropped, the error in pixel may be one of the integers (0, 1, 2. ..., 2^b-1). Assuming a uniform distribution of these error pixel values, the expected mean squared error (MSE) is given by

$$MSE = \frac{1}{2^b - 1} \sum_{k=1}^{2^b-1} k^2 \tag{2}$$

$$= (2 * 2^{2b} - 3 * 2^b + 1)/6 \tag{3}$$

The uniform distribution assumption holds best for lower values of b. Equation (3) can be derived from (2) using the Euler-Maclaurin summation formula [8]. From Equation (3), we can obtain b in terms of MSE by solving the quadratic equation in 2^b and taking log_2 giving:

$$b = log_2([3 + \sqrt{(48 * MSE + 1)}]/4) \tag{4}$$

Equation (4) can be used to compute the loss of radiometric resolution due to the mean squared error distortion for a give compression ratio. We can thus compare performance of lossy compression techniques in terms of radiometric efficiency. For a given compression ratio, let the MSE distortions from two lossy methods (for example, VQ and TLLC) be D_1 and D_2 , respectively. Let b1 and b2 be loss of radiometric resolutions from these methods that can be computed from Equation (4). Now if $b1 > b2$, there is gain in radiometric resolution, Δb, by using VQ instead of TLLC, which is given by

$$b1 - b2 = \Delta b = log_2 \left[\frac{3 + \sqrt{48 * D_1 + 1}}{3 + \sqrt{48 * D_2 + 1}} \right] \tag{5}$$

For large distortions Equation (5) can be simplified to give

$$\Delta b = \frac{1}{2} log_2 \left[\frac{D_1}{D_2} \right] \tag{6}$$

Using Equation (6) lossy compression techniques can be compared in terms effective radiometric gain by using one with lesser distortion than the other compression technique for a given rate. We have reported here the effective radiometric resolution gain of VQ, MVQ and JPEG/DCT with respect to TLLC.

4 Experimental Results

Three different multispectral image data sets are used in our experimentation. The first data set consists of spectral bands 1, 2, and 3 of a 2048-by-2048 pixel subimage of a Landsat Thematic Mapper (TM) scene collected in 1991 (path/row 46/28) from over the Gifford Ponchot National Forest in the state of Washington in the United States of America. The radiometric (pixel) resolution of this data is 8 bits. The second data set is the first two spectral bands from a 409x2048 pixel Global Area Coverage (GAC) data set from the Advanced Very High Resolution Radiometer (AVHRR) instrument taken from over the western pacific ocean. The pixel resolution of this data is 12 bits (stored as 16 bits per pixel). The third data set is made up of bands 22 and 23 from the Advanced Solid-state Array Spectroradiometer (ASAS) instrument. This data set also has 12 bit pixel resolution. We used for our test a 512x420 pixel image designated 92161553 from Volume 4 of the FIFE CD-ROM series ([10]).

A training data set is required for the VQ method. This training data set should be disjoint from the test data set, but should be from the same instrument with the same spectral bands and should have similar scene characteristics. We chose to use the first 512 columns of the TM data set for testing, and trained on columns 513 through 2048 (for all 2048 lines). The AVHRR data was divided into two equal parts. The first 1024 lines were used for testing, while the second 1024 lines were used for training. As mentioned above, we used bands 22 and 23 of ASAS data set 92161553 of size 512x420 for testing. For training we used the same bands from the 512x590 pixel data set designated 92161621, the 512x600 pixel data set designate 92161631, and 512x600 data set designated 92161727. The training data was used to generate codebooks for each instrument with vector sizes of 4, 8, 16 and 32 so that compressed data at four different compression ratios could be obtained.

The JPEG/DCT compression technique used here was implemented for 8-bit pixel resolution images. To compress the 12-bit AVHRR and ASAS using JPEG/DCT, the images were first converted to 8-bit images by finding the brightest pixel (g_{max}) and scaling down all the pixels by the factor $g_{max}/255$. (MVQ can compress images of pixel resolutions 8-16, and does not need any codebooks for compression.)

The compression results on the TM data set are given in Table 1.1. The table provides MSE distortions for different compression ratios using the four different compression methods (TLLC, JPEG/DCT, VQ, and MVQ). The plots of CR vs. MSE are shown for the above four techniques on the TM data set are shown in Figure 1. The gain in radiometric resolution using JPEG/DCT, VQ and MVQ compared to TLLC are derived from the plots. For three CR's, the MSE's are measured from the plots and the Δb is computed from Equation (6). The radiometric resolution, Δb , for different CR's are given in Table 1.2 and the plots are shown in Figure 2. The results on AVHRR data are given in Table 2.1 and 2.2 and ASAS data results are given in Table 3.1 and 3.2. The rate distortion curves for AVHRR data and ASAS data using three lossy compressions compared to TLLC techniques in the plots shown in Figures 3 and 5 respectively. The gain in the radiometric resolution obtained by employing lossy compression techniques compared to TLLC are shown in Figure 4 for AVHRR data and Figure 6 for ASAS data.

Table 1.1: CR Vs. MSE on TM data

TLLC		JPEG		VQ		MVQ	
CR	MSE	CR	MSE	CR	MSE	CR	MSE
3.8	0.5	2.3	0.32	8.81	3.23	12.5	15.1
5.8	3.36	13.4	3.49	17.9	5.76	22.6	27.2
9.7	17.1	21.3	5.73	34.1	8.55	40.1	41.2
18.9	70.1	33.1	9.86	-	-	-	-
23.1	489	-	-	-	-	-	-

Table 1.2: Δb w.r.t TLLC for TM

CR	Δb w.r.t TLLC		
	JPEG	VQ	MVQ
10.0	0.95	1.20	0.46
15.0	1.48	1.60	0.65
20.0	1.65	1.75	0.76

Table 2.1: CR Vs. MSE on AVHRR data

TLLC		JPEG		VQ		MVQ	
CR	MSE	CR	MSE	CR	MSE	CR	MSE
4.0	3.5	3.5	8.5	8.4	51.6	4.6	131
5.2	17.1	17.5	237	16.4	179	8.77	443
7.2	76.1	28.2	351	37.8	400	20.0	574
10.6	323	46.3	500	-	-	-	-
17.0	1317	-	-	-	-	-	-

Table 2.2: Δb w.r.t TLLC for AVHRR

CR	Δb w.r.t TLLC		
	JPEG	VQ	MVQ
10.0	0.95	1.20	0.46
15.0	1.48	1.60	0.65
20.0	1.65	1.75	0.76

Table 3.1: CR Vs. MSE on ASAS data

TLLC		JPEG		VQ		MVQ	
CR	MSE	CR	MSE	CR	MSE	CR	MSE
5.96	0.5	12.7	6.5	8.2	10.9	7.0	22.0
8.36	3.47	22.3	16.8	15.8	23.4	12.8	81.5
12.41	17.4	35.0	28.0	33.5	37.0	30.0	100.3
19.48	77.3	53	50	-	-	40.3	200.1
32.0	304	-	-	-	-	-	-

Table 3.2: Δb w.r.t TLLC for ASAS

CR	Δb w.r.t TLLC		
	JPEG	VQ	MVQ
15.0	0.95	0.3	0.00
20.0	1.30	0.8	0.00
25.0	1.52	1.18	0.43
30.0	1.64	1.38	0.65

5 Conclusions

The data rates possible from remote sensing instruments can often far exceed the channel capacity for downlinking this data to Earth. The required data rate reduction is often obtained by reducing the resolution of the instrument. We have modeled the radiometric version of this approach by dropping a number of least significant bits and applying an appropriate lossless compression method. We refer to this technique as Truncation followed by Lossless Compression (TLLC). We have shown in our study that using lossy compression techniques such as JPEG, VQ and MVQ would give a gain in radiometric resolution compared to TLLC for a given data rate. In our experiments on Landsat TM data, we have found that radiometric resolution improvements of 1 to 1.5 bits for bit rates ranging from 0.8 - 0.5 or compression ratios of 10-20 with the VQ or JPEG techniques. Similar improvements are obtained for AVHRR data using VQ and JPEG techniques. However for ASAS data, the improvements are seen only for compression ratios exceeding 10 in the case of JPEG and VQ and 20 for MVQ.

References

[1] W. B. Pennebaker and J. L. Mitchell, "JPEG Still Image Data Compression Standard," *Van Nostrand Reinhold, NY 1993*, pp.203-206

[2] A. Gersho and R. M. Gray, "Vector Quantization and Signal Compression," *Kluwer Academic Publishers, 1991*

[3] M. Manohar and J. C. Tilton, B. Kobler and P. C. Hariharan, "Model-Based Vector Quantization," *Proc of the Data Compression Conference*, March 29-31, 1994, Snowbird, UT, p. 497.

[4] M. Manohar and J. C. Tilton, "Progressive Vector Quantization on a Massively Parallel SIMD Machine with Application to Multispectral Image Data," *IEEE Trans in Image Processing*, to appear.

[5] S. Gupta and A. Gersho, "Feature Predictive Vector Quantization of Multispectral Images," IEEE Trans on Geoscience and Remote Sensing, Vol. 30, No. 3, May 1992, pp. 491-501

[6] Y. Linde, A. Buzo, and R. M. Gray, "An Algorithm for Vector Quantizer Design," *IEEE Trans. on Comm*, COM-26, pp. 702-710, April 1978.

[7] P. A. Chou, T. Lookabaugh, and R. M. Gray, "Optimal Pruning with Applications to Tree Structured Source Coding and Modeling," *IEEE Trans. Inform. Theory*, March 1989, pp. 299-315.

[8] M. Abramowitz and I. A. Stegun, *Handbook of Mathematical Functions with Formulas, Graphs, and Mathematical Tables*, Ninth Printing, November 1970, p. 16, U. S. Goverment Printing Office, Washington, D. C.

[9] I. H. Witten, R. M. Neal and J. G. T. Cleary, "Arithmetic Coding for Data Compression," *Communications of the ACM*, Vol. 30, 1987, pp. 520-540.

[10] D. R. Landis, D. E. Strebel, J. A. Newcomer and B. W. Meeson, "Archiving the FIFE Data on CD-ROM," *Proceedings of the 1992 International Geoscience and Remote Sensing Symposium*, May 26-9, 1992, Houston, TX, pp. 65-7.

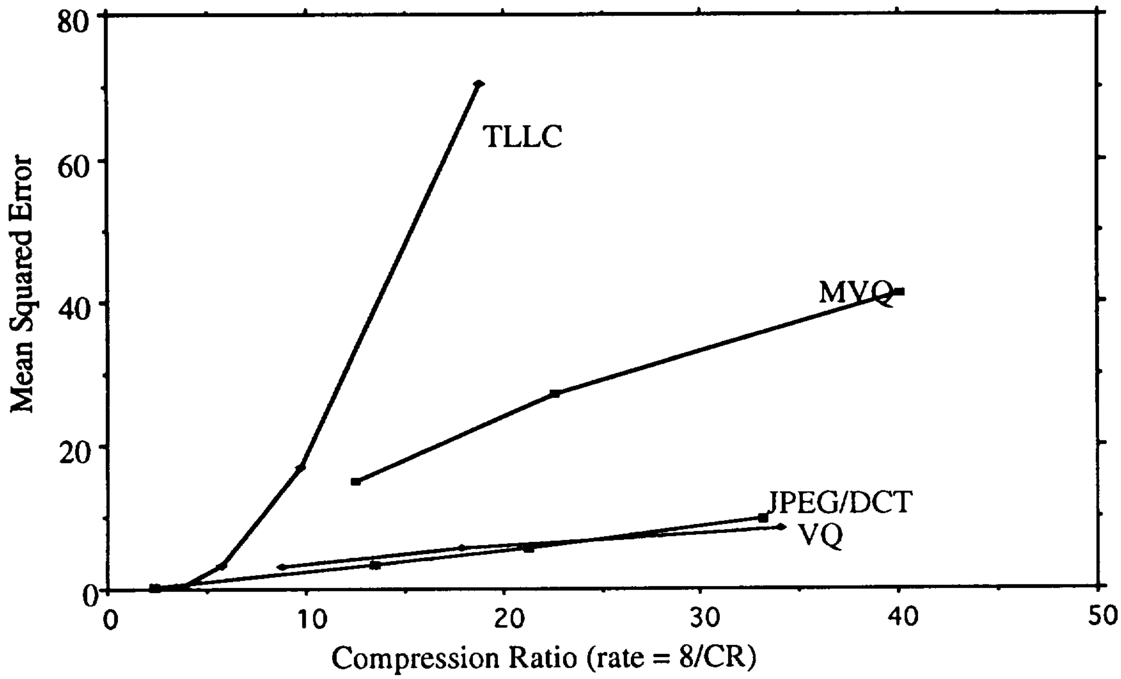

Figure 1. Rate-Distortion performance of lossy compression techniques and TLLC on the TM data set

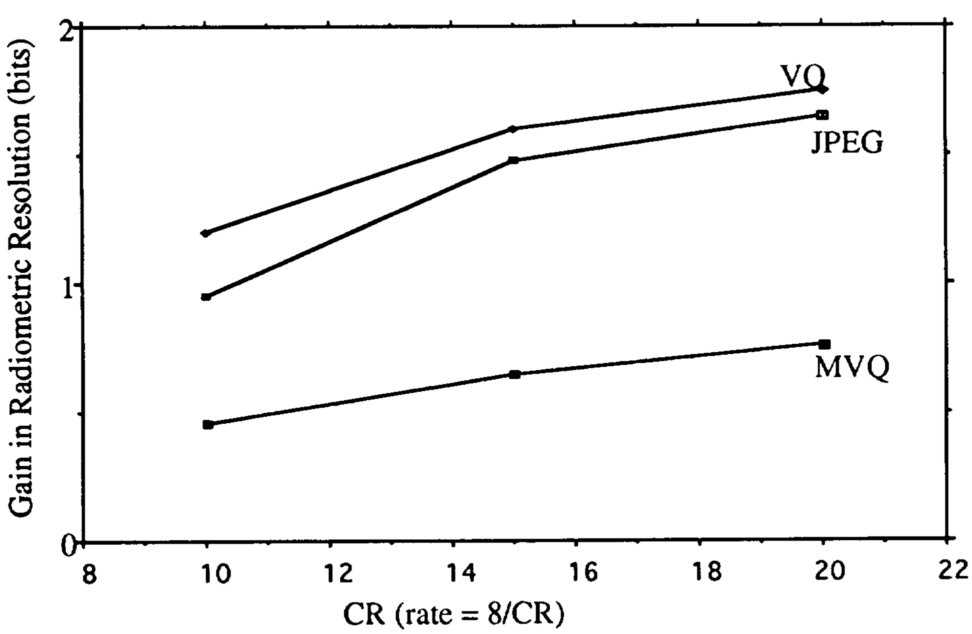

Figure 2. Radiometric Resolution of Lossy Compression techniques on the TM data set

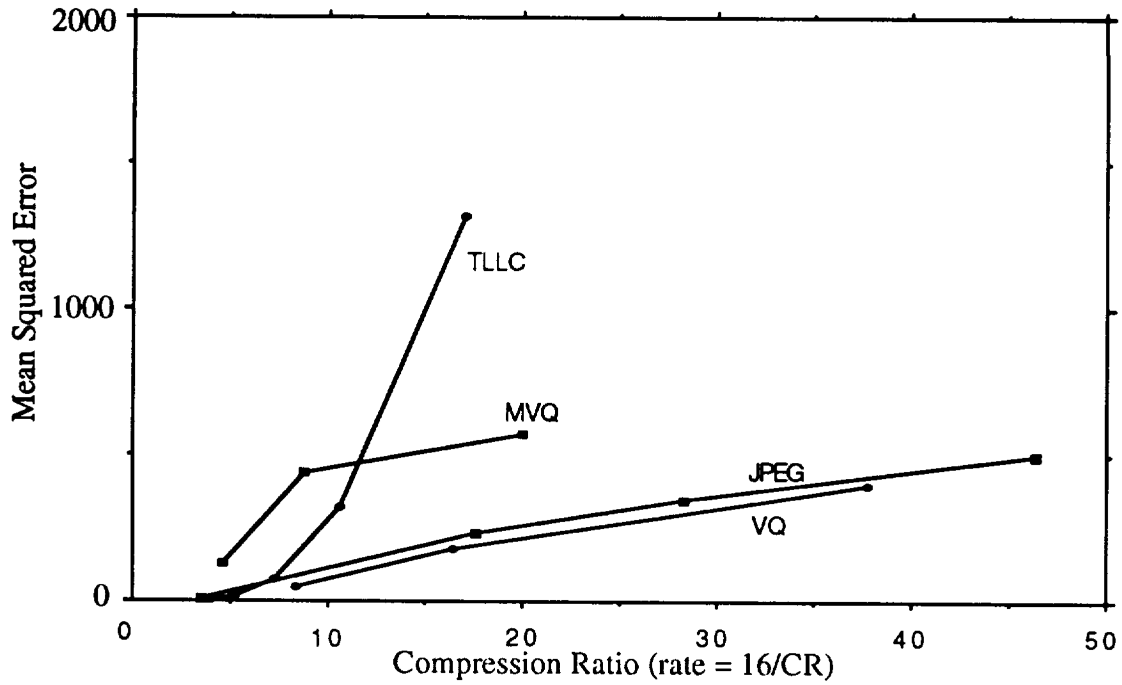

Figure 3. Rate-Distortion performance of lossy compression techniques and TLLC on AVHRR data set

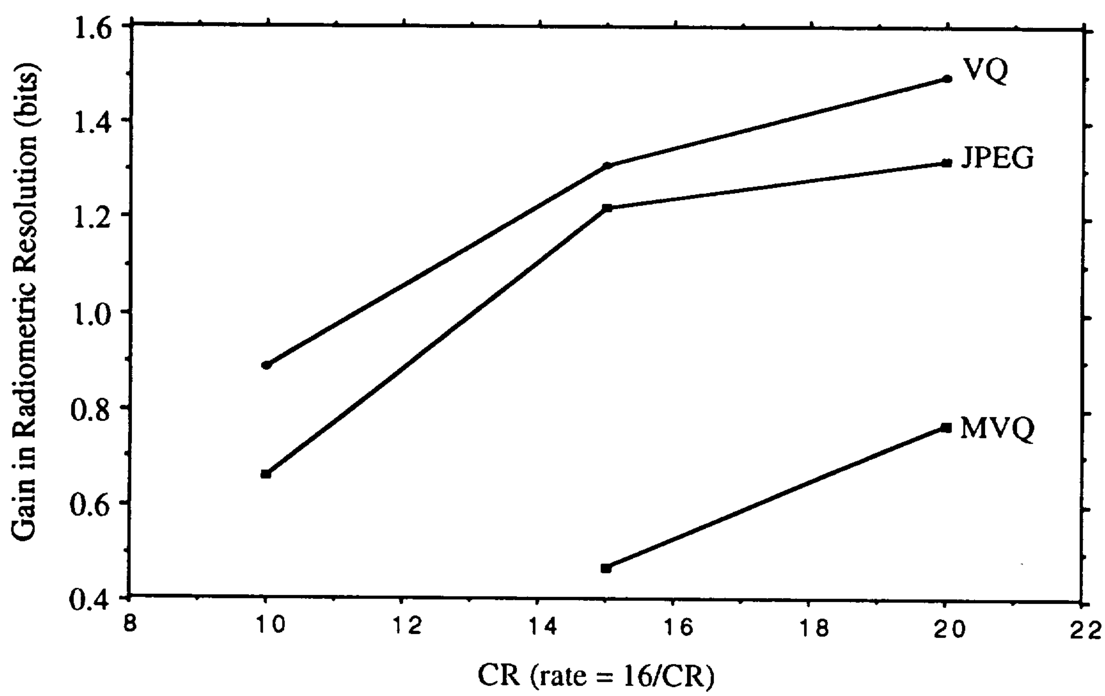

Figure 4. Radiometric Resolution Gain of Lossy Compression techniques on AVHRR data set

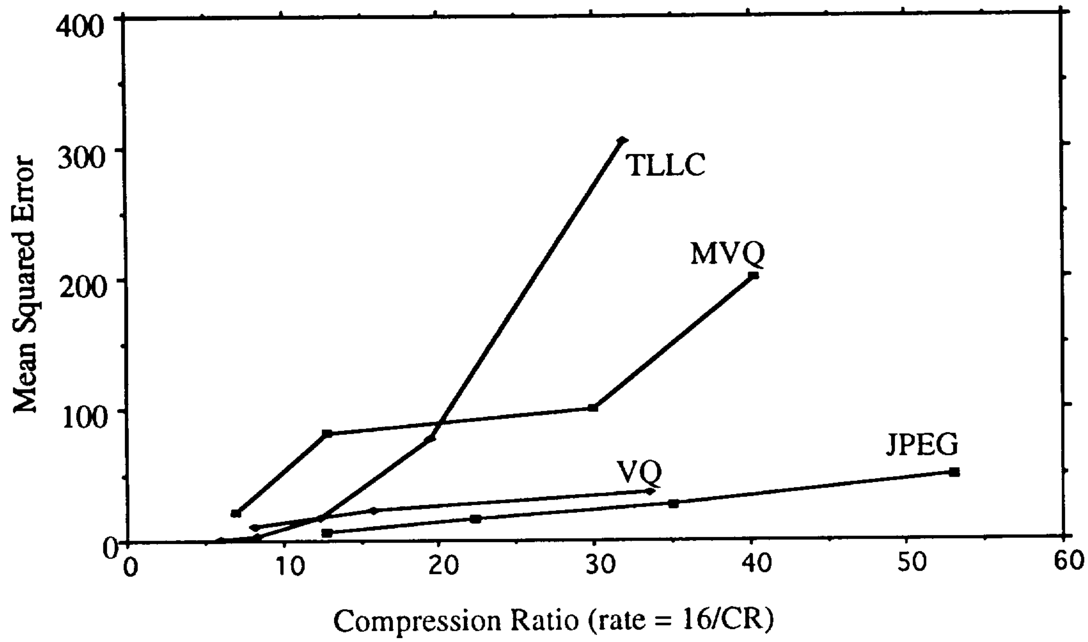

Figure 5. Rate-Distortion performance of lossy compression techniques on ASAS data set

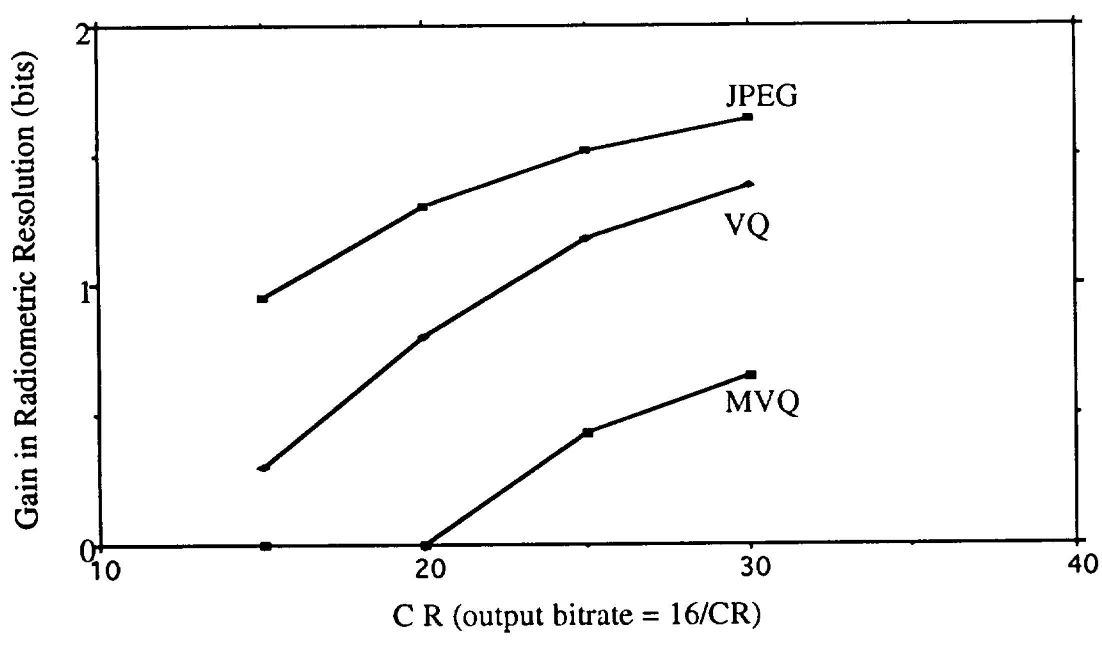

Figure 6. Radiometric Resolution of Lossy Compression techniques on ASAS data set