Near-lossless image compression techniques

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Abstract. *Predictive and multiresolution techniques for near-lossless image compression based on the criterion of maximum allowable deviation of pixel values are investigated. A procedure for near-lossless compression using a modification of lossless predictive coding techniques to satisfy the specified tolerance is described. Simulation results with modified versions of two of the best lossless predictive coding techniques known, CALIC and JPEG-LS, are provided. Application of lossless coding based on reversible transforms in conjunction with prequantization is shown to be inferior to predictive techniques for near-lossless compression. A partial embedding two-layer scheme is proposed in which an embedded multiresolution coder generates a lossy base layer, and a simple but effective context-based lossless coder codes the difference between the original image and the lossy reconstruction. Results show that this lossy plus near-lossless technique yields compression ratios close to those obtained with predictive techniques, while providing the feature of a partially embedded bit-stream. © 1998 SPIE and IS&T. [S1017-9909(98)00203-7]*

1 Introduction

Images in uncompressed digitized form place excessive demands on bandwidth and storage requirements in multimedia applications. In order to make many of these applications practicable, substantial compression often by a factor of 10 or higher is necessary. High compression factors inevitably force a loss of some of the original visual information. Since high compression factors are often needed in practice, a large body of the work in image compression has focused on lossy techniques where a variety of strategies for efficiently retaining the visually relevant informa-

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tion have been developed. For an excellent review of lossy image compression techniques, the reader is referred to Refs. 3, 9, 10, 2, 15, 20.

While retaining visual quality is important, in many applications, the end user is not a human viewer. Instead, the reconstructed image is subjected to some processing based on which ''meaningful'' information is extracted. This is especially true for remotely sensed images which are often subject to processing in order to extract ground parameters of interest. For example, remotely sensed microwave emission images of the Arctic are used to obtain a number of different parameters including ice concentration and ice type. In such a case, a scientist is concerned about the effects of the distortions introduced by the compression algorithm on the ice concentration estimates. Hence, in remote sensing applications, scientists typically prefer not to use lossy compression and use lossless compression instead. Another example is provided by medical images, where loss of diagnostic information cannot be tolerated. Lossy compression of medical images may remove or obscure very significant and life-saving information, while possibly introducing misleading artifacts into the image. The tolerance to loss may require the trained eye and intervention of an expert, which is not readily available. Other applications with low tolerance to loss of information are those in which the information of interest may be a weak component in the image. In certain satellite and astronomical images, weak signals are often a scientifically important part of the image and can be easily obscured by high compression. Such situations usually call for for lossless compression.

Unfortunately, compression ratios obtained with lossless techniques are significantly lower than those possible with lossy compression of common test images at a peak signal-to-noise ratio of about 35 dB. Typically, depending on the image, lossless compression ratios range from about 3-to-1

to 1.5-to-1. This leads to the notion of a *near-lossless* compression technique that gives quantitative guarantees about the type and amount of distortion introduced. Based on these guarantees, a scientist can be assured that the extracted parameters of interest, e.g., those related to ice concentration or microcalcification, will either not be affected or be affected only within a bounded range of error. Near-lossless compression could potentially lead to significant increase in compression, thereby giving more efficient utilization of precious bandwidth while preserving the integrity of the images with respect to the post-processing operations that are carried out. In addition to remote sensing applications, near-lossless compression techniques would also be of interest in the medical image community.

However, despite a need for near-lossless compression, there has been very little work done towards the development of such algorithms. In this paper we investigate a variety of near-lossless compression techniques. The near-lossless criterion we employ is defined in terms of the maximum allowable deviation of pixel values, which may be specified as ± 1, ± 2, etc. The maximum allowable deviation would depend on the strength of the information of interest that is intended for retention, relative to the noise introduced by the pixel value deviation. It is shown how predictive and multiresolution coding methods and their combinations can be adapted to meet the specifications of maximum allowable deviation.

The paper is organized as follows: In Sec. 2 we investigate near-lossless compression obtained by modifying lossless predictive coding techniques using prediction error quantization as determined by the specified tolerance. Simulation results with modified versions of two of the best predictive coding techniques known today, CALIC and JPEG-LS are provided. In Sec. 3, the use of lossless coding techniques based on reversible transforms in performing near-lossless compression is examined. Here, near-lossless compression is provided by a simple quantization of the image prior to lossless coding. Simulation results are reported with the recently proposed S+P technique,[19] an efficient reversible multiresolution technique based on the S-Transform. These results indicate that near-lossless compression based on predictive techniques provide superior compression performance as compared with those based on reversible transforms used in conjunction with prequantization. However, techniques based on reversible multiresolution transforms do provide a natural way to integrate lossy and lossless compression and can be designed to possess other attractive and useful features like progressive transmission. Hence, in Sec. 4, we examine a partially embedded two-layer scheme of lossy plus near lossless coding. In this approach an embedded multiresolution coder is used to generate a lossy base layer, and a simple but effective context-based lossless coder is designed to code the difference between the original image and the lossy reconstruction. Simulation results show that lossy plus near-lossless techniques provide compression ratios very close to those provided by predictive techniques, but at the same time retain the attractive features provided by a transform based approach. We conclude in Sec. 5 with a discussion on the results and avenues for further research.

2 Near-lossless Compression Based on Predictive Coding Techniques

Among various methods which have been devised for lossless compression, *predictive techniques* are perhaps the most simple and efficient. Here, the encoder (and decoder) process the image in some fixed order (say, raster order going row by row, left to right within a row) and predict the value of the current pixel on the basis of the pixels which have already been encoded (decoded). If we denote the current pixel by $P[i,j]$ and its predicted value by $\hat{P}[i,j]$, then only the *prediction error*, $e = \hat{P}[i,j] - P[i,j]$, is encoded. If the prediction is reasonably accurate then the distribution of prediction errors is concentrated near zero and has a significantly lower zero-order entropy than the original image.

If the *residual image* consisting of prediction errors is treated as a source with independent identically distributed (i.i.d.) output, then it can be efficiently coded using any of the standard variable length entropy coding techniques, like Huffman coding or arithmetic coding. Unfortunately, even after applying the most sophisticated prediction techniques, the residual image generally has ample structure which violates the i.i.d. assumption. Hence, in order to encode prediction errors efficiently we need a model that captures the structure that remains after prediction. This step is often referred to as *error modeling*.[7] The error modeling techniques employed by most lossless compression schemes proposed in the literature, can be captured within a *context modeling* framework described in Ref. 16 and applied in Refs. 22, 7. In this approach, the prediction error at each pixel is encoded with respect to a conditioning state or *context*, which is arrived at from the values of previously encoded neighboring pixels. Viewed in this framework, the role of the error model is essentially to provide estimates of the conditional probability of the prediction error, given the context in which it occurs. This can be done by estimating the probability density function by maintaining counts of symbol occurrences within each context[22] or by estimating the parameters (variance for example) of an assumed probability density function (Laplacian, for example) as in Ref. 7.

Extension of a lossless predictive coding technique to the case of near-lossless compression requires prediction error quantization according to the specified pixel value tolerance. In order for the predictor at the receiver to track the predictor at the encoder, the reconstructed values of the image are used to generate the prediction at both the encoder and the receiver. This is the classical DPCM structure. Uniform quantization leads to lower entropy of the output compared with minimum-mean-squared error quantization, provided the step size is small enough for the constant pdf assumption over each interval to hold.[26] For small values of k, as one would expect to be used in near-lossless compression, this assumption is reasonable. Hence, we consider a procedure where the prediction error is quantized according to the following rule:

$$Q[x] = \left\lfloor \frac{x+k}{2k+1} \right\rfloor (2k+1), \tag{1}$$

where x is the prediction error, k is the maximum recon-

Table 1 Performance of CALIC and JPEG-LS for different near-lossless criterion *k*—Lena image.

	CALIC			JPEG-LS		
k	Bpp	MSE	PSNR	Bpp	MSE	PSNR
±1	2.55	0.67	49.89	2.72	0.67	49.90
±2	1.90	1.99	45.15	2.09	1.99	45.15
±3	1.51	3.87	42.26	1.77	3.90	42.21
±4	1.23	6.17	40.23	1.54	6.35	40.11
±5	1.02	8.74	38.72	1.37	9.18	38.50
±6	0.86	11.60	37.49	1.24	12.48	37.17
±7	0.74	14.72	36.45	1.14	16.35	35.99

struction error allowed in any given pixel and $\lfloor . \rfloor$ denotes the integer part of the argument. At the encoder, a label *l* is generated according to

$$l = \left\lfloor \frac{x+k}{2k+1} \right\rfloor. \tag{2}$$

This label is encoded, and at the decoder the prediction error is reconstructed according to

$$\hat{x} = l \times (2k+1). \tag{3}$$

We now consider the application of the above quantization procedure in the predictive coding of test images. In Tables 1 and 2 we show bit rates and PSNR achieved for different error tolerance values *k*, by two of the best currently known predictive techniques. The first, CALIC,[29] is a context-based predictive technique of moderate complexity, that to the best of out knowledge, gives superior compression performance on the average over currently known practical and general purpose lossless compression techniques. The second technique, JPEG-LS, is the recently finalized international standard for lossless and near-lossless image compression.[8] JPEG-LS is a low complexity lossless image coding technique that, given its simplicity, provides compression performance within a few percent of the best known techniques while yielding a comparable PSNR. Results are shown for two standard 512×512 test images, Lena and Barb, in Tables 1 and 2, respectively.

Finally, we would like to note that the quantization technique we have employed is simple. In actuality, there is a complex dependency between the quantization error that is introduced and subsequent prediction errors. The quantization technique employed affects the prediction errors obtained. Furthermore, uniform quantization as in Eqs. (2) and (3) has an unpredictable effect on the elaborate error modeling and conditional coding techniques of an algorithm like CALIC, potentially leading to suboptimal compression. Recently, Ke and Marcellin[12] and Moayeri[14] have used a time varying trellis to minimize the entropy of the prediction error constrained to a $\pm k$ distortion criteria. However, optimizing the quantization in the context of sophisticated prediction and error modeling as employed by CALIC and JPEG-LS makes the trellis structure computationally intractable. Hence, simple prediction and context modeling is resorted to, a consequence of which is the inability to match the performance of near-lossless compression with CALIC and JPEG-LS. For a more thorough investigation of this phenomenon, the reader is referred to Ref. 28.

Table 2 Performance of CALIC and JPEG-LS for different near-lossless criterion *k*—Barb image.

	CALIC			JPEG-LS		
k	Bpp	MSE	PSNR	Bpp	MSE	PSNR
±1	3.03	0.67	49.90	3.30	0.67	49.89
±2	2.38	1.99	45.14	2.65	1.99	45.14
±3	1.97	3.91	42.21	2.27	3.92	42.20
±4	1.70	6.33	40.12	2.02	6.44	40.04
±5	1.48	9.20	38.49	1.82	9.46	38.37
±6	1.32	12.45	37.18	1.67	13.00	36.99
±7	1.20	16.16	36.05	1.54	17.00	35.82

Table 3 Performance of S+P for different near-lossless criterion k—Lena and Barb.

	Lena			Barb		
k	Bpp	MSE	PSNR	Bpp	MSE	PSNR
±1	2.78	0.67	49.90	3.27	0.67	49.89
±2	2.24	2.00	45.11	2.72	2.00	45.12
±3	1.95	4.00	42.16	2.39	4.01	42.10
±4	1.75	6.67	39.89	2.17	6.67	39.89
±5	1.60	9.96	38.15	2.01	10.04	38.12
±6	1.50	14.24	36.60	1.86	13.97	36.68
±7	1.40	19.01	35.34	1.76	18.61	35.43

3 Near-lossless Compression with Reversible Transform-based Techniques

Lossless image compression techniques based on a predictive approach process image pixels in some fixed and predetermined order, modeling the intensity of each pixel as dependent on the intensity values at a fixed and predetermined neighborhood set of previously visited pixels. Hence, such techniques do not adapt well to the nonstationary nature of image data. Furthermore, such techniques form predictions and model the prediction error based solely on local information. Hence they usually do not capture ''global patterns'' that influence the intensity value of the current pixel being processed. The performance limitations encountered in the predictive approach stem from this inability to handle the essential nonstationary nature of images and the highly local nature of the prediction.

Multiresolution techniques offer a convenient way to overcome highly localized processing by separating the information into several scales, and exploiting the predictability of insignificance of pixels from a coarse scale to a larger area at a finer scale. Another advantage of multiresolution techniques is the amenability to fully embedded coding. Some details of multiresolution techniques are discussed in the next section.

There has already been some work done towards applying multiresolution image coding techniques for lossless image compression. Among these, CREW (Compression with Reversible Embedded Wavelets)[32] and S+P (S-Transform with Prediction)[19] are perhaps the best known. They are based on the use of transforms akin to subband/wavelet transforms, but employing only simple addition and shift operations. Despite the attractive features provided by CREW AND S+P, their utility for near-lossless compression seems limited. This is due to the lack of a currently known suitable way of translating the near-lossless criterion of pixel value error tolerance into a suitable criterion in the transform domain. One way of providing near-lossless compression with such techniques is to quantize the image *prior* to encoding. After performing the quantization and mapping as defined in Eq. (2), the resultant image has a significantly lower dynamic range and can be compressed at a lower rate as compared to the original. The reconstructed image meeting the near-lossless criteria can be obtained after decompression and remapping intensity values as given in Eq. (3).

In Table 3 bit rates, MSE and PSNRs obtained with the two test images Lena and Barb for near-lossless criteria ranging from ±1 to ±7 are shown. In Figs. 1 and 2 we show a comparison of near-lossless compression with CALIC and S+P. It is seen that CALIC significantly outperforms S+P with prequantization, with the difference in
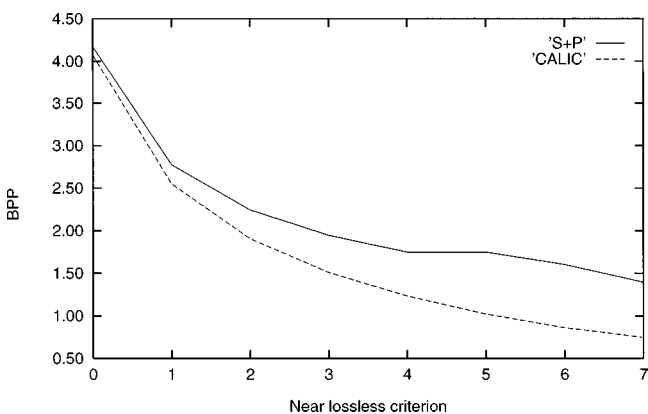
Fig. 1 Comparison of CALIC and SPP—Lena image.
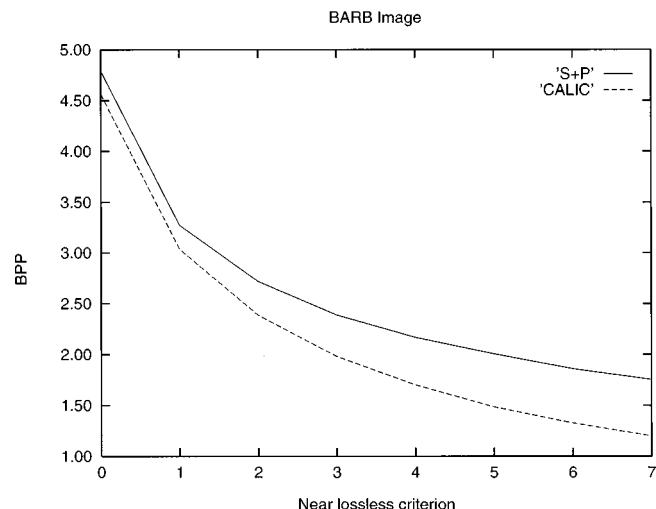
Fig. 2 Comparison of CALIC and SPP—Barb image.

performance being larger at higher values of k in the shown range of 1–7. Alternatives to simple prequantization may perhaps lead to better performance.

4 Lossy Plus Near-lossless Compression

Another way to provide near-lossless compression is in conjunction with a lossy technique. This can be done in a manner similar to a two-layered lossy plus fully lossless technique wherein a low-rate lossy representation containing a *preview* image or *browse* image is first made available to the user. If after a preview the user wishes to view the original image, a losslessly compressed version of the difference between the original and its lossy approximation is then made available. Lossy plus lossless/near-lossless compression is useful, for example, when a user is browsing through a database of images, looking for a specific image of interest. Within this framework, near-lossless compression can be provided by transmitting a suitably quantized version of the difference signal.

A partial embedding two-layer scheme of lossy plus near-lossless coding is described in this section. A fully embedded multiresolution coder is used to generate a lossy base layer, and a simple but effective context-based lossless coder is designed to code the difference between the original image and the lossy reconstruction. Another motivation for lossy plus near-lossless compression is the inferior performance that was obtained for near-lossless coding using S+P when used with simple prequantization.

In the two-layered lossy-plus-near-lossless scheme considered here, we propose to use a base layer of an embedded lossy image and a refinement layer which, when added to the base layer, produces an image that meets the specified near-lossless tolerance. Any efficient lossy coding method can be used to generate the base layer. A desirable feature in the lossy coding method is that it should generate an embedded bit-stream so that the decoding can be performed from the beginning of the bit-stream to any chosen termination point. In fully embedded coding, two bit-streams of any size N_1 and N_2 generated by the encoder to represent the image will contain identical data for the first $\min(N_1, N_2)$ bits. The quality of the reconstructed image improves with the increase in the size of data utilized in decoding, making it suitable for progressive transmission. Embedded coding methods using wavelet transforms have recently been shown to produce excellent compression performance.[21,18,31,11]

The lossy layer in our method uses transform coding, which is here meant to include block transform techniques, such as those based on Discrete Cosine Transform (DCT), and subband/wavelet methods. Let **P** denote the image to be coded, and let **T** denote the reversible transformation which, when applied to the image **P** produces the array *coefficient array* **C**

$$\mathbf{C} = \mathbf{T}(\mathbf{P}).$$

To get a lossy compressed representation of an image, the transform coefficients are quantized and suitably entropy coded. The transform coefficient magnitudes exhibit a pattern in their occurrence in the coefficient array. This feature is exploited in developing efficient methods of quantiza-
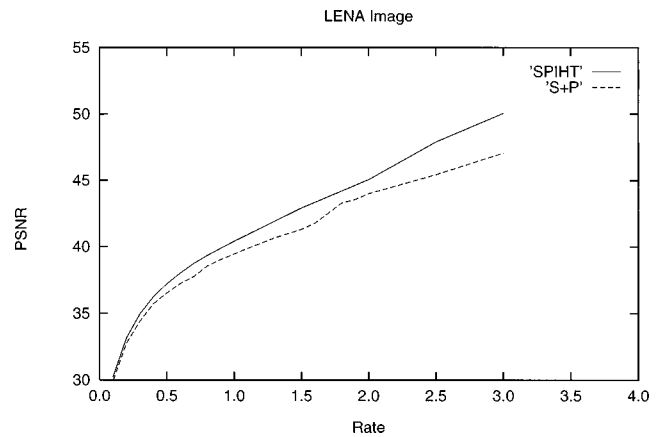

Fig. 3 Comparison of SPIHT and S+P—Lena image.

tion, symbol definition and coding. This was recognized early[4] for DCT, where a zig-zag scan and run-length coding was effectively utilized.

Recently, there has been tremendous interest in the application of subband/wavelet transforms.[1,6,17,23,25,27,24] in compressing visual information. A significant breakthrough in coding efficiency accompanied with the feature of embedded encoding occurred when the method of embedded zero-tree wavelet (EZW) encoding[21] was proposed. Spurred by this development many new algorithms have recently been proposed, including those described in Refs. 18, 31, 11 to name a few. A fast and efficient algorithm for wavelet-based image compression method called Set Partitioning in Hierarchical Trees (SPIHT)[18] has been developed for fully embedded coding. In this paper we use the SPIHT-based methods for lossy and lossless compression as tools in our near-lossless compression procedures. In Figs. 3 and 4 we show a comparison of S+P and SPIHT. From these figures it appears that a suitable lossy transform technique like SPIHT followed by near-lossless compression of the difference with the original could potentially provide better performance than a near-lossless compression technique based on prequantization followed by a transform based lossless compression technique like S+P.

The key to the improved performance of EZW, SPIHT and related algorithms is the observation that if a coeffi-
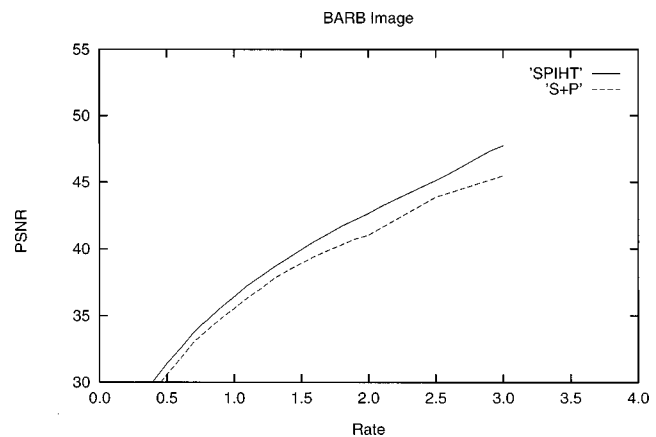

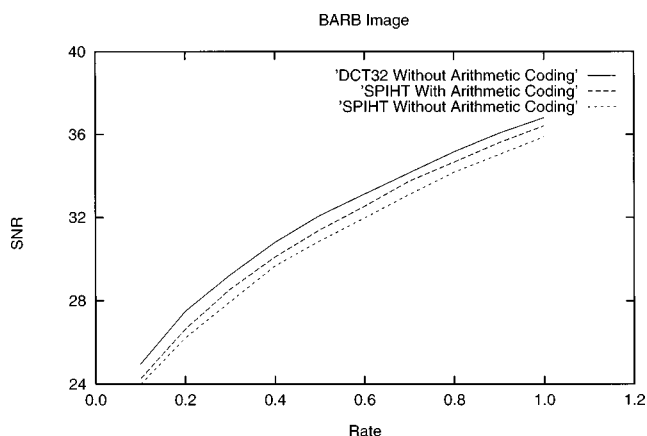**Fig. 4** Comparison of SPIHT and S+P—Barb image.

BARB Image

Fig. 5 Comparison of SPIHT and Embedded DCT based on 32 ×32 blocks with Barb image.
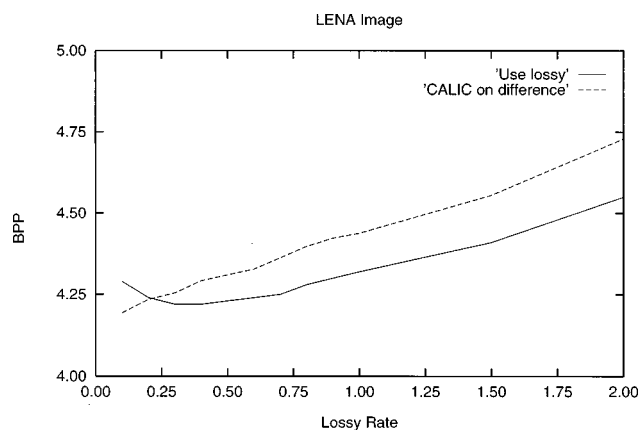
LENA Image

Fig. 6 Comparison of bit rates obtained with and without utilizing the lossy image while compressing the difference—Lena image.

cient is insignificant at a coarse scale in a multiresolution representation, then it is likely to be insignificant at the finer scale. Use of this predictability of insignificance leads to significant improvement in compression. This gain can be carried over to DCT-based coding by a suitable reconfiguration of the coefficients, leading to improved compression (with embedding) compared with JPEG procedure.[30,13] These algorithms are attractive for progressive transmission of information.

Performance of the coders can vary with the transform used and the image being coded. For example, we found that if the embedded coding procedure in Ref. 18 is used in conjunction with DCT performed on 32×32 blocks, then the results of coding on Barb show that coding in the range 0.1–1.0 bits/pixels *without* arithmetic coding produces better performance than the wavelet transform coding *with* arithmetic coding. This is shown in Fig. 5. Similar and more extensive results are given in Ref. 30. It should be mentioned that different types of transforms have been proposed and continue to be investigated. The use of nonlinear filters has also been examined.[5] The S+P transform[19] uses nonlinearity in the form of truncation in arithmetic.

In a two-layer approach, the rate of the lossy scheme could be determined by the fidelity and rate constraints of the particular application. The rate of the lossy coding algorithm could also be obtained as the lossy coding rate which would minimize the total (lossy plus lossless) coding rate. In practice, the former approach would probably be more useful than the latter. However, we explore the latter in order to compare the potential benefits provided by lossy plus near-lossless compression over the other near-lossless techniques that have been described so far.

If the difference image is encoded independent of the lossy image then this can be done by any lossless predictive coding technique like CALIC. In this case it is easy to see that the lower the bit rate of the lossy representation, the lower the number of bits required to send the lossy plus lossless residual. In fact the optimal point is when the original is encoded losslessly with zero bits for the lossy image. In Figs. 6 and 7 we show this happening with the two test

images using SPIHT at different bit rates to get the lossy representation and CALIC to encode the difference image losslessly.

Coding the difference image without regard to the lossy reconstruction fails to take into account the significant information provided by the latter about the original image and as a consequence about the difference image. In order to exploit the lossy reconstruction while encoding the difference image we designed a simple context based lossless coding technique similar to CALIC, except for a few differences. First of all, we eliminated the prediction step. This is because prediction captures the ''smoothness'' or uniformity of neighboring pixel values typically found in natural images. The difference image, however, is not smooth. This is especially true when the difference image is generated from a moderate to high quality lossy reconstruction.

Secondly, contexts were formed by using pixels in the lossy image at and around the location of the current residual pixel being encoded. Specifically, the following differences were computed;
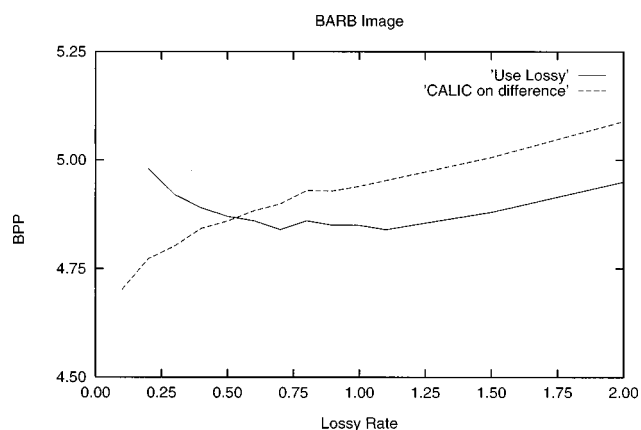
BARB Image

Fig. 7 Comparison of bit rates obtained with and without utilizing the lossy image while compressing the difference—Barb image.

Table 4 Performance of lossy plus near-lossless technique using lossy image obtained by SPIHT bpp for different near-lossless criterion *k*—using Lena image at 0.30 bpp and Barb at 1.10 bpp.

	Lena			Barb		
k	Bpp	MSE	PSNR	Bpp	MSE	PSNR
±1	2.69	0.67	49.89	3.31	0.67	49.89
±2	2.02	1.98	45.16	2.65	1.98	45.17
±3	1.59	3.76	42.38	2.23	3.77	42.36
±4	1.28	5.68	40.59	1.91	5.74	40.54
±5	1.03	7.50	39.38	1.67	7.54	39.36
±6	0.86	9.10	38.54	1.48	9.00	38.59
±7	0.73	10.43	37.95	1.35	10.06	38.10

$$D1 = L[i-1,j] - L[i,j],$$

$$D2 = L[i+1,j] - L[i,j]$$

$$D3 = L[i,j-1] - L[i,j] \tag{4}$$

$$D4 = L[i,j+1] - L[i,j]$$

where L denotes the lossy reconstructed image. The differences D1, D2, D3 and D4 were then quantized into 7 regions (labeled -3 to $+3$) symmetric about the origin with one of the quantization regions (region 0) consisting only of the difference value 0.

Further, contexts of the type (q_1,q_2,q_3,q_4) and $(-q_1,-q_2,-q_3,-q_4)$ are merged based on the assumption that

$$p(e|q_1,q_2,q_3,q_4) = p(-e|-q_1,-q_2,-q_3,-q_4).$$

The total number of contexts turns out to be $(7^4-1)/2 = 1200$. Within each context the conditional mean of the difference image value $\hat{\epsilon}[i,j]$ was estimated and subtracted from the actual value $E[i,j] = P[i,j] - L[i,j]$. The result $\hat{E}[i,j]$ was then quantized to get $\hat{E}[\hat{i},j]$ which was entropy coded, conditioned to a local activity measure Δ computed as defined below and then quantized to one of eight levels.

$$\Delta = D_h + D_v + 2 \cdot (|\hat{\hat{E}}[i-1][j]| + |\hat{\hat{E}}[i][j-1]|), \tag{5}$$

where

$$D_h = |L[i-1][j] - L[i][j]| + |L[i][j] - L[i+1][j]|, \tag{6}$$

$$D_h = |L[i][j-1] - L[i][j]| + |L[i][j] - L[i][j+1]|.$$

The quantization bins for Δ are defined by the following boundary points q_i:

$$q_1=7, \quad q_2=17, \quad q_3=28, \quad q_4=46, \tag{7}$$

$$q_5=65, \quad q_6=91, \quad q_7=148.$$

In the above scheme, if the lossy image utilized when compressing the residual is coded at a very low rate, then it will provide misleading information about the residual and lead to poor compression. A very high rate lossy image, on the other hand, would also lead to poor overall performance. This is because, as the bit rate for the lossy representation increases, the residual image consists more and more of random noise, and any approach which attempts to exploit residual correlations loses its advantage. This is confirmed again in Figs. 6 and 7 where it is seen that for Lena, a lossy image at 0.30 bpp results in the minimum overall rate and for Barb we need a lossy image at 1.10 bpp.

Table 4 shows bit rates, MSE and PSNR's achieved with a lossy plus near-lossless approach for different values of k for Lena and Barb.

5 Conclusions and Future Work

In this paper near-lossless compression techniques based on the criterion of maximum allowable deviation of pixel values are investigated. It is shown how predictive and multiresolution coding methods and their combinations can be adapted to meet the specifications of maximum allowable deviation. We have examined near-lossless compression by
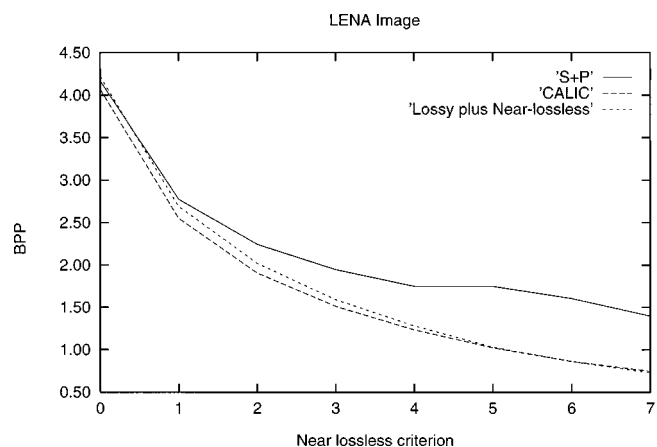

Fig. 8 Comparison of bit rates obtained by proposed lossy plus near-lossless technique and near-lossless S+P and CALIC—Lena image.
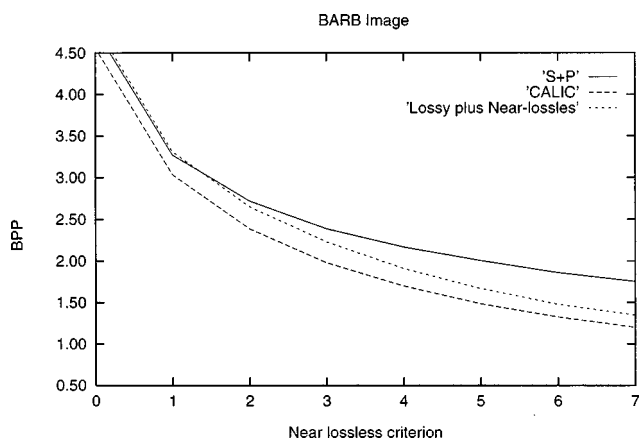
BARB Image

Fig. 9 Comparison of bit rates obtained by proposed lossy plus near-lossless technique and near-lossless S+P and CALIC—Barb image.

modifying lossless predictive coding techniques, near-lossless coding based on reversible transforms in conjunction with prequantization, and a partially embedded two-layer scheme of lossy plus near lossless coding. Figures 8 and 9 show an overall comparison of near-lossless compression with a predictive approach (CALIC), a reversible transform (S+P) and a lossy transform (SPIHT)+near lossless coding. The predictive approach clearly performs the best. The partially embedded two-layer scheme of lossy plus near-lossless coding offers a compromise in providing a preview image while performing close to the purely predictive approach. The S+P coder is attractive due to its simplicity and its feature of fully embedded coding, and should be investigated for improved performance by exploring alternatives to the simple prequantization procedure.

Acknowledgments

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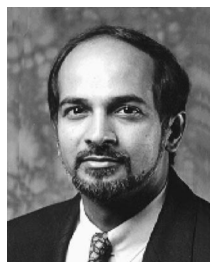
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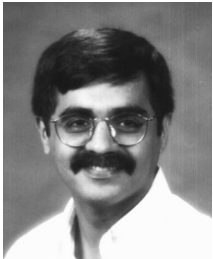
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