

Error Resilient Lossless Image Coding

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Abstract

We present an image compression scheme that is error resilient and offers lossless decompression in the absence of channel noise. Attempts are made to detect transmission errors and data found to be in error is discarded so as not to pollute the decompressed output. This is achieved while still maintaining a level of compression that is competitive with lossless image compression standards.

1 Introduction

Lossless image compression [1] is a useful technique for the storage and transmission of medical, scientific and pre-production image material. Although offering only moderate compression (rarely much better than 2:1) lossless techniques guarantee reversible decoding in the absence of channel noise. However, almost all reported schemes are extremely vulnerable to transmission or storage errors; a single bit error can easily render an encoded image useless.

Applying forward error correction coding to the output of a standard lossless image compression scheme is one possible solution to this problem. However, to be effective, it would be necessary to know the error rate of the channel in advance. If the error rate is not known, or is variable, then the error protection will either be too strong (poor overall compression) or too weak (chronic image corruption).

Another approach is to make a codec error resilient. That is, decompression is lossless in the absence of channel errors, and is a *best effort* decompression otherwise. This approach was used in [2] to counter the affects of packet loss in ATM networks when transferring medical image data.

An important feature of an error resilient lossless image codec should be that it avoids adding features to the output that were not in the original image. In order to do that, any data known to have been received in error should not be used in the reconstruction of the image. This suggests

a scheme based on widespread use of lightweight error detection codes. Such a scheme, as described in this paper, could be particularly useful for image storage on media whose bit error rate is generally low, but bursty (e.g. magnetic tape). It would also be appropriate for image transmission over channels prone to bursty errors.

Lossless image compression generally consists of three stages: mapping, modelling and entropy coding. Possible methods for adding error resilience to each of these stages are considered in the following sections.

2 Image Mapping

Many lossless image coding schemes use prediction to convert the original image data into prediction residuals, that can then be efficiently stored. However, if a transmission error has caused a pixel value to be incorrectly decoded, any prediction based on that pixel will lead to error propagation. Therefore, any pixel known to be in error should not be the basis for a prediction.

Prediction typically proceeds in raster scan order. This is undesirable, as once an error has occurred, further prediction is likely to be unproductive, and only part of the image will be correctly decoded.

An alternative is to use a hierarchical image representation. One such representation is the S-Transform, which has been widely used in lossless image coding. We use a variant described by Said and Pearlman [3] called the S+P-Transform where the P is added for prediction that is used between levels.

When used recursively, the S-Transform builds a multiresolution image pyramid, with a single low frequency band and several high frequency bands. Prediction of the high frequency coefficients is then used to further lower the entropy of the representation¹.

The low frequency band is particularly important to the quality of the received image, in the case of transmission

¹Prediction is based only on coefficients from a higher level. This corresponds to predictor A in [3].

errors. Hence, the low frequency band is protected by forward error correcting codes.

If some portion of a high frequency band is known to be in error (see Section 4 for details on the error detection used) then that information is assumed to be useless and replaced by zeros. Furthermore, subsequent high frequency coefficients, that would have added detail to the affected region, are also ignored. Thus a detected error in transmission will lead to portions of the image that lack fine detail rather than an image with features related solely to transmission error.

3 Modelling

The prediction residuals for the high frequency coefficients generally have a highly peaked distribution, making them amenable to efficient symbol coding. However, before coding we must form a model for the coder to use.

Many modern lossless image coding techniques use *context models* to estimate prediction residual distributions [4, 5]. These models use information from previous occurrences of the current image context, where a context is defined by some function of pixels neighbouring the current pixel. However, because these schemes are dependent on image characteristics surrounding the current location, any errors in the decoded image would ruin the model.

Another approach is to use a fixed model. However, this is undesirable as it tends to lead to poor compression performance.

The proposed scheme divides each band into blocks and the encoder determines and transmits the optimum coding parameters for each block. To be effective we require the coding parameters to be received without error, so the parameters are protected by an error correcting code.

4 Entropy Coding and Error Detection

As the parameters for the entropy coder must be sent, with error correction, a coding scheme that requires as few parameters as possible would significantly aid both compression and error resilience. Such a scheme is Golomb-Rice coding, as used in JPEG-LS [6]. These codes, which are optimal for a Laplacian distribution, require a single parameter k . To encode a symbol, the k least significant bits are used with the remainder of the symbol sent as a unary sequence. These codes can also be made reversible [7].

Golomb-Rice codes are *Variable Length Codes* (VLCs). Although efficient, VLCs are dependent on noiseless operation, as a single bit error can cause loss of synchronisation between encoder and decoder.

In order to avoid synchronisation loss, the image pyramid is divided into fixed blocks and the length, in bits, required for the coefficients in each block is also transmitted (protected with an error correcting code). The blocks used

Image	JPEG-LS	LJPEG	Proposed
General			
boats	3.93	4.60	4.50
goldhill	4.48	4.99	4.98
lena	4.25	4.70	4.59
Medical			
ct	1.32	1.93	2.19
mri	2.98	3.61	3.63
us	2.63	3.32	4.07
x_ray	2.20	2.63	2.67
Astronomical			
jupiter	3.79	4.01	4.03
m32	1.81	2.22	2.25

Table 1: Compression results in bits per pixel.

are the same as those used for modelling in the previous section.

Bit errors in the Golomb-Rice codes can be thought of as non-propagating and propagating. Non-propagating errors can occur in the first k bits of each symbol and do not cause loss of synchronisation. Propagating errors can occur in the unary section of each code and do cause loss of synchronisation. If a single propagating error occurs, the decoder will not use the determined number of bits to decode all the symbols in the block. This type of error is easily detected, and all coefficients in the block are marked as bad. Total loss of synchronisation does not occur, because the block length is known to the decoder and so the starting position of the next block can be found.

To improve error detection, a small number of parity check bits are added to each block, to ensure that non-propagating errors are caught. If a parity error of the data is detected the block is again marked bad. As a final aid to burst error resilience the output of the coder is passed through a fixed interleaving scheme.

5 Results

An error resilient, lossless image compression scheme was implemented based on the discussion above. Where forward error correcting codes were needed, the Golay (23,12) code [8] was used. A block size of 10x10 was used for modelling and the prevention of synchronisation loss.

In Table 1 the compression performance of the described scheme is compared to that of the new JPEG-LS standard [6] and the old lossless JPEG standard [9]. All the images used are 8-bit grey-scale and are available online².

²<ftp://ipl.rpi.edu/pub/>

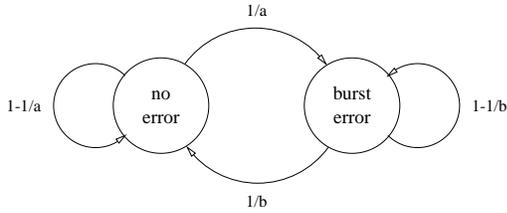


Figure 1: Two state model for channels prone to bursty errors.

The proposed scheme shows compression performance that is generally comparable with the older lossless JPEG, although it does fall behind the newer JPEG-LS. This is mainly due to the lack of sophisticated context modelling in the proposed method.

To test the error resilience of the proposed scheme, the test set of images were decoded one hundred times each over a simulated channel with burst errors. The model used for the test channels is shown in Figure 1. The probability of bit errors in the *no error* state is zero and it is $1/2$ in the *burst error* state. It is worth noting that the average burst length is b and the overall bit error rate is $\frac{b}{2(a+b)}$.

The results of these tests are shown in Table 2. Note that the PSNR values are calculated only for those images that are not losslessly decoded. As could be expected, the percentage of correctly decoded images varies with the size of the image. For example *x_ray* (2048x1680) was never losslessly decoded, whereas *mri* (256x256) was correctly received in most cases.

Those images that are not losslessly decoded have an excellent average quality. Visually, most such images differ from the original only in a slight loss of detail in some regions (see Figure 2).

Overall, a very high percentage of pixels are correctly decoded. Of those pixels that are affected by noise most are replaced by a sub-sampling of the original values surrounding the affected region and only a very small number (typically less than 0.25%) go undetected.

Figure 3 shows what happens when a is varied (b is fixed to 20) for the image *ct*. For comparison raw image data was also tested over these channels.

Due to the redundancy in raw data, it is much more error resilient than the output of typical compression schemes. However, the PSNR of images affected by error is almost identical for raw data and the proposed scheme. Furthermore, the proposed scheme prevents noise causing new image features and results in a smaller file size. This latter feature also accounts for why the percentage of correctly decoded images (PCDI) is much better for the proposed scheme than for raw data.

Image	Decoding with $a=10^6, b=50$			
	PCDI (%)	PCDP (%)	PUEP (%)	PSNR (dB)
General				
boats	16	96	0.21	49.3
goldhill	10	95	0.30	47.3
lena	25	96	0.24	49.1
Medical				
ct	56	98	0.24	53.3
mri	79	98	0.08	47.4
us	39	96	0.10	41.1
x_ray	0	97	0.12	54.7
Astronomical				
jupiter	10	96	1.65	58.3
m32	54	97	0.13	65.4

Table 2: Percentage of Correctly Decoded Images (PCDI), Percentage of Correctly Decoded Pixels (PCDP), Percentage of Undetected Error Pixels (PUEP) and Peak Signal to Noise Ratio (PSNR) for the proposed scheme over a channel with bursty errors.

6 Conclusions and Further Work

In this paper we have shown that a lossless compression scheme need sacrifice only a small amount of compression in order to become resilient to errors. The result on the decompressed image of errors in transmission, is generally a loss of fine detail in a region rather than the addition of new image features. This scheme would be suitable for use in situations where the error rate is generally low, but bursty.

If an error is detected, the proposed scheme discards the data involved as it may lead to unwanted image artefacts. Ongoing work is investigating whether some of the data in a block known to contain an error can be used. This could be accomplished by methods aimed at localising an error in a block of data.

Future work will investigate what guarantees can be made about the quality of the decompressed image and extensions of the scheme to multispectral images.

References

- [1] N. Memon and K. Sayood. Lossless image compression: A comparative study. *Proc. SPIE Still-Image Compression*, 2418:8–20, March 1995.
- [2] Alan L. Merriam, Albert L. Kellner, and Pamela C. Cosman. Lossless image compression over lossy packet networks. *International Conference on Signal Processing Applications and Technology (ICSPAT '97)*, 1997.

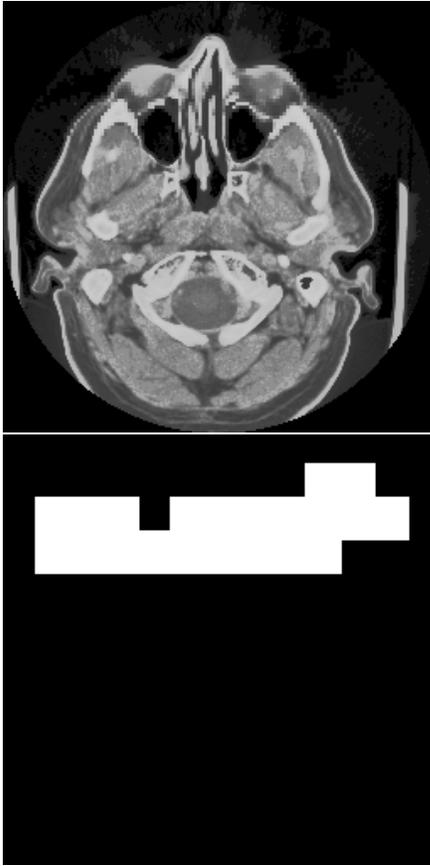


Figure 2: Top: The medical image *ct* decoded over a noisy channel. Bottom: The proposed scheme marks regions known to be decoded only to a coarse resolution due to errors in transmission.

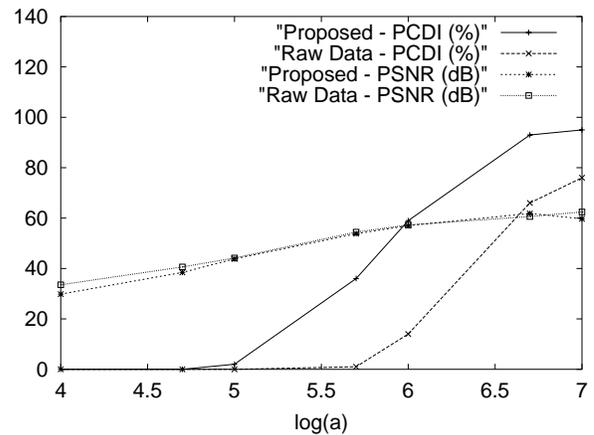


Figure 3: A comparison of the effects of varying a for the proposed scheme and raw data. b is fixed at 20 and all tests were run on the *ct* image.

[3] Amir Said and William A. Pearlman. An image multiresolution representation for lossless and lossy compression. *IEEE Trans. on Image Processing*, 5(9):1303–1310, September 1996.

[4] X. Wu and N. Memon. Context-based, adaptive, lossless image codec. *IEEE Trans. on Communications*, 45(4), April 1997.

[5] Marcelo J. Weinberger, Jorma J. Rissanen, and Ronald B. Arps. Applications of universal context modeling to lossless compression of gray-scale images. *IEEE Trans. on Image Processing*, 5(4):575–586, April 1996.

[6] ITU-T Rec. T.84 - Information Technology. Digital compression and coding of continuous-tone still images: Extensions, July 1996.

[7] Jiangtao Wen and John D. Villasenor. Reversible variable length codes for efficient and robust image and video coding. *Proc. Data Compression Conference*, pages 471–480, March 1998.

[8] W. Peterson and Weldon E. *Error-Correcting Codes*. The MIT Press, 1972.

[9] G. Wallace. The jpeg still picture compression standard. *Comms. of the ACM*, 34(4):30–44, April 1991.