ADAPTIVE DECORRELATION AND ENTROPY CODING FOR CONTEXT-BASED LOSSLESS IMAGE COMPRESSION

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ABSTRACT

In this paper we employ adaptive LMS filtering for the efficient decorrelation of still images. The decorrelation algorithm is coupled with a novel entropy coder and applied to lossless image coding. The proposed scheme is shown to have comparable performance with other known algorithms for context-based image coding.

1. INTRODUCTION

Lossless signal and image compression is necessary for many applications where perfect accuracy is needed, such as the transmission of depth maps for the construction of 3D views of a scene [1], the transmission of the lowest resolution image in logarithmically split subband coding schemes [2], multiple generation document reproduction and most notably for the efficient storage and communication of medical images [3].

The most popular techniques for image compression are based on predictive coding (DPCM) or transform coding (DCT, wavelet). Wavelet-based [4] techniques have gained much popularity lately, mainly due to their excellent lossy performance. However, the state-of-the-art coders for errorless image compression are context-based coders which sacrifice the progressive transmission capability of multiresolution methods in order to achieve superior lossless performance. Context-based coders usually employ a decorrelation pass and an entropy coding pass which parsimoniously encodes the error terms produced in the decorrelation pass.

Numerous context-based coders appeared in the literature [5, 6]. Most of them attempt to achieve image compression by using efficient predictor filters followed by adaptive arithmetic coding. The use of locally optimal filtering has attracted much less attention [7]. In this paper we examine the application of adaptive least squares filters to the lossless compression of still images. The LMS algorithm [8] is generally used for the design of adaptive filters such that, given the least squares estimate of the tap-weight vector of the filter at iteration $t-1$, the updated estimate of this vector may be computed at iteration t upon the arrival of new data.

The paper is organized as follows. Section 2 describes the proposed decorrelation scheme. An efficient entropy coder is presented in Section 3. In Section 4 experimental results are reported and finally conclusions are drawn in Section 5.

2. DECORRELATION OF IMAGES USING ADAPTIVE PREDICTION

A predictive coder for the efficient decorrelation of images using the LMS algorithm was implemented. In predictive coding each pixel intensity is predicted from a causal set of pixel intensities. Using the LMS adaptation procedure, the predictor of the DPCM coder adapts to the local features of the image.

Let $\mathbf{x}_{ij}$ denote the vector containing the intensities of the causally available pixels that will be used for the prediction of the current pixel intensity at position (i, j). Let also $p_{ij}[k], k = 1, \ldots, L$ denote the coefficients of the adaptive filter at position (i, j). The filter used in this paper is of length $L = 9$ (depicted in Fig. 1). The coefficients of the filter are initialized by setting $p_{00}[k] = 1/L$. The intensity of the current pixel is predicted using the following equation

$$\hat{d}[i,j] = \sum_{k=1}^{L} p_{ij}[k] x_{ij}[k] \quad (1)$$

The error between the original pixel intensity $d(i, j)$ and its prediction is subsequently computed as

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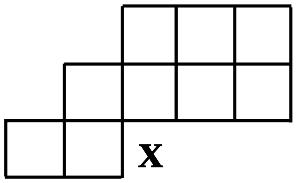


Figure 1: Causal filter used for the prediction of the current coefficient **X.**

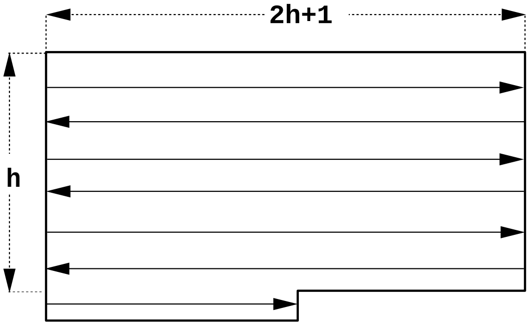


Figure 2: Causal window used for the training of the adaptive filter. Arrows indicate the scanning pattern.

$$e[i,j] = d[i,j] - \hat{d}[i,j] \qquad (2)$$

Finally, the updated coefficients of the filter that will be used for the prediction of the next pixel intensity at position (i',j') are given by

$$p_{i'j'}[k] = p_{ij}[k] + ne[i,j]x_{ij}[k], \quad k = 1,\dots,L \qquad (3)$$

The constant n is the adaptation step. Large values of n allow fast convergence of the adaptive filter. However, this comes at the risk of instability. In this paper n is valued 5×10^{-7}.

Adaptation using the LMS algorithm can be performed in two ways. The first approach is to visit each image pixel in a scan line order. This simple approach, which yields satisfactory results when a fast solution is required, has a serious drawback. It is unable to take advantage of the two dimensional nature of images. For example, the pixel lying exactly above the current pixel is considered to be W positions in the past (where W is the number of image columns).

A second approach which provides a remedy for the aforementioned drawback is to "train" the adaptive filter (perform LMS adaptation) in a local area *for every single pixel position*. Specifically, for each pixel position, a dedicated filter is derived by letting the LMS algorithm run in a causal local area such as that depicted in Fig 2 (h is the number of rows above the current pixel). In this way, the causal filter adapts to the local features of the image and is capable to perform very efficient prediction. This approach guarantees better convergence of the adaptive filter to the locally optimal filter, and thus yields superior decorrelation efficiency. However, the amount of computational load increases considerably since the steps given by equations (1),(2),(3) have to be repeated $h(2h+1)+h = 2h(h+1)$ times for each pixel position.

During the decoding process, all pixel intensities in the causal window of fig. 2 are recovered, and thus the decoder is able to duplicate the training and derive the same optimal filter that was used by the encoder for the decorrelation of the current pixel.

3. ENTROPY CODING OF PREDICTION RESIDUALS

For the coding of the error coefficients produced by the decorrelation method of the previous section, an entropy coder combining many features was implemented.

Initially, the image is divided into 8×8 blocks. The variance of each block is computed and then, using an adaptively selected threshold, the block is classified to one of two *activity* classes. Specifically, blocks having variance greater than the mean variance of all image blocks are classified as high-activity blocks. Otherwise, they are classified as low-activity blocks. The bits specifying the activity class in which each block is clasified are entropy coded and sent as side information to the decoder. For the coding of this information, 4 adaptive arithmetic models are used, and the current block is coded using the model whose index is equal to the number of adjacent high-activity blocks. The coefficients in the two activity classes are coded independently of each other.

The sequence of error coefficients in each activity class is further partitioned into a number of subsequences which consist of symbols having similar statistics. Each subsequence is coded using a separate arithmetic coder i.e. a variety of adaptive probability models are employed. Each coefficient is represented by the magnitude class in which it belongs, its sign and the residual bits specifying its exact magnitude. The magnitude classes used are shown in Table 1. For example a coefficient with a value of -80 is represented by the triad $(10, -, 16)$. The first number in the triad is the class number. Since the coefficient belongs to the 10th class, it is valued between 64-127. The symbol "-" is its sign and the number 16 is the residual difference between the number being depicted and the lowest number in its class: 16=80-64. This representation is similar to that used in

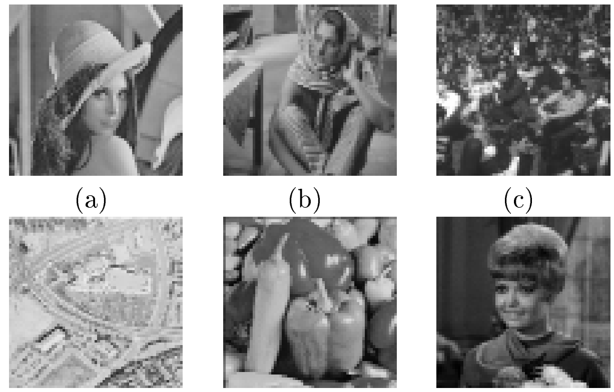
Figure 3: Classification of image blocks of "Lenna" into groups of high and low activity. Grey pixels represent low-activity blocks and black pixels represent high-activity blocks.

Class	magnitude
0	0
1	1
2	2
3	3
4	4
5	5
6	6-7
7	8-11
8	12-31
9	32-63
10	64-127
11	128-255

Table 1: Classes used for the coding of the magnitude information of coefficients

JPEG [9] and the S+P transform [10] for lossless coding, as well as in [11] for lossy compression. The whole range of the coefficients is divided into several classes. Due to the fact that the values of error coefficients are concentrated around zero, more classes are allotted to near-zero magnitudes (Table 1). Some classes (0-5) include only one coefficient magnitude. This means that a coefficient belonging to such a class does not require residual bits for its representation since the class itself identifies the exact magnitude of the coefficient.

Each error coefficient is conditioned using the values of adjacent coefficients. The causal contexts used presume that the exact value of these error coefficients is known i.e. all magnitude class, residual and sign bits of the previously coded coefficients are known. This means that the decoder while decoding the current coefficient has fully recovered past coefficients. In this way, past coefficients that were used as a conditioning context during encoding, are also *explicitly* known by the decoder during the decoding process. This fact makes the formation of modeling contexts more flexible in comparison to lossy coders since in the later case only quantized and not the original coefficient values are known.



(a) (b) (c)

(d) (e) (f)

Figure 4: Images used for the evaluation of the proposed adaptive coders. a) Lenna (512 x 512), b) Barbara (512 x 512), c) Crowd (512 x 512), d) Mall (512 x 512), e) Peppers (512 x 512), f) Girl (256 x 256).

4. EXPERIMENTAL RESULTS

The efficiency of the proposed method for lossless coding was evaluated using the gray scale images of fig. 4. The algorithms compared were a collection of context-based lossless coding algorithms inlcuding JPEG-LS [6] and CALIC [5] which is widely considered to represent the state-of-the-art in this area. In conjunction with the efficient conditional arithmetic coding strategy described in Section 3, the adaptive decorrelation algorithms presented in this paper form complete lossless compression methods. Three adaptive algorithms are evaluated, having training windows of dimension h = 5, 8, 16. The lossless compression performance of the adaptive scheme in terms of exact bitrates is reported in Table 2. As seen from this table, the LMS-based schemes are seen to be generally equivalent to the CALIC and JPEG-LS coders. The performance of the adaptive schemes can be further improved if more complicated entropy coding is used.

5. CONCLUSIONS

In this paper we examined the application of adaptive filters for lossless image coding. We presented novel

Image	CALIC	J-LS	LMS5	LMS8	LMS16
Lenna	4.11	4.24	4.16	4.14	4.10
Barbara	4.45	4.86	4.42	4.35	4.28
Crowd	3.76	3.91	3.85	3.85	3.85
Mall	4.76	4.94	4.86	4.85	4.84
Peppers	4.42	5.51	4.49	4.47	4.45
Girl	4.50	4.62	4.52	4.53	4.53

Table 2: Comparison of the proposed adaptive prediction scheme with state-of-the-art lossless compression coders.

adaptive coders based on the Least Mean Squares algorithm and we compared them to some classical context-based techniques for image coding. Experimenatal evaluation showed that locally adaptive techniques for image coding are able to remove very efficiently the redundundancy between adjacent pixels. However, the performance achieved comes at the expence of higher computational cost, especially when large training windows are used. The promising performance of adaptive coders requires further investigation that will enable faster implementation.

6. REFERENCES

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