ADAPTIVE FILTER BANKS FOR LOSSLESS IMAGE COMPRESSION

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ABSTRACT

A subband decomposition based lossless image compression algorithm based on adaptive is described. The decomposition is achieved by a two-channel adaptive filter bank. The resulting coefficients are lossy coded first, and th en the residual error between the lossy and error free coefficients are compressed. The locations and the magnitudes of the nonzero coefficients are encoded separately by a hierarchical enumerative coding method. The locations of the nonzero coefficients in children bands are predicted from those in the parent band. The proposed compression algorithm, on the average, provides higher compression ratios than the state-of-the-art methods.

1. INTRODUCTION

Lossless compression of images is required in many practical applications including medical and space imaging for archivingor transmission. Early lossless image coders including the JPEG lossless mode are based on the DPCM. Wu and Memon improved DPCM schemes by using adaptive prediction and context modeling in CALIC [13]. In [9], an efficient progressive lossless compression is achieved by introducing S+P transform, a subband decomposition scheme, and an embedded entropy coding. In [1, 2], *P*erfect *R*econstruction *F*ilter *B*anks (PRFB) employing adaptive LMS filters are introduced for subband decomposition, and they are used for lossy image compression in [2, 5]. In this paper, we use the adaptive PRFB structure in a lossless image compression algorithm and propose to code the subband coefficients by an extension of the method developed in [4] which exploits the multiresolution structure of the subband decomposition/wavelet transform.

2. LMS ADAPTIVE PREDICTION FILTER BANKS

The concept of the adaptive filterbanks are introduced in [6, 7, 8]. Classical adaptive prediction concepts are combined with the PRFB in [1, 2] where the key idea is to decorrelate the polyphase components of the multichannel structure by using an adaptive predictor P as shown in Figure 3. Adaptation of the predictor coefficients are carried out by the *L*east *M*ean *S*quare (LMS) algorithm, and this helps to cope with unstationary behavior of the input data. In Figure 3, $x_1(n)$ is the downsampled version of the original signal, $x(n)$, thus it consists of the even samples of $x(n)$. Similarly, the signal $x_2(n)$ consists of the odd samples. An LMS based FIR predictor of $x_2(n)$ from $x_1(n)$ can be expressed as

$$\hat{x}_2(n) = \mathbf{w}(n)\mathbf{x}_1^T(n), \tag{1}$$

where $\mathbf{x}_1(n) = [x_1(n-N), \dots, x_1(n+M)]^T$ is the observation vector, and $\mathbf{w}(n)$ is the vector of predictor coefficients which is adapted by the equation

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu \frac{\mathbf{x}_1(n)e(n)}{\| \mathbf{x}_1(n) \|^2}, \tag{2}$$

where the error signal $e(n)$ is given by

$$e(n) = x_2(n) - \hat{x}_2(n). \tag{3}$$

The subband decomposition structure shown in Figure 3 compacts the most of the energy in the lowest resolution band, and the resulting subsignals are expected to be decorrelated. A weakness of the structure shown in Figure 3 is that the subsignal $x_1(n)$ may suffer from aliasing due to downsampling. Aliasing affects the quality of prediction especially when further decompositions over $x_1(n)$ are carried out. In order to eliminate this problem an anti-aliasing filtering stage is introduced in [2],where $x(n)$ is lowpass filtered by a halfband filter of the form

$$H_l(z) = \frac{1}{2}[1 + z^{-1}A(z^2)]. \tag{4}$$

which are widely used in classical PR filter bank design [12]. With the use of the so-called “noble identity” [12], the lowpass filtering operation can be carried out after downsampling as shown in Figure2. For example, if

$$H_l(z) = 0.25z + 0.5 + 0.25z^{-1},$$

then the polynomial,

$$A(z) = (1 + z^{-1})/2.$$

In the filterbank structure of Figure 2, the subsignal $x_2(n)$ is adaptively predicted using $x_l(n)$ which is a smoothed version of $x_1(n)$.The above adaptive PRFB structures are extended to two dimensions in a separable manner.

3. APPLICATION TO LOSSLESS IMAGE COMPRESSION

The decomposition structure in Figure 2 is used for lossless image compression as follows: input image is decomposed into multiresolution bands by consecutive row-wise and column-wise operations. In order to obtain integer valued coefficients, both the predictor output and the low resolution coefficients $\mathbf{x}_l$, are rounded to the nearest integer at each stage. This rounding operation makes the perfect reconstruction of $\{\mathbf{x}_1\}$ impossible. It is experimentaly observed that transmitting the error between $\{\mathbf{x}_1\}$ and $\{\hat{\mathbf{x}}_1\}$ is generally costly. To overcome this problem, we apply quantization to $\{\mathbf{x}_l\}$ and transmit the quantized coefficients first. The decoder reconstructs $\{\hat{\mathbf{x}}_1\}$ by using $Q(\{\mathbf{x}_l\})$,where Q denotes quantization. Then, we transmit the residual error between $\{\mathbf{x}_1\}$ and $\{\hat{\mathbf{x}}_1\}$.

Both the subband decomposition coefficients and the residual error exhibit a multiresolution structure and energy compaction similar to the quantized wavelet coefficients of an image. Thus, any method designed for efficiently encoding the quantized wavelet coefficients of an image can be employed in encoding the subband decomposition coefficients and the residual error. The method we use is adopted from the encoding method proposed in [4]. Both the decomposition coefficients and the residual error are organized into subbands, and the subbands are encoded in order, starting from the lowest resolution subbands. Encoding of each subband proceeds as follows (The items of the subbands, either decomposition coefficient or residual error, will be referred to as ’coefficient’ in the following description):

- The 2-D subband is adaptively scanned into two 1-D arrays, one for the coefficients that are likely to be nonzero, and one for the rest. This idea was adopted from [11] in [4]. The adaptive scanning algorithm is reversible, so the decoder is able to reconstruct the subband after decoding the two 1-D arrays. The scanning algorithm of [4] uses the magnitudes of the parent subband coefficients as well as recursive region growing to determine the scanning order. The coefficients which are more likely to be nonzero are scanned earlier.
- The magnitudes of the resulting 1-D arrays can be modelled as more-or-less locally stationary sequences, and thus the bitplanes of the coefficient magnitudes as locally stationary binary sequences. Hierearchical Enumerative Coding (HENUC) [3] is an entropy coding algorithm which has been shown to compress locally stationary binary sequences efficiently, and it is simpler than arithmetic coding. So, the bitplanes of the two 1-D arrays are entropy coded by HENUC. In [4], HENUC was proposed for encoding the significance maps (i.e. zero/nonzero information) only; whereas we use it for encoding the magnitudes as well.
- For each nonzero coefficient, the associated sign information must be sent as well. The signs of the nonzero coefficients are sent uncompressed.

Hence, both are coded by using the method in [4], which was developed for lossy coding of the wavelet transform coefficients. The method of [4] is an improved version of the scheme in [11]. Its two most important features are scanning the coefficients of a band by magnitude preference, and employment of hierarchical enumerative coding [3] instead of arithmetic coding.

4. EXPERIMENTAL RESULTS

We used six 512×512 images and two 256×256 images, *House* and *Cameraman*, for testing our algorithm. The prediction neighborhood of a pixel is depicted in Figure 1. We check the variances of left diagonal neighborhood $\{d1, d2, d3\}$, right diagonal neighborhood $\{d4, d5, d6\}$, and horizontal neighborhood $\{h1, h2, h3, h4\}$ of the pixel to be predicted (shaded in Figure 1), and use the one with minimum variance if its variance does not exceed a threshold. Otherwise, we use the neighborhood $\{d2, n1, d5, h3, h4, d6\}$. Note that the neighborhood is still causal although $n1$ and $h2$ are pixels from $\mathbf{x}_2$. The bitrate results in Table 1 show that the proposed algorithm, on the average, achieves better performance than lossless JPEG [10], S+P [9], and CALIC [13] codecs.

5. CONCLUSIONS

A lossless image compression algorithm using multiresolution decomposition by LMS adaptive PRFB is proposed. The algorithm primarily transmits lossy coefficients and then transmits the residual error. The locations of the nonzero coefficients in children bands are predicted from those in the parent band through morphological dilation. Both the location and the magnitude information are entropy coded by hierarchical enumerative coding.The proposed compression algorithm, on the average, achieves better bit rate efficiency than that of the state-of-the-art lossless codecs, while proposing progressive transmission.

6. REFERENCES

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Fig. 1. Prediction neighborhood in column-wise processing

	d1				d4
		d2	n1	d5	
h1	h2	h3		h4	
		d6		d3	

Table 1. Bit rate results for different lossless compression methods.

Images	JPEG	S+P	CALIC	proposed method
Lenna	4.71	4.18	4.12	3.96
Mandrill	6.38	5.93	5.88	5.52
Harbour	5.23	4.73	4.44	4.64
Doex	5.59	4.18	3.79	3.81
House	4.95	4.22	4.00	3.57
Cameraman	5.51	4.48	4.19	3.83
Barbara	5.58	4.69	4.63	4.59
Goldhill	5.65	4.75	4.63	4.51

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Fig. 2. Filter bank structure with an antialiasing filter.

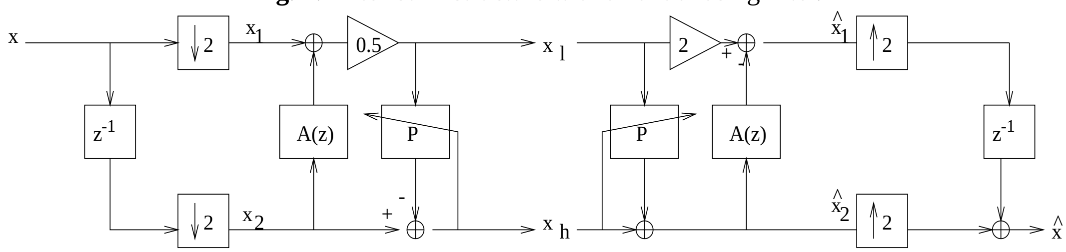

Fig. 3. Analysis and synthesis stages of the 2-channel adaptive filter bank structure.

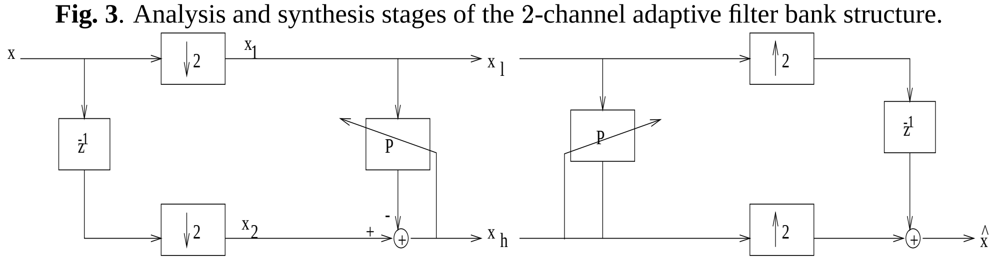

Fig.2. Adaptive −lter bank structure with an antialiasing −lter.