ADAPTIVE SCANNING METHODS FOR WAVELET DIFFERENCE REDUCTION IN LOSSY IMAGE COMPRESSION

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ABSTRACT

This paper describes methods for adapting the scanning order through wavelet transform values used in the Wavelet Difference Reduction (WDR) algorithm of Tian and Wells. These new methods are called Adaptively Scanned Wavelet Difference Reduction (ASWDR). ASWDR adapts the scanning procedure used by WDR in order to predict locations of significant transform values at half thresholds. These methods retain all of the important features of WDR: low-complexity, region of interest, embeddedness, and progressive SNR. They improve the rate-distortion performance of WDR so that it is essentially equal to that of the SPIHT algorithm of Said and Pearlman when arithmetic compression is not employed. When arithmetic compression is used, then the rate-distortion performance of the ASWDR algorithms is only slightly worse than SPIHT. The perceptual quality of ASWDR images is clearly superior to SPIHT.

1. INTRODUCTION

This paper describes methods for adapting the scanning order used in the Wavelet Difference Reduction (WDR) algorithm of Tian and Wells [1]. These new methods improve both the rate-distortion performance and the perceptual quality of the compressed images produced by WDR, while retaining its desirable features [such as low complexity, region of interest capability, embeddedness, and progressive SNR]. We refer to these new algorithms as Adaptively Scanned Wavelet Difference Reduction (ASWDR).

Two ASWDR algorithms will be described. The first algorithm, called ASWDR1, adapts the scan order through wavelet transform values using a parent/child and sibling prediction procedure (sig. parent implies sig. children and sig. value implies sig. siblings at half thresholds). The second algorithm, called ASWDR2, modifies the prediction scheme of ASWDR1 by using a weighted linear prediction function (based on a set of context values) to predict significant values at half thresholds.

Both of these algorithms improve the rate-distortion performance of WDR. They have a performance essentially equal to the performance of Said and Pearlman's SPIHT algorithm [2] when arithmetic compression is not used. Although SPIHT has better rate-distortion performance when arithmetic compression is used, the perceptual quality of SPIHT images at low bit rates is clearly worse than either WDR or ASWDR images. ASWDR images are slightly better perceptually than WDR images. An objective measure, edge correlation, will be used to quantify these improved perceptual qualities.

2. TEST RESULTS

We shall compare the performance of WDR, ASWDR1, ASWDR2, and the SPIHT algorithm of Said and Pearlman [2], in compressing the 8 bpp test images *Airfield, Lena, Goldhill,* and *Barbara.* (Airfield was obtained from [3], and the other three images were obtained from [4].) In Table 1 we list average PSNR values for all these algorithms at three different bit rates: 0.5 bpp, 0.25 bpp, and 0.125 bpp. These bit rates represent a fairly wide range of compression ratios from low to high compression. The data in Table 1 show that when arithmetic compression is *not* employed, then both ASWDR1 and ASWDR2 are equal in performance to SPIHT, while WDR is just slightly worse. But, when arithmetic compression is employed, then SPIHT produces the highest PSNR values. This points to the need for further research on the best model for performing arithmetic compression with ASWDR and WDR.

PSNR values, however, are not always a reliable criteria for image fidelity. In Fig. 1, we show compressions of Barbara at 0.25 bpp. All observers of these images preferred the ASWDR1 and WDR images over the ones produced by SPIHT. The SPIHT compression has severely distorted Barbara's left eye and erased large parts of the striping on the tablecloth. The ASWDR1 and WDR compressions are more difficult to distinguish. The ASWDR1 image does preserve some fine details which WDR erases or distorts, we show this in the bottom two figures. Preservation of de-

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Error\Method	WDR	ASWDR1	ASWDR2	SPIHT
0.5 bpp				
PSNR	31.76	32.03	31.97	32.06
PSNR, AC	31.99	32.22	32.19	32.51
Edge Corr	0.92	0.92	0.92	0.86
Edge Corr, AC	0.92	0.92	0.92	0.88
0.25 bpp				
PSNR	28.87	29.04	29.02	29.06
PSNR, AC	29.02	29.21	29.18	29.45
Edge Corr	0.79	0.81	0.80	0.74
Edge Corr, AC	0.80	0.81	0.81	0.76
0.125 bpp				
PSNR	26.45	26.59	26.55	26.57
PSNR, AC	26.57	26.74	26.73	26.92
Edge Corr	0.64	0.65	0.65	0.58
Edge Corr, AC	0.65	0.67	0.67	0.61

Table 1. Average PSNR and edge correlation values for four images, at three bit rates (0.5, 0.25, and 0.5 bpp) for 8 bpp originals. (AC denotes the use of arithmetic compression.)

tails at low bit rates is a vital property for applications such as remote medical diagnosis via rapid transmission of compressed images.

As an objective measure of preservation of edge detail (which seems to better correspond to subjective quality ratings than PSNR), we use *edge correlations.* To produce an image that retains only edges, we do the following. A high-pass filtered image is created by subtracting away the all-lowpass subband from a 3-level Daub 9/7 wavelet transform of an image (and then the remainder is inverse transformed). This is done for both the original image and a compressed version. Both of these highpass filtered images have mean values that are approximately zero. We define the *edge correlation* γ by

$$\gamma = \frac{\sigma_c^2}{\sigma_o^2}$$

where σ_c^2 denotes the variance of the values of the highpass filtered version of the compressed image, and σ_o^2 denotes the variance of the values of the highpass filtered version of the original image. Thus γ measures how well the compressed image captures the variation of edge details in the original image.

We list these edge correlations in Table 1. These data show that the ASWDR algorithms are the best, with WDR a close second, and SPIHT last. These results correspond well with subjective ratings of the compressed images.

3. DESCRIPTION OF ASWDR1

The ASWDR1 algorithm is a simple modification of the WDR algorithm ([1], [5]). Here is a 7-step procedure for performing ASWDR1 on a grey-scale image:

Step 1. Perform a wavelet transform of the image. We used a 7-level Daub 9/7 transform.

Step 2. Choose a *scanning order* for the transformed image, whereby the transform values are scanned via a linear ordering, say

$$x[1], x[2], \ldots, x[M]$$

where M is the number of pixels. In [1] and [5], the scanning order is a zig-zag through subbands from lower to higher [6]. Row-based scanning is used in the low-pass/high-pass subbands and column-based scanning is used in the high-pass/low-pass subbands.

Step 3. Choose an initial threshold, T, such that at least one transform value has magnitude less than or equal to T and *all* transform values have magnitudes less than $2T$.

Step 4 (Significance pass). Record positions for *new* significant values: new indices m for which $|x[m]|$ is greater than or equal to the present threshold. Encode these new significant indices using *difference reduction* ([1], [5]) .

Step 5 (Refinement pass). Record *refinement bits* for significant transform values determined using larger threshold values. This generation of refinement bits is the standard bit-plane encoding used in embedded codecs ([6], [2]).

Step 6 (New scan order). Run through the significant values at level j in the wavelet transform. Each significant value, called a *parent* value, induces a set of *child* values—four child values for all levels except the last, and three child values for the last—as described in the quad-tree definition in [2]. The first part of the scan order at level $j-1$ contains the insignificant values lying among these child values. Run through the insignificant values at level j in the wavelet transform. The second part of the scan order at level $j-1$ contains the insignificant values, *at least one of whose siblings is significant,* lying among the child values induced by these insignificant parent values. The third part of the scan order at level $j-1$ contains the insignificant values, *none of whose siblings are significant*, lying among the child values induced by these insignificant parent values. (*Note:* Although this description is phrased as a three-pass process through the level j subband, it can be performed in one pass by linking together three separate chains at the end of the one pass.)

Step 7. Divide the present threshold by 2. Repeat Steps 4–6 until either a bit budget is exhausted or a distortion metric is satisfied.

When decoding, the steps above are recapitulated to produce a quantized output. Finally each quantized value is rounded into the midpoint of the quantization bin that it lies in, and an inverse wavelet transform (followed by rounding to 8-bit integer grey levels) produces the decompressed image.

4. DESCRIPTION OF ASWDR2

The ASWDR2 algorithm utilizes a different version of Step 6 above. This alternate version of Step 6 consists of testing whether an insignificant child value is likely to be significant. The test is to use related values defined in [7]: For vertical and horizontal subbands these values are (Up), (Left), (Parent), (Diag. Cousin), and for diagonal subbands they are (Up), (Left), (Parent), (Horiz. Cousin), and (Vert. Cousin). A predicted magnitude m for the child value is computed by: $m = \sum_k w_k Q_k$, where Q_k are magnitudes of the related values and w_k are *weights.* For our (preliminary) version of ASWDR2, we used the following weights:

Horizontal and Vertical
$w_{\rm U} = 0.5, w_{\rm L} = 0.5, w_{\rm P} = 0.5, w_{\rm DC} = 0.5$

Diagonal
$w_{\rm U} = 0.5, w_{\rm L} = 0.5, w_{\rm P} = 0.5, w_{\rm HC} = w_{\rm VC} = 0.25.$

Although these weights were chosen blindly, they still produced essentially the same results as the ASWDR1 algorithm. Further research is needed in order to produce a better set of weights (most probably weights that depend on level as well as subband), using minimization of an error metric (such as least squares, as described in [7]) over a set of test images.

5. LOSSLESS COMPRESSION

Using an integer-to-integer wavelet transform [8] in Step 1, these ASWDR algorithms can be converted to *lossless* compression algorithms. In Table 2 we compare ASWDR1 (using the 2+2,2 transform [8] and arithmetic compression) with the $\rm S + P$ algorithm [9]. As with the lossy case, the ASWDR1 algorithm is better in preserving details (as measured by edge correlations) at the cost of poorer PSNR results. Unlike the $\rm S + P$ algorithm, however, the ASWDR1 algorithm enjoys the ROI capability.

Image\Method	S + P	ASWDR1
PSNR		
Barbara, 0.25 bpp	26.77	26.16
Lena, 0.25 bpp	33.46	32.85
Edge Corr.		
Barbara, 0.25 bpp	0.80	0.82
Lena, 0.25 bpp	0.88	0.95
Lossless bpp		
Barbara	4.72	4.80
Lena	4.21	4.27

Table 2. Comparison of the progressive, lossless compression algorithms, $\rm S + P$ and ASWDR1.

6. REFERENCES

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(a) Original (8 bpp)


(b) ASWDR1 (0.25 bpp)


(c) SPIHT (0.25 bpp)


(d) WDR (0.25 bpp)


(e) ASWDR1 (0.25 bpp)


(f) WDR (0.25 bpp)

Fig. 1. Compressions of Barbara image.