REAL-TIME IMAGE WAVELET CODING FOR LOW BIT RATE TRANSMISSION

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Abstract: Embedded coding for progressive image transmission has recently gained popularity in image compression community. However, current progressive wavelet-based image coders tend to be complex and computationally intense requiring large memory space. The encoding process usually sends information on the lowest-frequency wavelet coefficients first. At very low bit rates, images compressed are therefore dominated by low frequency information, where high frequency components belonging to edges are lost leading to blurring the signal features. This paper presents a new image coder for real-time transmission, employing edge preservation based on local variance analysis to improve the visual appearance and recognizability of compressed images. The analysis and compression is performed by dividing an image into blocks. Lifting wavelet filter bank is constructed for image decomposition and reconstruction with the advantages of being computationally efficient and boundary effects minimized. A modified SPIHT algorithm with more bits used to encode the wavelet coefficients and transmitting fewer bits in the sorting pass for performance improvement, is used to reduce the correlation of the coefficients at scalable bit rates. Local variance estimation and edge strength measurement can effectively determine the best bit allocation for each block to preserve the local features. Experimental results demonstrate that the method performs well both visually and in terms of quantitative performance measures, and offers error resilience feature that is evaluated using a simulated transmission channel with random error.

1 INTRODUCTION

The advent of multimedia computing has led to an increased demand for digital images (Hilton et al., 1994). The transmission of digital images is rapidly becoming popular on mobile telephones, personal digital assistant (PDA) technology and other wireless based image service. However, transmitting digital images via mobile device is often subject to bandwidth or cost constraints which are incompatible with high data rates. The demand for better quality images, means that effective and fast data compression techniques are essential for real-time transmission. In order to obtain the required degree of compression, lossy coding techniques have to be utilized (Pearlman, 2001). The current lossy JPEG image compression standards enjoy success due to its low complexity in implementation and its reasonable performance. However, when high compression ratio is needed (i.e., at lower bit rates), annoying blocking artifacts appear. The development of the lapped orthogonal transform (LOT) (Malvar, 1992) and its generalized version GenLOT (de Queiroz et al., 1996) helps solve the blocking problem to a certain extent at the price of increasing computational complexity.

More recently, the wavelet transform has emerged as a cutting edge technology, within the field of image compression. Wavelet-based coding (Vetterli and Kovacevic, 1995) provides substantial improvements in picture quality at higher compression ratios (Meyer et al., 2002; Claypoole et al., 2003; Rajpoot et al., 2003). The introduction of the embedded zero-tree concept (Shapiro, 1993) for wavelet-based image compression has generated a significant improvement in performance. In recent years embedded coding has gained popularity in image compression community due to its simplicity, high performance and nice properties. Some representative works of embedding include the embedded zerotree wavelet coding (EZW) (Shapiro, 1993), the set partitioning in hierarchical trees (SPIHT) (Said and Pearlman, 1996), the embedded block coding with optimized truncation (EBCOT)

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(Taubman, 2000), and set partitioning embedded bloCK (SPECK) (Pearlman, et al., 2004). EBCOT was adopted as the basic algorithm in the JPEG 2000 image compression standard (Adams, 2002), which is a fairly complex and computationally intense procedure. The ability to adjust the compression ratio by simply truncating the coding bitstream makes embedding very attractive for a number of applications such as progressive image transmission and low delay image communication (Li and Lei, 1999). However, current progressive wavelet-based image coders tend to send information on the lowest-frequency wavelet coefficients first (Schilling and Cosman, 1999). Such images have most of their energy in the low frequency bands. In wavelet domain, the energies of high frequency coefficients are mainly concentrated around edges in an image (Ye et al., 2004). In lossy image compression, most high frequency part of the image will be removed. The removal causes the edges of the image to be blurred (Lay and Wang, 2005). At very low bit rates, images compressed by these coders are therefore dominated by low frequency information, where high frequency components belonging to edges are lost leading to blurring the signal features. These effects combine to hamper recognition of objects in the images. This paper presents a fast image coder with error resilience by block processing and employing edge preservation based on local variance analysis to improve the visual appearance and recognizability of compressed images at very low bit rates.

2 LIFTING WAVELET FILTER BANK

Over the last decade wavelets have been applied successfully in many diverse fields. The need for improvement of wavelets comes from a shortcoming that is inherent because of its construction. Second generation wavelets named when the concept of lifting was introduced (Sweldens, 1996; Sweldens, 1998), open a new direction to construct wavelets which are not necessarily translates and dilates of one fixed function. The lifting scheme makes optimal use of similarities between the high and low pass filters so as to achieve a faster implementation of wavelet transform (WT). The flexibility afforded by the lifting scheme allows the basis functions associated with wavelet coefficients near a window's boundaries to change their general shape at the boundaries. In this manner, a basis function more accommodating to a boundary can be used to minimize boundary effects.

Classical implementation of WT uses two band filter bank with recursion on its low pass (LP). This can be represented by its equivalent polyphase matrix $\tilde{P}(z)$, which is assembled from even and odd filter components. With $\det[P(z)] = 1$, it always exist factorisation of $P(z)$ (Daubechies and Sweldens, 1998):

$$P(z) = \begin{bmatrix} K & 0 \\ 0 & \frac{1}{K} \end{bmatrix} \prod_{i=m}^{1} \left\{ \begin{bmatrix} 1 & s_i(z) \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ t_i(z) & 1 \end{bmatrix} \right\} \tag{1}$$

Equation (1) allows ladder realization of $\tilde{P}(z)$ by reversible lifting steps followed with normalization by factor K as shown in Figure1.

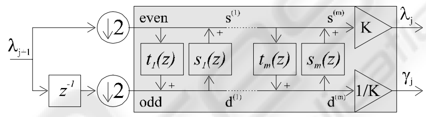


Figure 1: Ladder structure of lifting steps.

Signal is partitioned into even and odd components that are then mutually predicted by t_i and updated by s_i. After normalization the algorithm is recursively applied to LP part. Based on the structure of one dimensional (1D) wavelet transform, two dimensional (2D) lifting steps that can be used for predict/update steps on lattices, can then be built. The algorithm developed uses weighted coefficients of lifting factorisation of 1D prototype transform, but replacing 1D neighborhoods by 2D rings (Vargic, 1998). Weight w_i for lifting coefficient depends on number of pixels in actual ring:

$$w_i = \frac{2}{number\ of\ pixels\ in\ i{-}th\ ring} \tag{2}$$

Thus 2D version of forward predict/update steps can be expressed as follows:

$$\begin{aligned} d_{x,y}^{(st)} &= d_{x,y}^{(st)} + \sum_k \alpha_k^{(st)} w_k \sum_j ring_{k,j}\left\{d_{x,y}^{(st)}\right\} \\ s_{x,y}^{(st)} &= s_{x,y}^{(st)} + \sum_k \beta_k^{(st)} w_k \sum_j ring_{k,j}\left\{s_{x,y}^{(st)}\right\} \end{aligned} \tag{3}$$

where st = 1…m (m is number of predict/update steps), $ring_{k,j}\{center\}$ is 2D neighborhood operator which returns value of j-th point in k-th neighborhood of $center$, $\alpha_k^{(st)}$ and $\beta_k^{(st)}$ are lifting coefficients associated with actual predict/update step and k-th neighborhood of $center$, w_k is weight for k-th ring. Thus 2D versions of biorthogonal filters can be constructed. To implement them, the parameters $\alpha_k^{(st)}$ and $\beta_k^{(st)}$ need to be derived. In this study, symmetric biorthogonal wavelet is required for perfect reconstruction. Thus 9/7 filter pair for fast computation can be used. This filter pair is smooth and relatively short. The analysis low pass filter has 9 coefficients, while the synthesis high pass filter has 7 coefficients. The mathematical property of symmetry and compact support with 4 vanishing moments in both analysis and synthesis high pass filters, provides the advantages of 9/7 filter bank over other wavelet families in many applications. The factoring process of 9/7 filter pair starts from the analysis filter

$$\tilde{h}_e(z) = h_4(z^2 + z^{-2}) + h_2(z + z^{-1}) + h_0$$
$$\tilde{h}_o(z) = h_3(z^2 + z^{-1}) + h_1(z + 1) \qquad (4)$$

The lifting coefficients can be computed as

$$r_0 = h_0 - 2h_4h_1/h_3, \quad r_1 = h_2 - h_4 - h_4h_1/h_3,$$
$$s_0 = h_1 - h_3 - h_3r_0/r_1, \quad t_0 = r_0 - 2r_1$$

The 2D wavelet filter bank can then be implemented with boundary effects minimized by changing wavelet shape for handling filtering near the boundaries using:

$$\alpha_1^{(1)} = h_4/h_3, \quad \beta_1^{(1)} = h_3/r_1 \quad \alpha_1^{(2)} = r_1/s_0, \quad \beta_1^{(2)} = s_0/t_0, \quad K = t_0$$

3 EMBEDDED CODING

The wavelet transform (WT) provides an efficient representation of image data for compression. The structure of spatial orientation trees by wavelet decomposition is shown in Figure2 with LH1, HL1, HH1 in the highest frequency band. WT localizes signal energy in both frequency and spatial domains, and large wavelet coefficients in different frequency subbands tend to be produced at the same spatial location. This correlation can be reduced by a modified SPIHT algorithm.

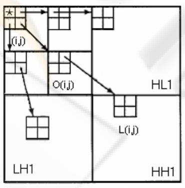


Figure 2: Spatial orientation trees.

3.1 Modified SPIHT

SPIHT (Said and Pearlman, 1996) builds on the principle that spectral components with more energy content should be transmitted. It is provided with an order of the coefficients defined in the form of trees as shown in Figure2, where $O(i,j)$={the 4 offspring of coordinates $\{(i,j)\}$}, $L(i,j) = D(i,j) - O(i,j)$, $D(i,j)$={all descendants of coordinates $\{(i,j)\}$}. The algorithm employs a number of linked lists (LIP-list of insignificant pixels, LSP-list of significant pixels, LIS-list of insignificant sets) which are manipulated according to a significance test that is at first applied to sets and then eventually to individual coefficients. The algorithm tests available coefficients and sets of coefficients to determine if those coefficients whose magnitudes are greater than the threshold 2^n. The encoder output consists of sorting information that is required to identify the significant coefficients with respect to an actual bitplane and refinement information for enhancing the accuracy of significant coefficients. To save bits for encoding coefficients, a modified SPIHT is developed by simplifying the header stream and transmitting fewer bits in the sorting pass. In the header stream, the logarithm of the maximum value of wavelet coefficients ($n_{max} = \log_2(\max_{\{(i,j)\}}\{|d(i,j)|\})$) is calculated and rounded into integer to allocate bits for coding at the beginning of the encoder output bitstream. Information such as the matrix dimension and the number of wavelet decomposition levels, is set to reside in the encoding and decoding algorithm, so that more bits can be used for coefficient coding. The reconstruction quality level thus is increased with more bits containing signal information. In the sorting pass, the maximum values of coefficients in logarithm at $O(i,j)$ and $L(i,j)$ are calculated as $n_O = \log_2(\max_{\{(i,j)\}}\{|O(i,j)|\})$, $n_L = \log_2(\max_{\{(i,j)\}}\{|L(i,j)|\})$. The significant tests compare n with n_O and n_L. If n is greater than n_O and n_L, then it is not necessary to check $O(i,j)$ and $L(i,j)$ because they are insignificant. In the case when at least one of the coefficients at $O(i,j)$ is significant but all coefficients at $L(i,j)$ are not, the sorting pass can be improved by transmitting fewer bits. The procedure of the modified SPIHT is as follows:

(1) Initialization: output $n = \log_2(\max_{\{(i,j)\}}\{|d(i,j)|\})$

LSP={}

LIS={$(i,j) \mid (i,j)$ has descendants and is in the lowest level subband}

LIP={$(i,j) \mid (i,j)$ is in the lowest level subband}

$n_O = \log_2(\max_{\{(i,j)\}}\{|O(i,j)|\})$

$n_L = \log_2(\max_{\{(i,j)\}}\{|L(i,j)|\})$

(2) Sorting Pass:

LIP-processing

For each $\{(i,j)\}$ in LIP:

if $\{(i,j)\}$ is significant
output 1 and the sign of the coefficient then move $\{(i,j)\}$ to LSP.
else
output 0.
LIS-processing
For each $\{(i,j)\}$ in LIS:
if $\{(i,j)\}$ is significant
process the children of $\{(i,j)\}$ differently depending on n_o and n_L.
else
ouput 0

(3) Refinement Pass:
output the *n*-th bit of the coefficients in LSP added prior to this round.

(4) Quantization-step Update:
decrement *n* by 1 and repeat step (2) to (4).

3.2 Bit Allocation and Error Resilience

The modified SPIHT is used to reduce the correlation of wavelet coefficients and encode the data into bit streams. As images from different categories tend to show different spatial domain characteristics. An area with the smallest variation represents a homogeneous region, while regions containing edges will have a higher variance than more homogeneous regions. In order to improve the visual appearance and recognizability of compressed images at very low bit rates, an image can be divided into 64 x 64 pixel blocks (large images can have bigger block sizes), and each block can be transformed into wavelet domain. Local variance estimation and edge strength measurement can be used to effectively determine the best bit rate allocation for each block to preserve the local features of the original image corresponding to the boundaries of the objects by assigning more bits for blocks with higher variance and edge strength. To take advantage of local analysis, block size tends to be small. However too small size does not allow wavelet decomposition in enough levels required by wavelet based image compression. The size of 64 is a balance having maximum 5-level spatial-frequency decomposition. Local variance and edge analysis is based on the block in wavelet and image domain. The development of lifting wavelet filter bank for spatial-frequency decomposition and reconstruction of images, not only speeds up the calculation, but also minimises the boundary effects. This allows local variance and edge analysis to be performed for bit allocation. For a given block *j* the bit allocation factor can be expressed as:

$$\lambda_j = \varepsilon \hat{\sigma}_x \quad (5)$$

where ε is the measure of the image edge strength , $\hat{\sigma}_X{}^2$ is the local estimated signal variance on the subband considered. The noise variance is estimated as the median absolute deviation of the diagonal detail coefficients on level 1 (highest frequency subband HH_1 32 x 32 block) (Chang et al., 2000):

$$\hat{\sigma} = \frac{Median(|W_{ij}|)}{0.6745}, W_{ij} \in subband\ HH_1 \quad (6)$$

The estimate of the signal standard deviation is

$$\hat{\sigma}_X = \sqrt{\max(\hat{\sigma}_W{}^2 - \hat{\sigma}^2, 0)} \quad (7)$$

where $\hat{\sigma}_W{}^2 = \frac{1}{n^2}\sum_{i,j=1}^{n} W_{ij}{}^2$, $\hat{\sigma}_W{}^2$ is an estimate of the variance of the observations, with $n \times n$ being the size of the wavelet coefficients on the subband under consideration. In case $\hat{\sigma}^2 \geq \hat{\sigma}_W{}^2$, all coefficients from the subband are set to zero. The local edge strength is measured by using image gradient (Saha and R. Vemuri, 2000):

$$\varepsilon = \frac{1}{64*64}\left[\sum_{i=1}^{63}\sum_{j=1}^{64}|f(i,j) - f(i+1,j)| - \sum_{i=1}^{64}\sum_{j=1}^{63}|f(i,j) - f(i,j+1)|\right] \quad (8)$$

where $f(i,j)$ is image pixel value. The measure indicates how busy the image is in terms of the number of edges and contours in it.

Variance and edge measure are locally computed at each block. The bit allocation for block *j* is

$$B_j = \frac{\lambda_j}{\sum_{j=1}^{M}\lambda_j} B$$

where *B* is the total bit number for all the wavelet coefficients to encode, *M* is the total number of image blocks to divide. Each block is encoded into B_j bits. This allows more bits to be allocated to regions containing edges and having a higher variance, and fewer bits to areas with small variation representing homogeneous regions, such that high frequency components belonging to edges and local features of the original image can be preserved.

To save the bits for transmitting maximum value of wavelet coefficients and bit number for each block, their logarithms are calculated and the differences from the maximum of all the blocks are stored to form an image matrix:

(1) If $2M \leq 64$, the image size is 8x8, padding 0 if data length is not enough.

(2) If $2M \leq 128$, the image size is 8x16, padding 0 if data length is not enough.

(3) If $2M \le 256$, the image size is 16x16, padding 0 if data length is not enough.
(4) If $2M > 256$, using bigger block size

Using the 2D lifting wavelet filter bank and the modified SPIHT, the image can be encoded into 32 bits and transmitted in the header stream. The decoded data will be used for bit allocation for each block to keep the overall bit rate constant.

Error resilience is one of the most desirable properties in real-time transmission applications. Using fast SPIHT embedded coding, it is much easier to design efficient error-resilient schemes (Yang and Cheng, 2000; Alatan et al., 2000) for error protection. This is because with embedded coding the information is sorted according to its importance, and the requirement for powerful error correction codes decreases from the beginning to the end of the compressed data. If an error is detected, but not corrected, the decoder can discard the data after that point and still reconstruct the signal obtained with the bits received before the error. Also, with bitplane coding the error effects are limited to below the previously coded planes. In the face of transmission errors, joint source-channel SPIHT coding scheme for unequal error protection can be easily designed by varying both source coding bit rate and channel coding redundancy with added complexity and delay depending on the channel error degree.

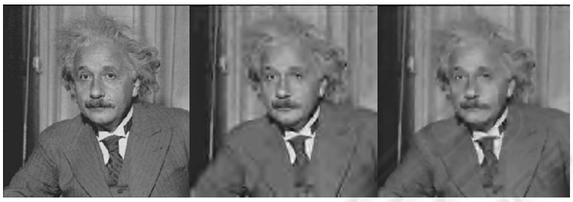
4 EXPERIMENTAL RESULTS AND DISCUSSION

2D lifting wavelet filter bank by changing wavelet shape at the boundaries was developed for fast implementation of spatial-frequency decomposition and reconstruction with boundary effects minimized. A modified SPIHT algorithm is used to encode wavelet coefficients at each block, which gives more efficient implementation both in terms of memory usage and execution time. In some situations, an image may be quite large in comparison to the amount of memory available to the codec. Consequently, it is not always feasible to code the entire image as a single atomic unit. Image tiling reduces memory requirements and allows better bit allocation based on image contents, and since they are also reconstructed independently, they can be used for decoding specific parts of the image instead of the whole image.

To demonstrate the proposed coder, a standard Einstein image was used (with size of 512 x 512 for all the example images). The quality of the compression can be objectively evaluated using the peak signal-to-noise-ratio (PSNR) defined below. For a given reconstructed image $\hat{f}(i,j)$ of image $f(i,j)$, the PSNR on dB scale is

$$PSNR = 10\log_{10}\frac{[\max(f(i,j))]^2}{\frac{1}{IJ}\sum_{i=1}^{I}\sum_{j=1}^{J}(f(i,j)-\hat{f}(i,j))^2}$$

where I,J is the image size.

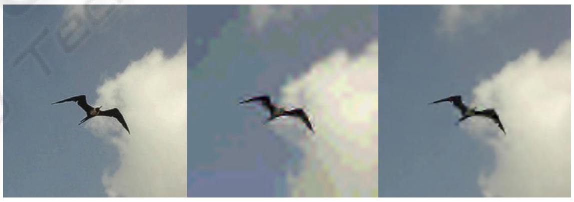


(a) (b) (c)

Figure 3: Einstein image (a) original (b) reconstructed by SPIHT (c) reconstructed by proposed coder.

(a) (b) (c)

Figure 4: Boat image (a) original (b) reconstructed by SPIHT (c) reconstructed by proposed coder .



(a) (b) (c)

Figure 5: Bird image (a) original (b) reconstructed by SPIHT (c) reconstructed by proposed coder .

(a) (b) (c)

Figure 6: Car image (a) original (b) reconstructed by SPIHT (c) reconstructed by proposed coder.

As SPIHT, in the term of compression efficiency versus implementation complexity, is still the most successful image coding method to date, the SPIHT wavelet coder with 9/7 filters and 5-level decomposition is used here as a reference of the state of the art coder. Figure3 shows the reconstructed images using SPIHT coder and the proposed coder by compression at the bit rate of 0.05 bpp (bits per pixel). It can be seen that the decoded SPIHT image is more blurred. Some edges preserved by the proposed coder are lost by the SPIHT algorithm. It is worth noting that, blocking artifacts is not noticeable as block boundary effects are minimized by changing wavelet shape at the boundaries. Table 1 lists the test results of Einstein image at different bit rates (0.01, 0.05, 0.1, 0.25 and 0.5 bpp) in terms of PSNR. Notice that the proposed coder performs better than SPIHT at low bit rates, but when bit rates increase SPIHT performs better. Another standard Boat image with more edges across the image (more difficult to compress) was used for comparison. Figure4 shows the decoded images at 0.08 bpp. It is noted that both coder achieved similar results, although the proposed one performs slightly better. Further examples are given using color images compressed at low bit rates with similar reconstruction quality. Figure5 shows a Bird image with fewer edges across the image and the decoded images at bpp. Figure6 shows a Car image with more edges across the image and the decoded images at 0.12 bpp. For comparison, test results are summarized in Table 2. It can be seen that the proposed coder outperforms SPIHT and the edges are better preserved. The evaluation of the algorithm indicates that the proposed coder outperforms SPIHT at very low bit rates, both visually and in terms of the quadratic error.

Table 1: PSNR (dB) of Einstein image at different bit rates.

Bit Rate (bpp)	SPIHT with 9/7 filters	Proposed Coder
0.01	20.49	20.97
0.05	25.43	26.14
0.1	28.78	28.69
0.25	32.85	32.64
0.5	36.81	35.98

Memory usage is an important issue for image coder, especially for large images and implementation in small devices. The most common method is to partition the image into stripes or tiles and encode these partitions independently. The proposed coder is based on block processing using fast wavelet transform and modified SPIHT and encoding different parts of an image with different bit rates depending on their importance. This allows the encode and decode to be processed in parallel, microscopic parallelism at the level of individual coding passes and more efficient hardware implementations thus can be exploited for real-time applications.

Table 2: PSNR (dB) of Einstein, Boat, Bird, Car image at low bit rates.

Image	Bit Rate (bpp)	SPIHT with 9/7 filters	Proposed Coder
Einstein	0.05	25.43	26.14
Boat	0.08	25.18	25.85
Bird	0.1	25.51	26.32
Car	0.12	25.41	26.19

To evaluate the error resilience features of the proposed codec in the absence of channel coding, the test image was decoded one hundred times each over simulated transmission channel with random errors. Bitstream header is transmitted without errors. The average reconstructed image quality after decompression was evaluated and shown in Table 3. As can be seen, the reconstructed image quality under transmission errors is still high at moderately low error rates (i.e. 10^{-6}) and does not decrease quickly when error rates increase at low bit rates. This is due to the fact that the coder transmits the most important information first for each block, and the decoder can discard the data after that point and still reconstruct the image obtained with the bits received before the error. When the error rate is high, almost all blocks are affected. For a particular bitplane in a block, lower bitplanes may not be decoded and therefore useless, but the whole image can still be reconstructed with some block information missing. In other words, the error resilience of the codec decreases moderately with an increase in error rates. Thus joint source-channel coding scheme for unequal error protection can be designed with added complexity and delay depending on the channel error degree.

Table 3: PSNR in dB corresponding to the average of the test Einstein image by averaging 100 runs of the decoded data when transmitted over a noisy channel with various bit error rates (BER) at low bit rates.

Bit Rate (bpp)	BER (10^{-6})	BER (10^{-5})	BER (10^{-4})
0.01	20.08	19.23	17.96
0.05	24.89	22.78	19.92

5 CONCLUSIONS

Two dimensional (2D) fast lifting wavelet filter bank using lifting steps for predict/update steps on lattices with 2D rings, was developed with the advantages of being computationally efficient and boundary effects minimized by changing wavelet shape for handling filtering near the boundaries. Images from different categories with different spatial domain characteristics thus can be coded by a modified fast 2D SPIHT algorithm with more bits used to encode the wavelet coefficients and transmitting fewer bits in the sorting pass for performance improvement. The compression is performed based on block processing with local variance estimation and edge strength measurement for the determination of the best bit allocation to preserve the local features of the original image corresponding to the boundaries of the objects by assigning more bits for blocks with higher variance and edge strength. Experimental results demonstrate that the proposed image coder is fast with error resilience and provides superior image quality, both objectively and subjectively, at very low bit rates, and is suitable for real-time applications with less memory requirements.

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