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ABSTRACT

In this paper, we present techniques based on multiple wavelet-tree coding for robust image transmission. The algorithm of set partitioning in hierarchical trees (SPIHT) is a state-of-the-art technique for image compression. This variable length coding (VLC) technique, however, is extremely sensitive to channel errors. To improve the error resilience capability and in the meantime to keep the high source coding efficiency through VLC, we propose to encode each wavelet tree or a group of wavelet trees using SPIHT algorithm independently. Instead of encoding the entire image as one bitstream, multiple bitstreams are generated. Therefore, error propagation is limited within individual bitstream. Two methods based on subsampling and human visual sensitivity are proposed to group the wavelet trees. The multiple bitstreams are further protected by the rate compatible puncture convolutional (RCPC) codes. Unequal error protection are provided for both different bitstreams and different bit segments inside each bitstream. We also investigate the improvement of error resilience through error resilient entropy coding (EREC) and wavelet tree coding when channels are slightly corruptive. A simple post-processing technique is also proposed to alleviate the effect of residual errors. We demonstrate through simulations that systems with these techniques can achieve much better performance than systems transmitting a single bitstream in noisy environments.

Keywords: Wavelet tree coding, SPIHT, multiple bitstreams, robust image coding and transmission.

1. INTRODUCTION

Currently there is great interest in developing error-resilient tools and algorithms for image transmission over noisy channels. Early work considered either channel optimized source coding (COSC)[1–3] where quantization design in the source is based on the knowledge of both source model and channel condition, or the source optimized channel coding (SOCC)[4, 5] where the source coding is for the noiseless channel and errors are handled by the channel coding. Recently, joint source and channel coding (JSCC) schemes[6–8] investigate the integration of source coding and channel coding for give channel conditions. These schemes target to allocate the given bit rate between the source coder and the channel coder optimally to achieve the minimum end-to-end distortion. This joint design includes a derivation of an explicit rate-distortion function and an corresponding optimization algorithm. The fixed length source coding is generally adopted in such a joint design due to its easy derivation of the R-D function. Consequently, the source coding efficiency is compromised.

The variable length coding (VLC), as a major component in almost all successful image compression algorithms such as the embedded zerotree wavelet coding (EZW)[9] and the set partitioning in hierarchical trees (SPIHT),[10] however, is difficult to apply to R-D based schemes because its sensitivity to channel noise is hard to formulate explicitly. The error effect caused by a bit flip in a VLC coded bitstream may propagate until to the next synchronization symbol. Recently, there is a strong interest to improve the robustness of the image transmission and in the meantime to keep the source coding efficiency through VLC.

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Based on Shannon's separation coding theorem that an optimized end-to-end system can be designed by separately optimizing the source encoder-decoder pair and the channel encoder-decoder pair, Sherwood and Zeger proposed a scheme[11] that cascades the SPIHT source coder with a rate-compatible punctured convolutional/cyclic redundancy check (RCPC/CRC) channel coder. This scheme has achieved better performance compared with previously designed systems in binary symmetric channels (BSC) with known channel bit error rates (BERs). This improvement mainly comes from exploiting the VLC coding efficiency and the tree structure dependence in the source coder. However, it implicitly requires that the designed channel coder is able to remove all the channel errors. Otherwise, any uncorrected bit error may cause the decoder to discard all subsequent bits even though these bits may be received correctly. This scheme[11] also exhibits lower complexity than previous schemes due to the elimination of the computationally complicated iterative optimization. Because of these performance and complexity advantages, several extended schemes[12, 13] have been proposed and reported good performance in their considered scenario.

Since the SPIHT algorithm encodes and decodes the wavelet coefficients bit-plane by bit-plane, to exploit the different importance of bits in the coded stream, unequal error protection (UEP) has been applied[14] so that bits in different bit-planes are protected with different channel code rates. It has shown significant peak signal to noise ratio (PSNR) improvement over a wide range of channel BERs with a slight performance degradation at the designed channel BER. Schemes[11, 14] use the SPIHT algorithm over the entire image, and consequently, generate one progressive bitstream. As the channel BER increases away from the designed point, the performance drops dramatically once an error occurs in the beginning of the bitstream. For example, the PSNR reduces to less than 25dB when BER increases to 0.05,[14] which suggests a very poor visual quality of the reconstructed images.

In this research, we propose to code an image into multiple bitstreams by using multiple wavelet-tree coding. The coding and decoding of one bitstream is independent of the others. As a result, error propagation effect can be limited within a single bitstream. A good coding process should be able to keep the source coding efficiency as high as possible, and in the meantime, to possess error resilience capability once the channel is corruptive. Based on the relationship between the wavelet coefficients in terms of wavelet-trees and the spatial blocks in the original image, we propose two methods to code the wavelet coefficients into multiple bitstreams. One is based on subsampling so that each coded bitstream is a coarse representation of the original image. The other is based on the human visual sensitivity[15] so that different bitstreams correspond to different image areas such as smooth area, edges or texture area. We adopt the RCPC/CRC as the channel coding method to provide UEP and facilitate a list Viterbi decoding at the receiver. UEP is designed for two levels. First, the bits in a higher bit-plane will be provided with more protection due to their greater contribution to the PSNR. Second, different bitstreams corresponding to different visual quality will be protected differently. The bitstream representing edge information will be protected more than those representing other regions such as texture areas. When channel corruption is slight, we also propose using the error resilient entropy coding (EREC) and the wavelet tree coding to improve the error resilience capability. In addition, exploiting the SPIHT decoding characteristics, we also develop a post-processing method to further improve the PSNR and visual quality of the reconstructed image.

The rest of paper is organized as follows. Section 2 describes in detail the component techniques to be used in the multiple wavelet-tree coding based system. These techniques include wavelet tree coding, construction of multiple bitstreams, unequal error protection, EREC, and error concealment. Section 3 presents the experimental results and Section 4 draws the conclusion.

2. SYSTEM DESCRIPTION

2.1. Multiple bitstreams vs. Single Bitstream

The SPITH algorithm generates progressive data in which once one bit is corrupted, the following bits may not be used at all in decoding. The error resilience capability can be introduced if the single bitstream is split into multiple bitstreams, each still being progressive but decoding independent. The error propagation is thus limited within one bitstream. As a result, the amount of data that can be used in decoding after the channel corruption will be much more than that for a single bitstream transmitted over the same channel.

This reception improvement has been shown by Creusere.[16] In the case of BSC channels, suppose the BER, ε, is given and total of S bits are to be transmitted with L bitstreams. The probability of correctly receiving the first k consecutive bits in each bitstream will be:

$$p(k) = \begin{cases} (1-\varepsilon)^k \times \varepsilon & 0 \le k < S/L \\ (1-\varepsilon)^k & k = S/L \end{cases} \tag{1}$$

So the Mean value of k is:

$$m_L = \sum_{k=0}^{S/L} k \times p(k) \tag{2}$$

Therefore, the expectation of the total correctly received bits that can be used in decoding will be:

$$R = L \times m_L \tag{3}$$

In general, m_L is less than m_1, where m_1 is the mean value of k if one bitstream is used. However, m_L approaches to m_1 when $S/L \gg 1/\varepsilon$. That is, in the limit case, the total number of correctly received bits in L bitstreams is approximately L times the number of correctly received bits using a single bitstream. In practice, the number of the correctly received bits may not approach the limit. However, experimental results using four bitstreams in our simulation show that about twice useful bits can be received compared to using the single bitstream. More received bits lead to better restored image quality. In the following, we propose methods to construct the multiple bitstreams.

2.2. Wavelet Tree Coding

After the hierarchical wavelet decomposition, there is a direct relationship between wavelet coefficients and what they represent in the image content. Coefficients corresponding to the same image content block can be grouped into a wavelet tree structure. One tree structure is the spatial orientation tree proposed by Said et al,[10] as shown in Figure 1. The tree is rooted at the lowest frequency subband. Each node of tree has either no descendants or four offspring grouped in 2×2 adjacent coefficients. In each tree, if one node is insignificant with respect to a given threshold, all its offspring may be insignificant with respect to the same threshold with a high probability. This is the well known self-similarity property in insignificance across different wavelet frequency scales.

Figure 1. Wavelet tree and its image content.

The same SPIHT algorithm[10] can be employed to encode each wavelet tree independently, from the highest bit-plane to the lowest bit-plane. It can generate a completely embedded bitstream in which the more important bits in decreasing MSE occur earlier. Since the self-similarity of the image wavelet coefficients has been fully exploited, a very high source coding efficiency can be achieved. For SPIHT without arithmetic coding, this self-similarity is the only resource that can be exploited. As a result, coding wavelet trees independently will not suffer any bit budget or PSNR loss compared to coding the whole image using a single SPIHT without arithmetic coding. Therefore, the multiple wavelet tree coding can be regarded as the re-organization of the single SPIHT coded bitstream into multiple variable length segments, each segment corresponding to a single wavelet tree and thus a single spatial block in the original image. Consequently, this scheme can also be regarded as a block-based coding scheme.

These wavelet trees can also be divided into several groups, and each group will be encoded by the SPIHT algorithm individually to generate one bitstream. We propose two grouping methods. One is based on subsampling, and the other is based on visual sensitivity.

2.2.1. Multiple bitstream based on subsampling

As shown in Figure 2, subsampling can be done either at every other coefficient in each direction (as shown on the left) or at every other block (as shown on the right). All coefficients labeled with the same pattern are grouped together to form a tree structure that is suitable for coding with SPIHT. Four bitstreams are formed in this research, but more bitstreams with the number in the power of 4 may be constructed by adjusting the interval of the subsampling.

In the first case, each bitstream is a coarse representation of the original image, while the combination of all bitstreams will result in a full resolution of the original image. In the second case, the original wavelet tree structure is retained so that a higher source coding efficiency can be achieved. In this case, because of the relationship between the image domain and the transform domain, each wavelet tree will represent a particular block in the original image. Consequently, each coded bitstream will no longer be a coarse representation of the original image. Any corruption in a wavelet tree due to channel errors will result in an erroneous block in the reconstructed image. Since for many applications, the coarse representation of the whole image is more desired in each bitstream, the coefficient-based subsampling, as opposed to the block-based subsampling, is adopted in our research. Even though the source coding efficiency may be slightly reduced due to the break of the wavelet trees, channel corruption will not result in the loss of an entire block. Therefore, the overall visual quality may be preserved.

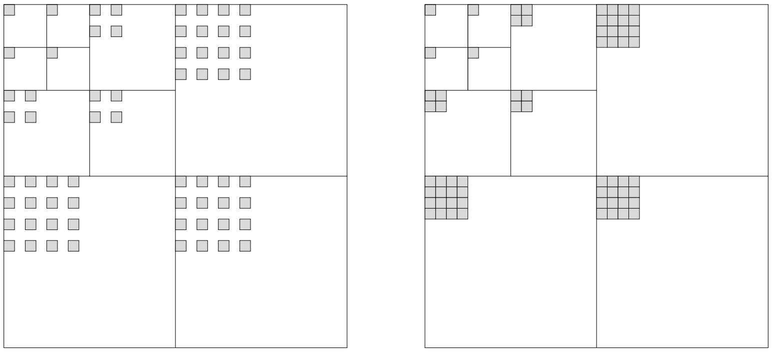

Figure 2. Subsampling decomposition in wavelet domain.

2.2.2. Multiple bitstream based on Human Visual Sensitivity

Study on HVS[15] suggests that image content can be categorized into three groups: edges, textured regions and smooth regions. Image-based recognition is highly sensitive to image edges. This suggests that it is desired to link the coded data with their visual content and protect these bits according to their importance in terms of visual content. Such content based error protection requires that we are able to classify the image blocks according to their visual content and encoded all wavelet trees in one class together.

In this research, we adopt the method of equal mean-normalized standard deviation (EMNSD)[17] to classify those wavelet blocks. Instead of average energy, we chose AC energy as the criterion for classification. The block gain is defined as the square root of the AC energy. All the wavelet blocks are arranged in an increasing order of gains. Then, the first N_1 blocks are assigned to class 1, the next N_2 blocks to class 2, and so on. The classification algorithm finds $N_1, N_2, ..., N_{k-1}$ so that the mean-normalized standard deviations of the gains in the resulting classes are equal. Suppose we divide all the blocks into two classes. The total N blocks are organized in an increasing order of their gain values $g_j, j = 1, 2, ..., N$. We seek an integer N_1 so that blocks indexed from 1 to N_1 belong to the first class and the remaining blocks belong to the second class. The gain g_j, the energy E_j, mean value m_i and standard deviation σ_i of class $i, i = 1, 2$, are defined by

$$g_j = \sqrt{E_j} \tag{4}$$

$$E_j = \sum_{u=0}^{L-1} \sum_{v=0}^{L-1} [F_j(u,v)]^2 - [F_j(0,0)]^2 \tag{5}$$

$$m_1 = \frac{1}{N_1} \sum_{j=1}^{N_1} g_j, \qquad m_2 = \frac{1}{N - N_1} \sum_{j=N_1+1}^{N} g_j \tag{6}$$

$$\sigma_1^2 = \frac{1}{N_1} \sum_{j=1}^{N_1} (g_j - m_1)^2, \qquad \sigma_2^2 = \frac{1}{N - N_1} \sum_{j=N_1+1}^{N} (g_j - m_2)^2 \tag{7}$$

where $F_j(u,v)$ is the DWT coefficient in position (u,v) of the jth block. $L \times L$ is the block size. N_1 will be chosen so that

$$q_1 = q_2, \quad \text{where} \quad q_i = \frac{\sigma_i}{m_i}, \qquad i = 1, 2 \tag{8}$$

The classification results of 4 classes for the Lena image is shown in Figure 3.

Figure 3. Left, original Lena 512×512 image. Right, classification map with 4 classes. Grey levels from dark to bright represent the "smooth area", "mild change area", "textures", and "edges", respectively.

Although this is a gain based classification method, it also demonstrates a good classification of the image content since the gain is defined as the square root of the AC energy. For example, when the blocks are divided into four classes, we can see that the first and the second classes show the smooth and mild changing image blocks; the third class corresponds to texture image blocks and the fourth class contains more edge information. Based on this classification, the wavelet trees in each class will be grouped together and encoded by a single SPIHT algorithm to generate one bitstream. At a result, four bitstreams are generated, each corresponding to a different class of data.

2.3. Unequal Error Protection Through RCPC

With the two proposed wavelet tree grouping methods, multiple coded bitstreams can be formed for a single image. When one bitstream is corrupted or even lost, it will not affect the decoding of other bitstreams. Therefore, the error resilience is improved. However, data in each bitstream are still progressive, which means that bits occurring earlier are more important. Furthermore, the different bitstreams may also have different importance in visual quality. As a result, unequal error protection through channel coding should be designed. We consider two levels UEP in this research.

First, since the coding of SPIHT is bit-plane based, error protection is applied to different bit planes. Suppose the uniform threshold quantizer is applied to the range $[-Q/2, Q/2]$ with n bits, the MSE of the quantization noise can be estimated as

$$\epsilon_n = \frac{1}{12}\left(\frac{Q}{2^n}\right)^2. \tag{9}$$

The MSE caused by channel noise will not only depend on the number of error bits, but also depend on the positions of the individual bit-planes where the bit errors occur. The magnitude of sensitivity for the jth bit-plane is[8]

$$\epsilon_{n,j} = \left(2^j \frac{Q}{2^n}\right)^2, \quad \text{for} \quad j = 0, ..., n-2, \tag{10}$$

where $j = 0$ denotes the least significant bit (LSB); $j = n-2$ denotes the most significant bit (MSB); and $j = n-1$ denotes the sign bit (SB). The higher the bit-plane, the more important the bits in the reconstructed image. The SB has even higher error sensitivity as it is the summation over all possible corruptions in other bit planes. For example, if k is the MSB level of the coefficient, the coefficient magnitude A is in the range of $2^k\delta \leq A < 2^{k+1}\delta, \delta = \frac{Q}{2^n}$. Sign bit reverse will gives a square error of $(2A)^2$. As we discussed in the last section, the fact that the SPIHT operates according to bit planes directly links the unequal error protection scheme to the bits from different bit-plane. More channel coding protection will be assigned to bits from the higher bit-planes. The first few bit-planes usually have a small number of bits.[14] This allows us to apply more powerful channel coding to these bit-planes with only slightly overall increase in data size.

Second, HVS is incorporated by applying unequal error protection to bitstreams of different classes. There are three perceptually significant regions in an image: edges, textured regions and smooth regions. Each class has its own characteristics in the image recognition. For example, edges have the most important role in recognition as we can recognize an image given only the basic edge information. Smooth regions contribute most to the background luminance and their energy concentrates in DC and the few lowest frequency subbands. Textured regions have the characteristic that the introduced distortion in these areas is less likely to be visually perceived. Therefore, more protection should be assigned to the bitstream that represents the crucial information such as edges. On the other hand, the texture information can be less protected.

The implementation of UEP channel coding is similar to that developed in scheme.[14] It is a concatenate coder consisting of an outer CRC[18] code and an inner RCPC code for successful protection of coded image data. CRC has extremely low computational complexity and is used for error detection. RCPC[4] code has a useful characteristic that all the coded bits of a punctured high rate code are embedded in those of a low rate code of the same family. Since the codes in the entire family are compatible, different coding rates for an input bitstream can be designed using only one encoder/decoder pair. We also implemented the list Viterbi decoding at the receiver so that the final survival path should also subject to the CRC detection.

2.4. Error Resilient Entropy Coding (EREC)

In this research, we also test a scheme that one bitstream is constructed from one wavelet tree. Therefore, a maximum number of bitstreams have been constructed to improve the resilience capability. However, to transmit these data sequentially over a noisy channel may cause a synchronization problem, because error propagation may destroy the boundaries of adjacent bitstreams. In addition, adding $N-1$ synchronization symbols, where N is the number of bitstreams, increases much redundancy. As a result, we employ EREC to gain the self-synchronization.

EREC is originally proposed by Redmill et al[19] to handle the sequential transmission of variable length coded DCT blocks over noisy channels. The key idea of the EREC is to re-organize the variable length data blocks into fixed length slots. Data in the blocks are allocated to the corresponding slots, starting from the beginning of each block. Blocks that are larger than the slot size are chopped and the remained data are put into those slots that still have available space, according to a pre-defined offset sequence. Figure 4 shows the process of EREC reorganization according to an offset sequence {1,2,3,4,5,6}. A number of steps up to the total number of blocks (6 in Figure 4) are required to complete the reorganization. At the receiving end, the start of each block can be automatically determined as the start of each fixed length slot. Without channel errors, the decoder can follow the same algorithm to recover all the variable length blocks using the same offset sequence.

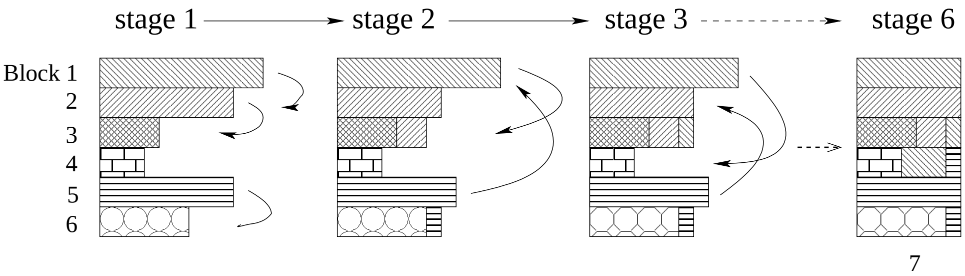

Figure 4. The reorganization process of EREC.

When the channel error exist, the error propagation will affect the data near the ends of each block more than the data near the beginning of each block. This characteristic of EREC suggests that it is better to encode more important information in the beginning of each block. For DCT block-based image coding schemes, the error effects generally impact the high frequency information which is often coded later in a block. The wavelet tree coding, unlike the DCT based coding schemes, has even stronger sequential importance in each variable length block since it encodes the coefficients from the highest bit-plane to the lowest bit-plane. As discussed previously, because bits in the i-th bit-plane contribute twice in terms of magnitude as bits in the $(i-1)$-th bit-plane, the distortion energy caused by the i-th bit-plane is four times that of $(i-1)$-th bit-plane. Apparently, such decreasing of bit importance along the bitstream fits very well with the characteristic of EREC. In the case of noisy channels, the error propagation will more likely to impact the low bit-layers, which generally contribute less to the distortion energy.

Following the wavelet tree coding and EREC discussed above, the basic idea of the integration of wavelet tree coding and EREC is shown in Figure 5.

2.5. Error Concealment

The multiple hierarchical representation of the source coding facilitates the design of a post-processing scheme to further improve the PSNR as well as visual quality of the reconstructed image. In particular, the SPIHT source coding algorithm encodes and decodes in the order of wavelet coefficient bit-planes. At the receiver, it is easy to determine the bit-plane in which the decoding stops. Suppose the value of the highest bit-plane is L. It means that the possible coefficient values are between -2^L and 2^L due to the uniform quantization used in the SPIHT. If decoding stops at bit-plane $S(S < L)$, the bit values of the highest $L-S$ bit-planes are known to be decoded correctly. However, information of the bit-planes from 0 to $S-1$ is not available. So the uncertain range for all the decoded coefficients is between -2^{S-1} and 2^{S-1}. In other words, let x be the decoded value of the corresponding coefficient, then the actual value of the coefficient should be $z = x + y$, where $y \in (-2^{S-1}, 2^{S-1})$ is the uncertain value that cannot be determined by the decoding.

Now, suppose that decoding of the received ith bitstream ends at bit-plane $S_i, i = 0, 1, ...M$, respectively, where M is the number of classes. Different S_i means that the uncertain value ranges for the coefficients in

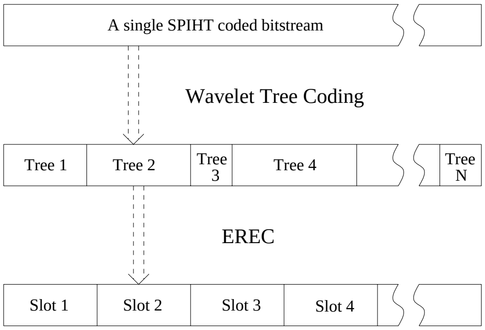

Figure 5. Same content in different representation (without arithmetic coding). The results are fixed length slots for error resilient transmission.

different bitstreams are not the same. This make it possible to recover some corrupted wavelet coefficients with large uncertain value range from neighboring blocks with small uncertain value range. An appropriate post-processing would be applied only to DC coefficients, as they are highly correlated. Generally high frequency coefficients among neighboring blocks can be considered uncorrelated. Thus we leave them unchanged.

Therefore, after the positions of the corrupted blocks are identified, the post-processing is applied to the wavelet coefficients within the lowest frequency subbands. Only those coefficients that have a neighbor with smaller uncertain value range are considered. Coefficients with the smallest S will not be processed because it represents the finest quantization resolution that can be preserved during the transmission. The coefficient with a larger uncertain range is modified by averaging itself with the neighbors that have smaller uncertain value ranges. In addition, the difference between the changed value and the received value should also be limited in the uncertain value range. As a result on visual quality, the average luminance of some blocks may be increased and that of others may be decreased. The change of luminance among these blocks will become smoothed.

3. EXPERIMENTS

Three schemes based on multiple wavelet-tree coding have been tested for coding and transmission of the Lena 512×512 8 bpp image. In scheme 1, we construct four bitstreams based on subsampling. All bitstreams have the same length. Within each bitstream, RCPC code rates $\{8/24, 8/24, 8/22,/8/20,8/18,8/16,8/14,8/12\}$ are associated to data in different bit-planes to provide unequal error protection. Original seven levels of wavelet decomposition is used. In scheme 2, we still generate four bitstreams but different bitstreams correspond to image areas with different visual sensitivities. Four levels of wavelet decomposition is used to generate 32×32 blocks for the entire image. We stop the encoding of each bitstream at the same bit layer. RCPC rates of $\{8/24, 8/22, 8/20,8/18,8/16,8/14,8/12\}$ and $\{8/16,8/14,8/12\}$ are assigned to classes 2,4 and classes 1,3, respectively. The packet size is 200 information bits plus 16 CRC bits. The total code rate for both schemes is 0.5 bpp(bit per pixel), but the source data rate is 0.243bpp in scheme 1 and 0.275 bpp in scheme 2. For scheme 3, we assume the channel corruption is very slight, and thus we use EREC but not the channel coding for error resilience. Error concealment technique were used for all schemes.

The PSNR of the reconstructed image vs. the channel BER is shown on the Left in Figure 6. Schemes of Sherwood[11] and Li[14] considered the single bitstream only. The adopted RCPC with the highest code rate of 8/12 can well remove the channel errors when BER is less than or equal to 0.01. It can be found in the figure, when BER increases, the performance will be reduced dramatically. Both of our schemes with multiple bitstreams present better performance than the single bitstream based schemes due the reception improvement.

Though scheme 1 shows the lowest source coding efficiency, it provides the best PSNR performance when channel corruption is severe. This is because each bitstream has a fixed length and is a coarse representation

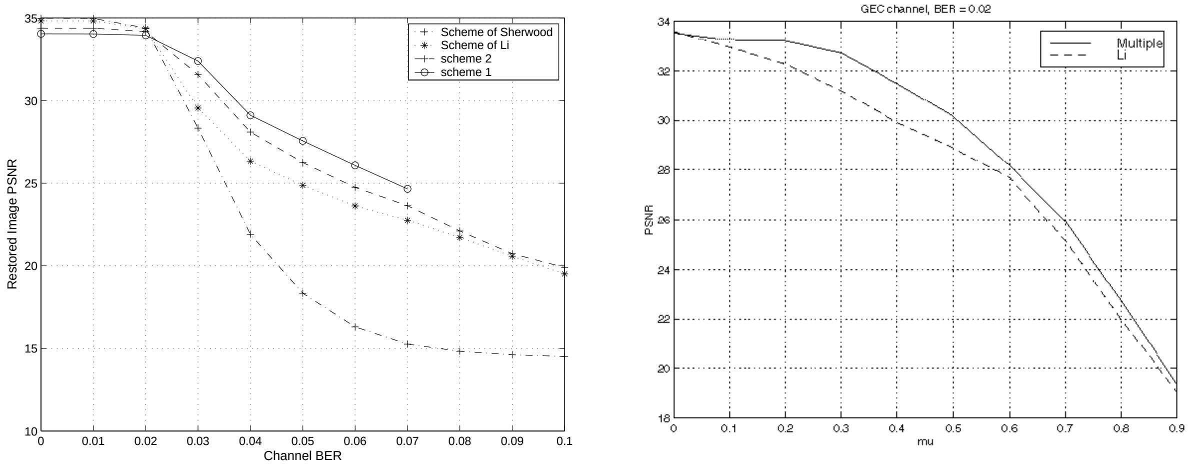

Figure 6. Total data rate is 0.5 bpp. Left: PSNR vs. BER performance of different schemes. Right: Comparison between the proposed scheme and that in[20] over GEC channel, BER = 0.02, μ is from 0.0 to 0.9.

of the entire image. When corruption occurs in a bitstream, post-processing may compensate it from other bitstreams. This scheme is also good for burst error conditions. The Right in Figure 6 compares its performance with Li's scheme[14] in a two-state Gilbert Elliott channel (GEC) as shown in Figure 7. BER $(= (P \times E_B + Q \times E_G)/(1-\mu))$ is set to 0.02 and $\mu(= 1-P-Q)$ is set from 0 to 0.9. Consistent improvement is observed.

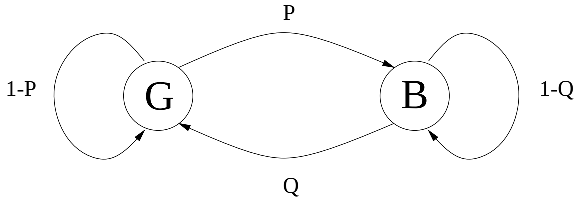

Figure 7. Gilbert Elliott Channel (GEC) Model.

PSNR values of scheme 2 are between the scheme of Li[14] and scheme 1 when channel noise is high. However, it generally provides excellent visual quality because visual sensitive areas such as edges were protected more than other areas. Figure 8 shows some sample images of this scheme compared with SPIHT decoded images at the same PSNR values.

Scheme 3 is for low BER cases where the channel coding is not employed. Each wavelet generates one bitstream. Since EREC requires that the decoding knows the stop of each bitstream in error-free case, we set the coding and decoding of each bitstream stop at the same bit-plane. Figure 9 shows the results with and without error concealment for the stop bit-plane at 2, 3, 4, respectively. This results also show that the error resilience is helpful only for very low BER cases ($\leq 10^{-3}$). Channel coding must be applied when BER increases.

4. CONCLUSION

In this paper, we investigated several techniques based on wavelet-tree coding for robust image coding and transmission. Two methods based on subsampling and visual sensitivities were proposed to group the wavelet trees and generate multiple bitstreams. Superior performance over existing single bitstream based schemes have been observed through the simulations. We also proposed to use EREC with wavelet tree coding to

Figure 8. PSNR = 24.80, 22.07, reconstructed from BER=0.06, 0.08, respectively. Left, reconstructed image samples from scheme. Right, reconstructed from the original SPIHT algorithms.

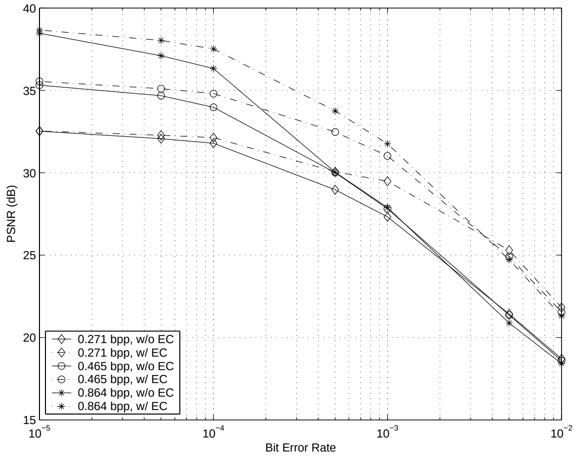

Figure 9. Image PSNR vs. BER in scheme 3, with and without error concealment.

improve the error resilience capability when the channel is slightly corrupted. The simulation also indicates that channel coding must be applied when channel BER increases.

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