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Multiple Description Wavelet Based Image Coding with Classification

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***Abstract*—In this paper, a multiple description image coding scheme with classified method is presented, in which the wavelet coefficients in each class can be processed separately according to its own source distribution. All the classes will be divided into two larger classes again. One of them is quantized by MDSQ and the other is subsampled by quadtree and quantized subsequently. The two parts are combined to form two descriptions. It is the number of class quantized by the above two ways that determines the tradeoff between side and central performance. The whole scheme is applied to natural images and simulation demonstrates that the system outperforms other related works. Most important of all, by employing the classified scheme, the central performance can get improved even when the side performance is close to its corresponding single description one.**

***Keywords*-Image coding; Multiple description coding; Classification;**

I. Introduction

Multiple description (MD) coding has emerged as an effective method to protect multimedia transmitted over non-prioritized networks. It can effectively combat packet loss without any retransmission thus satisfying the demand of real time services and relieving the network congestion. In the MD approach, more than two coded streams (descriptions) are generated individually and sent through separate channels. If only one channel works, the source can be reconstructed by side decoder with certain acceptable quality. When more channels work, the reconstruction quality can be enhanced up to the smallest central distortion upon the reception of all descriptions. However, achieving the best central and side coding performance at the same time is shown to be conflicting, and a good tradeoff tuning method between central and side performance is the main objective of any MD schemes [1]. MD has also been combined to watermarking scheme to provide some robustness [2].

MD scalar quantization (MDSQ) is one of the practical solutions to the MD problem, which provides an asymptotic performance close to the rate-distortion bound [1]. In MDSQ, the index information of a quantizer is structured on the diagonals of a matrix. It is the numbers of diagonals filled with indexes that controls the tradeoff between central and side performance. In [3], MDSQ is used in their design of MD encoders for images. Noticeably, there is little gain by using index assignments other than the two diagonals case (or staggered case) on MD image coding [3]. To gain less than 1dB in PSNR for the central performance, the side quality of the images has to be reduced by 7-8 dB. Hence, paper [4] makes use of stagger case alone. In this paper, we will just consider the practical application of MD on image coding case. The deadzone quantizer is often employed in image coding with its good performance. However, it is not straightforward to apply MDSQ to the quantizer with deadzone case. Hence, we propose an MD scheme with classification to solve this problem. In the proposed work, the best side performance or the best central performance corresponding to that of single description scheme (SDC) can be achieved.

The remainder of this paper is organized as follows. In Sec. II, an MD scheme with classification is proposed. Sec. III provides the experimental results of the proposed scheme including the related comparisons and analysis. Then the work is concluded in the last section.

II. The proposed scheme

In the proposed work, we will limit to image coding with wavelet transform because most of the state-of-art image coders are based on wavelet transform. The advantage of deadzone quantizer is that it considers the probability distribution function (PDF) of wavelet transformed image. It has been shown that the PDF of wavelet transformed image is often like generalized Gaussian distribution with long tails, and deadzone quantizer is suitable to this PDF [5]. In Fig. 1, the wavelet coefficients of image "Lena" are shown, in which a lot of coefficients are around zero. Then most of the coefficients will be quantized to zero by deadzone quantizer, which is beneficial to the following entropy coding. In addition, we can see that the coefficients except for the areas around zero are close to uniform distribution. The distribution of other images is not shown because of space, however, it shows the similar distribution. Hence, we try to employ the classified method in [6] to separate the coefficients into certain classes and quantize them subsequently. It will be shown that the PDF of the sorted classes are similar to uniform distribution, so the uniform quantizer instead of the deadzone one is better for the coefficients in these classes. After classification, a scheme combining MDSQ and subsampling by quadtree is proposed by exploiting the PDF of each class to form the two descriptions.

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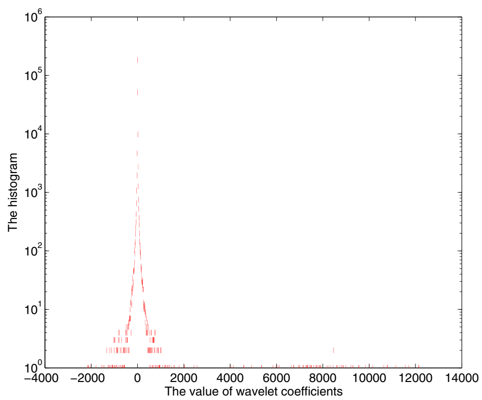

Figure 1. The coefficients distribution of image "Lena" with 6-level wavelet decomposition.

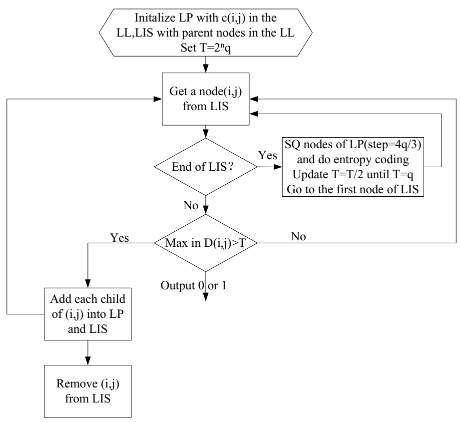

Figure 2. QSQ scheme with classification.

A. *Quadtree classification and scalar quantization(QSQ) on image coding*

The proposed QSQ image coding scheme is mainly modified from quadtree classification and trellis coded quantization (QTCQ) [6]. For convenience, QSQ algorithm is shown in Fig. 2, where $c_{i,j}$ denotes the wavelet coefficients, LL is the lowest subband, LP and LIS represent the list of pixels and list of insignificant sets, respectively. The quality factor that determines the performance is represented as q and all the descendants of the node (i, j) are denoted as $D(i, j)$. In each sorting, part of the coefficients is classified into one class (LP) controlled by the quality factor q. Then we quantize the classes with uniform quantizer of step $\frac{4}{3}q$, which is selected by empirical tests to provide the best performance in rate-distortion sense. In fact, the coefficients in each class have been filtered by a threshold($2^n q$) and the PDF for the coefficients in each class does not match the generalized Gaussian model again [6]. In Fig. 3, some PDFs of the classified coefficients are shown to demonstrate this case.

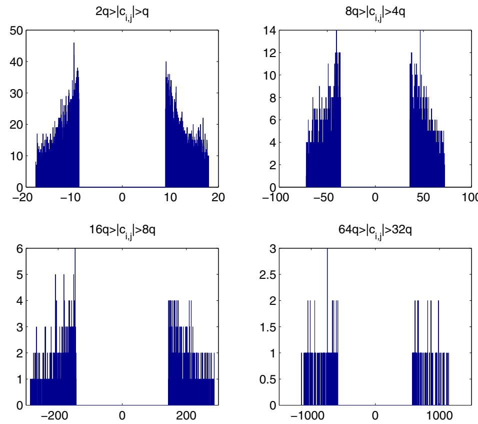

Figure 3. PDF of each sorted class.

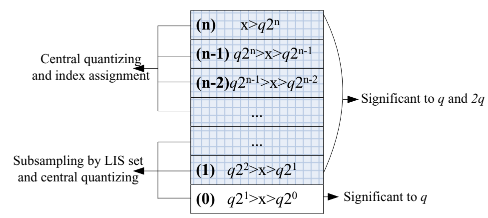

Figure 4. The whole class map related with quantization step.

The classified PDF is much closer to uniform distribution, in fact. Most important of all, although the coefficients in the interval $[-q, q]$ are like Gaussian distribution, they will not be quantized and coded. Since the energy of coefficients in this interval is lower and its contribution to the PSNR is smaller, it is reasonable that no bits are distributed on this interval. The problem of MDSQ is on how to assign the index of zero or combine the two zero indexes in the deadzone area. Therefore, the classified scheme can solve this problem by avoiding the quantization process in the deadzone area.

B. *The MD scheme based on classification*

The QSQ algorithm reveals that it is the quality factor q that determines the number of class and there is a fixed relation between the quality factor and the quantization step. A class map with the relationship of quantization step is shown in Fig. 4. Denote class n as the nth significant coefficients set with respect to q and $n = \lfloor \log 2(\max |(c(i,j)| / q) \rfloor$. From class to class 1, the coefficients are either significant to q or $2q$ and they can be quantized with any of the two steps. Both of the steps are optimal with their corresponding class. For class 0, the coefficients are only significant to q and should be quantized with this step alone. All the classes will be divided into two larger classes again. One of them is processed by MDSQ and the other is subsampled by quadtree and quantized. It is the number of class in the above two ways that controls the tradeoff tuning. If the side performance is the focus, we can use quality factor $2q$ to classify n(except for class 0 in Fig. 4) kinds of coefficients and quantize them with central quantizer of step $\frac{4}{3}q$ following index assignment as MDSQ. By this way, side performance is almost the same as that of its corresponding SD scheme quantized with step $\frac{4}{3}2q$, while the corresponding central performance can still get some gain compared to the side performance. For the scheme [3] and [4], however, the side performance will have some loss due to the inefficient employing the deadzone quantization in this situation. When the central performance is the focus, the quality factor q is selected to classify the coefficients. Then the classified coefficients are subsampled by quadtree and quantized with step $\frac{4}{3}q$ to form the two descriptions. In this way, the central performance will be optimal. In between, we can tune the number of classes processed by MDSQ or that by quadtree subsampling. An MD scheme based on classification is formed in the following.

Procedure 1 MD image coding scheme with classification

Initialization: Do as Fig. 2. set n_s n_c n, and
$n = \lfloor \log 2(\max |(c(i,j)| / q) \rfloor$
Sorting1: for $m = 0 : n_s - 1$
Do as Fig. 2. if $m == n_s - 1$, save odd quadtree to LIS1 and even quadtree to LIS2;
Quantization1: Do quantization as Fig. 2 and do MDSQ.
Update1: Do as Fig. 2
Sorting2:
for $m = n_s : n_c$
for each node in LIS1:
Do as sorting 1, move coefficients to LP1,
save the bits into side description 1.
for each node, in LIS2:
Do as sorting 1, move coefficients to LP2,
save the bits into side description 2.
Quantization2:
for each element in LP1 and LP2:
quantize them with step $4q/3$ respectively,
do entropy coding for LP1 and LP2.
Update2: Remove all the elements in LP1 and LP2,
replace T by $T/2$; go to **sorting2**.

In the procedure, n_s and n_c correspond to the number of class in sorting 1 and sorting 2, which is the key factor affecting the central or side performance. When n_s and n_c are equal to $n - 1$, the scheme equals to MDSQ scheme. If $n_s = 0$ and $n_c = n$, the scheme amounts to the scheme of subsampling by quadtree. In between, we can tune n_c and n_s to get different tradeoff points. The classes coded with MDSQ are inclined to side performance, while the classes coded by subsampling method are beneficial to central performance.

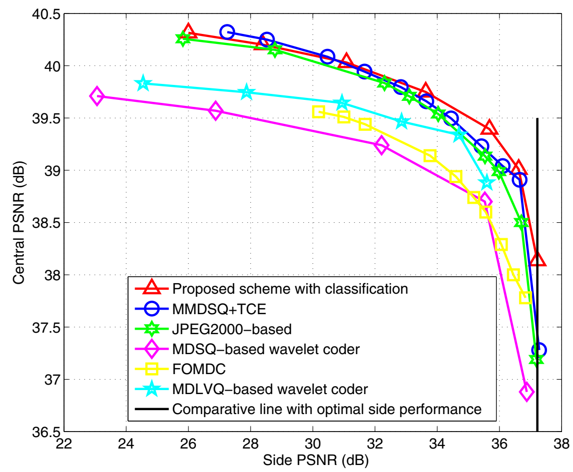

Figure 5. Comparison of central-side PSNR curves at 0.5bpp/description for ”Lena”.

III. Simulation Results and Analysis

In this section, the experiments are implemented to test the proposed scheme. For the sake of comparison, we also give the performance of MDSQ-based wavelet coder [3], modified MDSQ based on Tarp filter image coder with classification for embedding (MMDSQ+TCE) [4], the JPEG2000-based MD approach [7], feature-oriented MD (FOMDC) [8] and the optimized MD with lattice vector quantization (LVQ) for wavelet image (MDLVQ+Wavelet) [9]. All the schemes including ours employ wavelet transform in their coding scheme. A six-level wavelet decomposition is applied with the Daubechies 9/7 filters in the QSQ scheme and the tested rate is selected to be 0.5bpp per description. In Fig. 5, the central versus side performances for ”Lena” (of size 512×512) are shown. The result on image ”Barbara” demonstrates the similar performance, which is not shown here. It can be seen that the proposed scheme achieves better central-side distortion performance than almost all of the other MD image coders, but is a little inferior to MMDSQ+TCE when side PSNR is lower than 30 dB. MMDSQ+TCE has a two-stage structure that is similar to ours, however, it requires to calculate the residual and sort the coefficients of residual in the second stage again, which costs some extra bits and time. For our case, sorting 2 follows sorting 1 in a seamless way, so there is no need to calculate the residual, which can be seen from the algorithm. Table I shows the extra bits cost on the two-stage scheme compared with ours, where the bit rate is fixed as 0.5bpp in total and $k = n_s$ denotes the sorted times in the first stage. For the images ”Lena” and ”Barbara”, the total number of classes is 9 and 8 respectively, which is determined by the fixed rate. It can be seen the extra bits cost is larger as k is larger. For wavelet transformed image, if a wavelet

Table I
THE EXTRA BITS COST ON SORTING AND QUANTIZATION.

Image / k	8	7	6	5	4
Lena(bits)	10432	11485	8233	4606	-
Barbara(bits)	-	10747	9532	3427	1644

coefficient at a coarse scale is insignificant with respect to a given threshold T, then all the wavelet coefficients of the same orientation in the same spatial location at finer scales are likely to be insignificant with respect to T. The efficiency of our QSQ, embedded zerotree wavelet algorithm (EZW) [10] and set partitioning in hierarchical trees (SPIHT) are based on the above fact. However, if some classes have been quantized in the first stage, the residual in the second stage will be smaller and the non-significant roots with significant descendants will be prominent, which costs extra bits reflected in Table I. Nevertheless, the two-stage scheme has its own advantages. Because the quantization steps in each of the two stages can be different, there are much room to tune the tradeoff between the side and central performance. Moreover, the extra cost will be smaller as k is smaller and the flexibility of the two-stage scheme will exhibit its advantage, which explains the performance comparison in Fig. 5 to a certain degree. In fact, the tradeoff tuning in the proposed can be processed in fractional class level (like half of the coefficients in one class), and then more tradeoff points can be obtained, which is not the focus of the current work. Considering the simplicity of the proposed scheme, our results are competitive.

Furthermore, the comparative line is included in the figure to compare each of the central performance when their side performance is optimal. The comparative line reveals that the SD scheme of ours can achieve similar performance to JPEG2000 and TCE. At this case, the central performance of the proposed scheme is still about 1dB better than its side performance. Other schemes including MMDSQ+TCE, however, can not get better central performance than its side ones. Noticeably, the point with the best side performance of MMDSQ+TCE is obtained from [4] at one diagonal case. For MDSQ-based wavelet coder and MMDSQ+TCE, the central performance cannot get improved when side performance is optimal because the side performance can only be optimal by using MDSQ with one diagonal. The JPEG2000-based [7] applies coarse and fine quantizer to obtain two descriptions, where the two optimal side descriptions will be the same and there is no improvement on central quantizer. Hence, the central performance of any compared schemes is the same as its corresponding side one, which reveals the effectiveness of the proposed scheme.

IV. CONCLUSION

In this work, a classified multiple description image coding scheme is proposed. Due to the uniform distribution of the sorted classes, the deadzone quantizer is avoided. Different tradeoff points between central and side performance can be obtained by tuning the number of classes processed by MDSQ or quadtree subsampling method. The experimental results of the proposed scheme outperform other related ones. In addition, the side description can achieve the same performance as its corresponding single description one, while its central performance can still get certain improvement, which can not be obtained from other compared schemes. This demonstrates the effectiveness of the classified method.

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REFERENCES

[1] V. A. Vaishampayan and J. C. Batllo, “Asymptotic analysis of multiple description quantizers,” *IEEE Trans. Inf. Theory*, vol. 44, no. 1, pp. 278–284, Jan. 1998.

[2] J.-S. Pan, Y.-C. Hsin, H.-C. Huang, and K.-C. Huang, “Robust image watermarking based on multiple description vector quantisation,” *Electronics Letters*, vol. 40, no. 22, pp. 1409–1410, 28 2004.

[3] S. D. Servetto, K. Ramchandran, V. A. Vaishampayan, and K. Nahrstedt, “Multiple description wavelet based image coding,” *IEEE Trans. on Image Proc.*, vol. 9, no. 5, pp. 813–826, May 2000.

[4] C. Tian and S. Hemami, “A new class of multiple description scalar quantizer and its application to image coding,” *IEEE Signal Proc. Letters*, vol. 12, no. 4, pp. 329–332, April 2005.

[5] Bo Tao, “On optimal entropy-constrained deadzone quantization,” *IEEE Trans. Circuits Syst. Video Technol.*, vol. 11, no. 4, pp. 560–563, Apr. 2001.

[6] B. A. Banister and T. R. Fischer, “Quadtree classification and tcq image coding,” *IEEE Trans. Circuits Syst. Video Technol.*, vol. 11, no. 1, pp. 3–8, Apr. 2001.

[7] T. Tillo, M. Grangetto, and G. Olmo, “Multiple description image coding based on Lagrangian rate allocation,” *IEEE Trans. on Image Proc.*, vol. 16, no. 3, pp. 673–683, Mar 2007.

[8] Yilong Liu and Soontorn Oraintara, “Feature-oriented multiple description wavelet-based image coding,” *IEEE Trans. Image Process.*, vol. 16, no. 1, pp. 121–131, Jan. 2007.

[9] Huihui Bai, Ce Zhu, and Yao Zhao, “Optimized multiple description lattice vector quantization for wavelet image coding,” *IEEE Trans. Circuits Syst. Video Technol.*, vol. 17, no. 7, pp. 912–917, July 2007.

[10] J. Shaprio, “Embedded image coding using zerotrees of wavelet coefficients,” *IEEE Trans. Signal Processing*, vol. 41, no. 12, pp. 3445–3462, Dec. 1993.