Short Paper

A Nearly Optimum Generalized Multilevel Block Truncation Coding Algorithm With a Fast Nonexhaustive Search Based on a Mean Square Error Criterion

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Block Truncation Coding (BTC), using a one-bit moment preserving quantizer to quantize a block, is a simple compression method; however, compression with BTC cannot be used to obtain a sufficiently high quality image, especially an image with many edges. In this paper, a new generalized multilevel BTC algorithm, which arbitrarily specifies the number of quantization levels, is developed. In the proposed algorithm, a nearly optimum quantizer is proposed based on a multiplication-free and nonexhaustive search such that the computational complexity is very low. The simulation results indicate that both the computational complexity and the reconstructed image quality obtained using the proposed multilevel BTC algorithm are better than those obtainable with other existing multilevel BTC algorithms.

Keyword: image compression, block truncation coding (BTC), quantization, nonexhaustive search, mean square error criterion

1. INTRODUCTION

Recently, the most popular method for the compression of still images has been Joint Photographic Expert Group (JPEG), which is based on discrete cosine transform coding. Nevertheless, if very high quality of the reconstructed image is required after decompression, using the JPEG to compress the image is not economical because the computational complexity of JPEG, which requires the performance of discrete cosine transform (DCT) between the spatial and frequency domains, is very high. In this case, compression using block truncation coding is more appropriate than that using JPEG.

The block truncation coding (BTC) technique [1-3], also called a moment preserv-

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ing quantizer, uses a two-level quantizer to quantize a pixel within a fixed-size block such that some statistical characteristics of the block are still preserved after the block is quantized. The advantages of this technique are that it is easy to implement, and that a fixed bit rate can be obtained. In general, the bit rate for BTC requires 2 bits per pixel (bpp). However, BTC does not perform equally well in every region, resulting in ragged edges and introduces noise at edges. Thus, it is necessary to develop a version of BTC with more than two quantization levels to improve the quality of the image. The major problem with multilevel BTC lies in the search for an optimal set of codewords to quantize the pixels in the block. With the original BTC proposed in [1-3], it is easy to search all of the possible threshold candidates exhaustively to obtain the optimal codewords [4-5]. However, this exhaustive search requires a large amount of computation if the number of the quantization levels is larger than 2.

The three-level BTC algorithms proposed by Efrati et al. [6] and Mor et al. [7], denoted as E3BTC and M3BTC in this paper, respectively, improve the quality of the image. But these algorithms can not be generalized to the number of quantization levels arbitrarily such that the quality of the image can not be greatly improved. Meanwhile, Wu and Coll proposed a generalized multilevel BTC algorithm, denoted as WMBTC in this paper, with a minmax error criterion [8]. Though this method specifies the number of the quantization levels arbitrarily, it does not produce a better mean square error (MSE).

Recently, we were the first to propose a generalized multilevel BTC algorithm [9], denoted as GMBTC(old) in this paper, based on a multiplication-free mean absolute error (MAE) criterion. The concept behind this algorithm is to try to find a better MAE by iteratively moving the threshold based on matching the proposed criterion. This method can obtain a nearly optimum MAE and MSE progressively when the number of iterations is increased. Because only one pixel movement is allowed at a time, the convergence rate of the algorithm is not fast and the computational complexity can not be greatly reduced. To solve this problem, in this paper, a fast-convergence generalized multilevel BTC algorithm, denoted as GMBTC in this paper, based on a mean square error criterion, is proposed. In each iteration, the proposed algorithm can directly determine a set of thresholds based on the proposed multiplication-free criterion such that the convergence rate of the search algorithm increases and the computational complexity is greatly reduced.

In this paper, the mean square error of GMBTC is analyzed first in Section 2. Based on MSE analysis, a fast nonexhaustive search method to obtain a set of nearly optimum codewords is proposed in Section 3. Section 4 gives simulations of and comparisons between reconstructed images and the computational complexity for the existing BTC and the proposed GMBTC algorithms. A conclusion is provided in Section 5.

2. ANALYSIS OF THE MEAN SQUARE ERROR FOR GMBTC

Let a block with m by m pixels be sorted into a sequence X which has $N = m^2$ pixels. That is,

$$X = \{x_0, x_1, x_2, ..., x_{N-2}, x_{N-1}\}, \tag{1}$$

where $x_0 \le x_1 \le x_2, ..., \le x_{N-2} \le x_{N-1}$. For n-level BTC, the sequence X is segmented into n regions. The codeword for each region is obtained by averaging all the pixels of the region such that all of the pixels in the region are reconstructed using the codeword by the receiver. Assume that $x_{j,i}$ expresses the value of the ith pixel at the jth region in sequence X. The codeword for region j ≤ (0 ≤ j ≤ n-1), Q_j, can be expressed as:

$$Q_j = \frac{1}{N_j}\sum_{i=0}^{N_j-1} x_{j,i}, \tag{2}$$

where N_j is the number of pixels in region j.

The mean square error (MSE) for the block performed by n-level BTC can be expressed as:

$$MSE = \frac{1}{N}\sum_{j=0}^{n-1}\sum_{i=0}^{N_j-1}(Q_j - x_{j,i})^2 = \frac{1}{N}\sum_{j=0}^{n-1}[\sum_{i=0}^{N_j-1} x_{j,i}^2 - N_j Q_j^2]. \tag{3}$$

Let $\Delta\mu_j$ express the difference between Q_j and the mean of the block, μ, that is,

$$\Delta\mu_j = Q_j - \mu. \tag{4}$$

Substituting Eqs. (2) and (4) into Eq. (3), the MSE can be obtained as:

$$MSE = \frac{1}{N}\sum_{j=0}^{n-1}[\sum_{i=0}^{N_j-1}(x_{j,i}^2 - \mu^2) - 2N_j\mu\Delta\mu_j - N_j\Delta\mu_j^2]$$

$$= \sigma^2 - \frac{2\mu}{N}\sum_{j=0}^{n-1} N_j\Delta\mu_j - \frac{1}{N}\sum_{j=0}^{n-1} N_j\Delta\mu_j^2, \tag{5.a}$$

where σ^2 is the variance of the block (the sequence X). From Eqs. (2) and (4), we have

$$\sum_{j=0}^{n-1} N_j\Delta\mu_j = \sum_{j=0}^{n-1} N_j(Q_j - \mu) = \sum_{j=0}^{n-1}\sum_{i=0}^{N_j-1} x_{j,i} - \sum_{j=0}^{n-1} N_j\mu = 0\,. \tag{5.b}$$

Therefore, Eq. (5.a) can be simplified as

$$MSE = \sigma^2 - \frac{1}{N}\sum_{j=0}^{n-1} N_j\Delta\mu_j^2 = \sigma^2 - \sigma_r^2, \tag{5.c}$$

where the last term $\frac{1}{N}\sum_{j=0}^{n-1} N_j\Delta\mu_j^2$ is the variance of the reconstructed block performed by n-level BTC, say σ_r^2. It should be noted that the MSE for GMBTC is the difference between the variances of the original and reconstructed blocks. Eq. (5.c) reveals that the maximum mean square error is equal to the variance of the block when one quantization level BTC($\Delta\mu_1 = 0$) is performed. In addition, if the variance of the original block is very large, that is, if edges are included in the block, then the MSE can obviously be improved by BTC with more levels.

3. THE PROPOSED GMBTC ALGORITHM BASED ON A MEAN SQUARE ERROR CRITERION

The proposed GMBTC algorithm first segments a block into n regions and then uses the average value of a region as a codeword for the region. The choice of a set of thresholds for segmenting n regions is an important factor in obtaining a smaller quantization error, and the number of sets of threshold candidates for GMBTC is O(N×n). Therefore, a huge amount of computation is needed to obtain the best set of thresholds from these candidates for a large n. To solve this problem, in this paper, an alternative method for finding a suboptimum set of thresholds based on a nonexhaustive search is proposed.

First, the proposed algorithm divides sequence X into n uniform regions; that is, each region has the same number of pixels. Let the jth threshold be moved left one pixel (see Fig. 1); that is, the largest pixel in the jth region, x_{j,N_j-1}, is moved into the (j+1)th region. From Eq. (5.c), the MSEs before and after moving the threshold, denoted as MSE_{pre} and MSE_{next}, are given as:

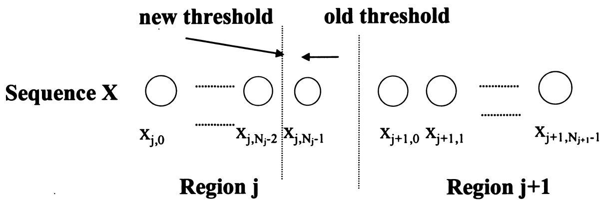

Fig. 1. Move the threshold left.

$$MSE_{pre} = \sigma^2 - \frac{1}{N}\sum_{k=0}^{n-1} N_k (Q_k - \mu)^2$$

$$= \sigma^2 - \frac{1}{N}[\sum_{k=0}^{j-1} N_k (Q_k - \mu)^2 + N_j (Q_j - \mu)^2 +$$

$$N_{j+1}(Q_{j+1} - \mu)^2 + \sum_{k=j+2}^{n-1} N_k (Q_k - \mu)^2] \tag{6}$$

and

$$MSE_{next} = \sigma^2 - \frac{1}{N}[\sum_{k=0}^{j-1} N_k (Q_k - \mu)^2 + N'_j (Q'_j - \mu)^2 +$$
$$N'_{j+1} (Q'_{j+1} - \mu)^2 + \sum_{k=j+2}^{n-1} N_k (Q_k - \mu)^2], \tag{7}$$

respectively, where N'_{j+1}, N'_{j+1}, Q'_j, and Q'_{j+1} are the new numbers of pixels and codewords in the jth and (j+1)th regions after moving x_{j,N_j-1} into the (j+1)th region, respectively. The difference between MSE_{next} and MSE_{pre} is

$$\begin{aligned}\Delta MSE_{j,j+1} &= MSE_{next} - MSE_{pre} \\ &= \frac{1}{N}[N_j(Q_j-\mu)^2 + N_{j+1}(Q_{j+1}-\mu)^2 - \\ &\quad N'_j(Q'_j-\mu)^2 - N'_{j+1}(Q'_{j+1}-\mu)^2] \\ &= \frac{1}{N}\{N_jQ_j^2 + N_{j+1}Q_{j+1}^2 - N'_jQ'^2_j - N'_{j+1}Q'^2_{j+1} - \\ &\quad 2\mu[N_jQ_j + N_{j+1}Q_{j+1} - N'_jQ'_j - N'_{j+1}Q'_{j+1}]\}. \end{aligned} \quad (8)$$

From Eq. (2), we have the following relation:

$$N_jQ_j + N_{j+1}Q_{j+1} - N'_jQ'_j - N'_{j+1}Q'_{j+1} = 0. \quad (9)$$

Substituting Eq. (9) into Eq. (8), we obtain

$$\begin{aligned}\Delta MSE_{j,j+1} &= \frac{1}{N}\{N_jQ_j^2 + N_{j+1}Q_{j+1}^2 - N'_jQ'^2_j - N'_{j+1}Q'^2_{j+1}\} \\ &= \frac{1}{N}\{S_jQ_j + S_{j+1}Q_{j+1} - S'_jQ'_j - S'_{j+1}Q'_{j+1}\}, \end{aligned} \quad (10)$$

where S_j represents the sum of the jth region and has the following relations:

$$S_j = N_jQ_j, \quad (11.a)$$

$$S'_j = N'_jQ'_j = S_j - x_{j,N_j-1,} \quad (11.b)$$

$$S_{j+1} = N_{j+1}Q_{j+1}, \quad (11.c)$$

and

$$S'_{j+1} = N'_{j+1}Q'_{j+1} = S_{j+1} + x_{j,N_j-1}. \quad (11.d)$$

Substituting Eq. (11) into Eq. (10), ΔMSE is modified as

$$\begin{aligned}\Delta MSE_{j,j+1} &= \frac{1}{N}\{S_jQ_j - (S_j - x_{j,N_j-1})Q'_j + S_{j+1}Q_{j+1} - (S_{j+1} + x_{j,N_j-1})Q'_{j+1}\} \\ &= \frac{1}{N}\{S_j(Q_j - Q'_j) + S_{j+1}(Q_{j+1} - Q'_{j+1}) - x_{j,N_j-1}(Q'_{j+1} - Q'_j)\}. \end{aligned} \quad (12)$$

To simplify the computation, four codewords Q_j, Q'_j, Q_{j+1}, and Q'_{j+1}, are given the approximate value, the average of the largest and smallest pixels in the region, that is,

$$Q_j \approx (x_{j,0} + x_{j,N_j-1})/2, \tag{13.a}$$

$$Q_j' \approx (x_{j,0} + x_{j,N_j-2})/2, \tag{13.b}$$

$$Q_{j+1} \approx (x_{j+1,0} + x_{j+1,N_j-1})/2, \tag{13.c}$$

and

$$Q_{j+1}' \approx (x_{j,N_j-1} + x_{j+1,N_{j+1}-1})/2. \tag{13.d}$$

This simplification reduces the sum-division operation to one addition and one shift operations. Substituting Eq. (13) into Eq. (12), we have

$$\Delta MSE_{j,j+1} \approx \frac{1}{2N}[(x_{j,N_j-1} - x_{j,N_j-2})S_j + (x_{j+1,0} - x_{j,N_j-1})S_{j+1} - x_{j,N_j-1}(x_{j+1,N_{j+1}-1} - x_{j,0} + x_{j,N_j-1} - x_{j,N_j-2})]. \tag{14}$$

Considering the characteristics of high correlation in an image, the distribution of pixels within a very small region can be considered to be uniform. In this case, the small dynamic range for regions j and j+1 is given as:

$$d_{j,j+1} = x_{j,N_j-1} - x_{j,N_j-2} \approx x_{j+1,0} - x_{j,N_j-1}, \tag{15.a}$$

the full dynamic range for regions j and j+1 is

$$D_{j,j+1} = x_{j+1,N_{j+1}-1} - x_{j,0} \approx (N_j + N_{j+1} - 1)d_{j,j+1}, \tag{15.b}$$

and the total sum of regions j and j+1 is

$$S_j + S_{j+1} \approx (N_j + N_{j+1})[(x_{j,0} + x_{j+1,N_{j+1}-1})/2]. \tag{15.c}$$

Substituting Eq. (15) into Eq. (14),we have

$$\Delta MSE_{j,j+1} \approx d_{j,j+1}(N_j + N_{j+1})(x_{j,0} + x_{j+1,N_{j+1}-1} - 2x_{j,N_j-1})/4N. \tag{16.a}$$

Let

$$L_{j,j+1} = x_{j,0} + x_{j+1,N_{j+1}-1} - 2x_{j,N_j-1}; \tag{16.b}$$

we have

$$\Delta MSE_{j,j+1} \approx \frac{d_{j,j+1}(N_j + N_{j+1})}{4N} L_{j,j+1}. \tag{16.c}$$

From above equation, we can find that if $\Delta MSE_{j,j+1}$ or the quantity $L_{j,j+1}$ is less than 0, then moving the jth threshold left can reduce the MSE. Similarly, we can find that if the quantity

$$R_{j,j+1} = 2x_{j+1,0} - (x_{j,0} + x_{j+1,N_{j+1}-1}), \tag{17}$$

is less than 0, moving the jth threshold right can reduce the MSE.

From Eqs. (16.b) and (17), for regions j and j + 1, we can move the jth threshold left or right until the quantity $L_{j,j+1}$ or $R_{j,j+1}$ is not less than 0. Let

$$T_{j,j+1} = \frac{x_{j,0} + x_{j+1,N_{j+1}-1}}{2}. \tag{18}$$

After moving the jth threshold p times, we have

$$x_{j,N_j-p-1} < T_{j,j+1} < x_{j,N_j-p} \text{ if we move the threshold left} \tag{19.a}$$

or

$$x_{j+1,p-1} < T_{j,j+1} < x_{j+1,p} \text{ if we move the threshold right.} \tag{19.b}$$

It is obvious that $T_{j,j+1}$ is a threshold such that we can find a local optimum MSE. After finishing regions j and j+1, we can repeat the same process for regions j-1 and j to move the (j-1)th threshold and further reduce the MSE. After the 0th threshold is moved, one iteration is finished, and a better set of thresholds can be selected from the candidate sets of thresholds. Clearly, the more iterations are performed, the better the set of thresholds selected will be. The entire iteration can be summarized as the following steps:

Step 1: Specify the number of quantization levels, n, and segment sequence X uniformly into n regions.
Step 2: Set j as n-2.
Step 3: Calculate $T_{j,j+1}$ for regions j and j+1 using Eq.(18).
Step 4: Move the threshold left or right until the condition in Eq. (19) is satisfied.
Step 5: Decrease j. If $j \geq 0$, then go to Step 3; otherwise, repeat (go to Step 2) or stop.

It should be noted that the better the initial segmentation is, the smaller the number of iterations is. In general, not more than 3 iterations can obtain a nearly optimum MSE if initial segmentation is conducted in Step 1. After segmentation is finished, the n quantization values, Q_js, are obtained, and the pixels in the jth region are encoded with the index of the region, j, except that the block is performed with one-level BTC.

From Eq. (18), only one addition and one shift operation are required to calculate $T_{j,j+1}$ to adjust the location of the jth threshold. Therefore, if the number of quantization levels is n, and if S iterations are performed, then the proposed algorithm requires only S(n-1) additions and S(n-1) shifts to finish the segmentation of the block. In addition, (N-n) additions and n divisions are also required to calculate n codewords.

4. SIMULATIONS AND COMPARISONS

The image "LENA" was utilized to simulate the proposed GMBTC. The block size for GMBTC was 4 × 4 pixels. Fig. 2 shows the PSNRs of the reconstructed image with different numbers of iterations and quantization levels after performing compression using the proposed GMBTC, where the PSNR is defined as:

$$\mathrm{PSNR} = 10\log_{10}(255^2/\mathrm{MSE}). \quad (20)$$

From Fig. 2, the proposed GMBTC only requires 2 iterations, regardless of the number of quantization levels, to obtain a nearly optimum PSNR. Fig. 3 shows the convergence rate comparison between GMBTC(old) [9] and proposed GMBTC and we can find that the convergence rate of the proposed GMBTC is faster than that of GMBTC(old). Table 1 shows the PSNRs with the proposed GMBTC and some BTC techniques proposed in [1-9].

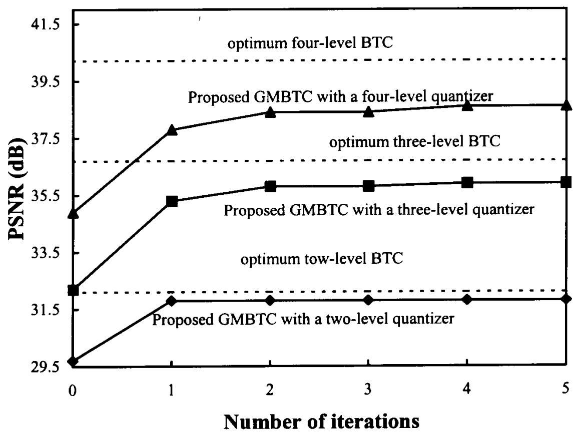

Fig. 2. The PSNR of the reconstructed image using the proposed GMBTC with different numbers of iterations and quantization levels.

Table 2 shows the numbers of multiplications (×), additions (+), square roots (√), shifts (SFT), comparisons (IF), and Look-Up-Table (LUT) operations for the above methods to facilitate comparison of computational complexity. The estimation results of the two-level BTC and three-level BTC shown in Table 2 are the same as those in [5] and [7], respectively. It should be noted that one division for calculating the codeword is estimated to consist of one multiplication and one LUT, and that the proposed GMBTC with two quantization levels only requires one iteration. From Tables 1 and 2, both the computational complexity and the PSNR can be obtained using the proposed GMBTC are better than those obtainable with the existing BTC techniques proposed in [1-9].

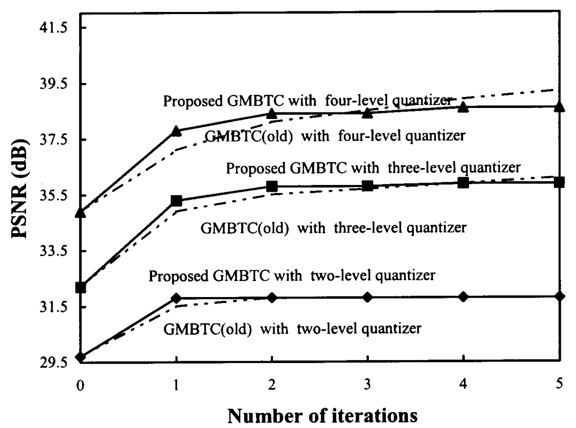

Fig. 3. The convergence rate comparison between the proposed GMBTC and GMBTC (old).

Table 1. A PSNR comparison for the BTC methods. (* means the procedure is not available; the number of iterations for the proposed GMBTC, I3BTC, and M3BTC is 2.)

method \ levels	2	3	4
BTC[1]	30.9	*	*
AMBTC[2]	31.1	*	*
MBTC[3]	31.1	*	*
I3BTC[6]	*	35.2	*
M3BTC[7]	*	35.8	*
WMBTC[8]	30.3	34.0	36.6
GMBTC (old) [9]	31.5	35.3	38.1
Proposed GMBTC	31.8	35.8	38.4
Optimum BTC	32.1	36.7	40.1

Table 2. (a) A comparison of the computational complexity of two-level BTC algorithms.

method \ operation	×	+	SFT	IF	√	LUT
BTC[1]	20	36	0	18	1	1
AMBTC[2]	3	25	0	34	0	1
MBTC[3]	3	25	0	16	0	1
WMBTC[8]	4	32	0	$59_{(avg)}$	0	2
GMBTC (old) [9]	2	22	4	88	0	2
Proposed GMBTC	2	15	1	$82_{(avg)}$	0	2
Optimum BTC[4]	46	127	1	256	0	10
Optimum BTC[5]	37	108	1	256	0	9

Table 2. (b) The comparison of the computational complexity of three-level BTC algorithms.

method \ operation	×	+	SFT	IF	LUT
I3BTC[6]	15	50	0	70	6
M3BTC[7]	12	50	0	115	4
WMBTC[8]	9	32	0	$69_{(avg)}$	3
GMBTC (old) [9]	3	29	8	90	3
Proposed GMBTC	3	17	4	$88_{(avg.)}$	3

Table 2. (c) The comparison of computational complexity for four-level BTC algorithms.

method \ operation	×	+	SFT	IF	LUT
WMBTC[8]	16	40	0	$80_{(avg)}$	4
GMBTC (old) [9]	4	36	12	88	4
Proposed GMBTC	4	18	6	$88_{(avg.)}$	4

Note: The number of comparisons of the proposed GMBTC is the average number because the number of the comparisons in Step 4 of the search algorithm can not be estimated exactly .

5. CONCLUSIONS AND FUTURE WORK

In this paper, a new generalized multilevel BTC has been proposed. The proposed BTC algorithm can be used with an arbitrary number of quantization levels and can obtain a nearly optimum PSNR based on fast nonexhaustive search. The simulation results indicate that both the computational complexity of and the PSNR that can be obtained using the proposed GMBTC are better than those obtainable with other existing multilevel BTC algorithms.

Though the compression ratio of BTC is lower than that of JPEG, hybrid coding for BTC can be used to efficiently increase the compression ratio. For example, we have recently found that the bit rate of BTC can be effectively reduced by applying the interpolation technique and VQ method to BTC [10]. Therefore, in our future work, we will develop an efficient hybrid algorithm which uses the proposed GMBTC and other compression techniques to reduce the bit rate of BTC.

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