Image Compression Using Block Truncation Coding

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***Abstract*—The present work investigates image compression using block truncation coding. Two algorithms were selected namely, the original block truncation coding (BTC) and Absolute Moment block truncation coding (AMBTC) and a comparative study was performed. Both of two techniques rely on applying divided image into non overlapping blocks. They differ in the way of selecting the quantization level in order to remove redundancy. Objectives measures were used to evaluate the image quality such as: Peak Signal to Noise Ratio (PSNR), Weighted Peak Signal to Noise Ratio (WPSNR), Bit Rate (BR) and Structural Similarity Index (SSIM).The results have shown that the ATBTC algorithm outperforms the BTC. It has been show that the image compression using AMBTC provides better image quality than image compression using BTC at the same bit rate. Moreover, the AMBTC is quite faster compared to BTC**

***Index Terms*—BTC, AMBTC, WPSNR, SSIM.**

I. INTRODUCTION

The amount of image data grows day by day. Large storage and bandwidth are needed to store and transmit the images, which is quite costly. Hence methods to compress the image data are essentially now-a-days. The image compression techniques are categorized into two main classifications namely Lossy compression techniques and Lossless compression techniques [1]. Lossless compression ratio gives good quality of compressed images, but yields only less compression whereas the lossy compression techniques [2] lead to loss of data with higher compression ratio. JPEG [1] and Block Truncation Coding [3] is a lossy image compression techniques .It is a simple technique which involves less computational complexity. BTC is a recent technique used for compression of monochrome image data. It is one-bit adaptive moment-preserving quantizer that preserves certain statistical moments of small blocks of the input image in the quantized output. The original algorithm of BTC preserves the standard mean and the standard deviation [9]. The statistical overheads Mean and the Standard deviation are to be coded as part of the block. The truncated block of the BTC is the one-bit output of the quantizer for every pixel in the block .Various methods have been proposed during last twenty years for image compression such BTC and Absolute Moment Block Truncation Coding AMBTC [6].AMBTC preserves the higher mean and lower mean of the blocks and use this quantity to quantize output. AMBTC provides better image quality than image compression using BTC. Moreover, the AMBTC is quite faster compared to BTC this paper represents comparative study between BTC and AMBTC .This paper is organized as follows: Section II explains BTC algorithm. Section III explains algorithm of AMBTC. Section IV explains image characteristic Section V briefly explains the performance evaluation criteria. Section VI introduces the experimental results and Section VII gives the concluding remarks.

II. BTC ALGORITHM

Block Truncation Coding (BTC) is a well-known compression scheme proposed in 1979 for the grayscale images. It was also called the moment-preserving block truncation [4]-[5] because it preserves the first and second moments of each image block. The BTC algorithm involves the following steps:

- Step1: The given image is divided into non overlapping rectangular regions. For the sake of simplicity the blocks were let to be square regions of size m x m.
- Step 2: For a two level (1 bit) quantizer, the idea is to select two luminance values to represent each pixel in the block. These values are the mean $\bar{x}$ and standard deviation σ .

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (x_i - \bar{x}_i)^2} \tag{2}$$

Where x_i represents the i^{th} pixel value of the image block and n is the total number of pixels in that block.

- Step3: The two values $\bar{x}$ and σ are termed as quantizers of BTC. Taking $\bar{x}$ as the threshold value a two-level bit plane is obtained by comparing each pixel value x_i with the threshold. A binary block, denoted by B, is also used to represent the pixels. We can use “1” to represent a pixel whose gray level is grater than or equal to $\bar{x}$ and “0” to represent a pixel whose gray level is less than

$$B = \begin{cases} 1 & x_i \geq \bar{x} \\ 0 & x_i \prec \bar{x} \end{cases} \tag{3}$$

By this process each block is reduced to a bit plane. For example, a block of 4 x 4 pixels will give a 32 bit compressed data, amounting to 2 bit per pixel (bpp).

- Step 4: In the decoder an image block is reconstructed by replacing '1's in the bit plane with H and the '0's with L, which are given by:

$$H = \bar{x} + \sigma\sqrt{\frac{p}{q}} \quad (4)$$

$$L = \bar{x} - \sigma\sqrt{\frac{q}{p}} \quad (5)$$

Where p and q are the number of 0's and 1's in the compressed bit plane respectively.

III. ALGORITHM OF AMBTC

Lema and Mitchell [7] presented a simple and fast variant of BTC, named Absolute Moment BTC (AMBTC) [8] that preserves the higher mean and lower mean of a block. The AMBTC algorithm involves the following steps:

- Step 1: An image is divided into non-overlapping blocks. The size of a block could be (4 x 4) or (8 x 8), etc.
- Step 2: Calculate the average gray level of the block (4x4) as equations(6):
- Step 3: Pixels in the image block are then classified into two ranges of values. The upper range is those gray levels which are greater than the block average gray level ($\bar{x}$) and the remaining brought into the lower range. The mean of higher range XH and the lower range XL are calculated as :

$$x_H = \frac{1}{K}\sum_{x_i \succ \bar{x}}^{n} x_i \quad (6)$$

$$x_L = \frac{1}{16-K}\sum_{x_i \prec \bar{x}}^{n} x_i \quad (7$$

Here k is the number of pixels whose gray level is greater than $\bar{x}$.

- Step 4: Binary block, denoted by B, is also used to represent the pixels. We can use "1" to represent a pixel whose gray level is grater than or equal to $\bar{x}$ and "0" to represent a pixel whose gray level is less than $\bar{x}$. The encoder writes XH , XL. Then the total number of bits required for a block is 8+8+16 =32 bits. Thus, the bit rate for the AMBTC algorithm is 2 bpp .

$$B = \begin{cases} 1 & x_i \geq \bar{x} \\ 0 & x_i \prec \bar{x} \end{cases} \quad (8$$

- Step 5: In the decoder, an image block is reconstructed by replacing the `1' s with XH and the '0''s by XL In the AMBTC, we need 16 bits to code the bit plane which is same as in the BTC. But, AMBTC requires less computation than BTC

$$X = \begin{cases} X_L & B = 0 \\ X_H & B = 1 \end{cases} \quad (9)$$

AMBTC has several advantages over BTC one advantage is in the case that the quantizer is used to transmit an image from transmitter to a receiver, it is necessary to compute at the transmitter the two quantities, the sample mean and the sample standard deviation for BTC and sample first absolute central moment for AMBTC. When we compare the necessary computation for deviation information, we will see that in case of standard BTC it is necessary to compute a sum of m values and each of them will be squared while in case of AMBTC it is only necessary to compute the sum of these m values. Since the multiplication time is several times greater than the addition time in most digital processors, thus using AMBTC the total calculation time at the transmitter is significantly reduced.

VI. IMAGE CHARACTERISTICS

The spatial frequency measurement (SFM) [9] indicates the overall activity level in an image. SFM is defined as follow:

$$SFM = \sqrt{(R)^2 + (C)^2} \quad (10)$$

$$C = \sqrt{\frac{1}{MN}\sum_{n=1,m=2}^{N,M}[x(m,n) - x(m-1,n)]^2} \quad (11)$$

$$R = \sqrt{\frac{1}{MN}\sum_{m=1n=2}^{M,N}[x(m,n) - x(m,n-1)]^2} \quad (12)$$

Where R is row frequency, C is column frequency, x (m, n) denotes the samples of image, M and N are number of pixels in row and column directions, respectively. The large value of SFM means that image contains components in high frequency area. It returns that low redundant image, which is difficult for compression. Small value of SFM means that image contains components in low frequency area. It returns that high redundant image, which is easy for compression.

V.IMAGE QUALITY MEASUREMENTS

Image quality measures play important roles in various images processing application .Once image compression system has been designed and implemented, it is important to be able to evaluate its performance. This evaluation should be done in such a way to be able to compare results against other image compression techniques. The image quality metrics can be broadly classified into two categories, subjective and objective. Subjective image quality is a method of evaluation of images by the viewers read images directly to determine their quality. In objective measures of image quality metrics, some statistical indices are calculated to indicate the image quality. In our work we will focus in objective[9]-[10] measures such as Peak Signal to Noise Ratio (PSNR), Weighted Peak Signal to Noise Ratio (WPSNR), Bit Rate (BR) and Structural Similarity Index (SSIM).

A. Peak Signal to Noise Ratio (PSNR)

The PSNR is most commonly used as a measure of quality of reconstruction of lossy compression It is an attractive measure for the loss of image quality due to its simplicity and mathematical convenience .Peak signal-to-noise ratio (PSNR) is a qualitative measure based on the mean-square-error of the reconstructed image´.If the reconstructed image is close to the original image, then MSE is small and PSNR takes a large value .PSNR is dimensionless and is expressed in decibel . Peak Signal-to-Noise Ratio (PSNR) avoids this problem by scaling the MSE according to the image range .PSNR is defined as follow:

$$MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} \left[y(i,j) - x(i,j) \right]^2 \qquad (13)$$

$$PSNR = 10 \log \left(\frac{L^2}{MSE} \right) \qquad (14)$$

Where L is the dynamic range of the pixel values (255 for 8-bit grayscale images).

B. Weighted Peak Signal to Noise Ratio (WPSNR)

The weighted PSNR (WPSNR) has been defined as an extension of the traditional PSNR. It weights each term of the PSNR by local "activity" factor (linked to the local variance)[11].weighted PSNR (WPSNR) take into account the local human visual system (HVS) sensitivity, it is a measure criteria which hold account of the neighbors of the studied pixels.

$$WPSNR = 10 \log \left(\frac{L^2}{\| (y - x).NVF \|^2} \right) \qquad (15)$$

Where $NVF = 1 / (1 + \theta \sigma_x^2 (i,j))$ (16)

$$\sigma_x^2(i,j) = \frac{1}{(2L+1)^2} \sum_{m=-L}^{L} \sum_{n=-L}^{L} (x(i+m, j+n) - \bar{x}(i,j))^2 \qquad (17)$$

$$\theta = \frac{D}{\sigma_{x\,\max}^2} \qquad (18)$$

Where $ó^2_{xmax}$ is the maximum local variance of a given image and $D \in [50, 150]$ is a determined parameter.

C. Bit Rate (BR)

The performance of image compression schemes can be specified in terms of compression efficiency. Compression efficiency is measured by the compression ratio or by the bit rate. Compression ratio is the ratio of the size of original image to the size of the compressed image; the bit rate is the number of bits per pixel required by the compressed image

CR = size of original image / size of the compressed image

The compression ratio and bit rate are related. Let b be the number of bits per pixel (bit depth) of the uncompressed image, CR the compression ratio, and BR the bit rate. The bit rate ratio is given by

$$BR = \frac{b}{CR} \qquad (19)$$

D. Structural Similarity Index (SSIM).

Another category of image quality measures is based on the assumption that the human visual system is highly adapted to extract structural information from the viewing field [12]. The error sensitivity approach estimates perceived errors to quantify image degradations, while this approach considers image degradations as perceived structural information variation. The structural Similarity (SSIM) index can be calculated as a function of three components: luminance, contrast and structure.

$$SSIM(x,y) = [l(x,y)]^{\alpha} \cdot [c(x,y)]^{\beta} \cdot [s(x,y)]^{\gamma} \qquad (20)$$

This results in a specific form of the SSIM index:

$$SSIM(x,y) = \frac{(2\mu_x \mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \qquad (21)$$

Where C1= (K1 L)2, K1<<1 and C2= (K2 L)2, K2<<1.

VI. Experimental Results

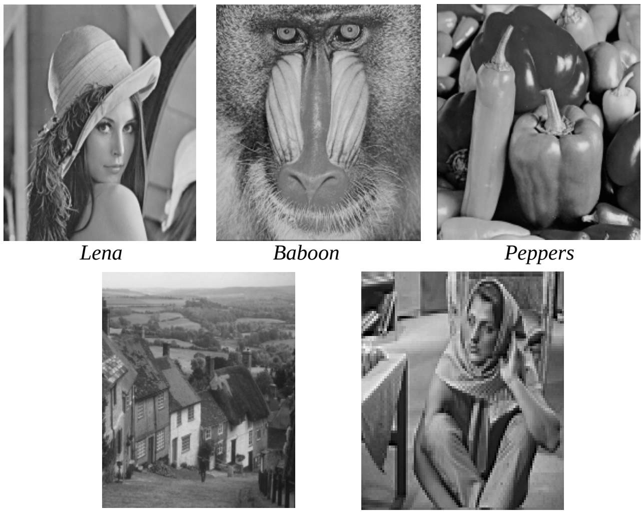
Five test images (512×512, 8 bits per pixel) with different spatial and frequency characteristics, as shown in Fig.1: Lena, Baboon, peppers, Goldhill and Barb are used. Characteristics of test images are evaluated in spatial domain using spatial frequency measure (SFM) [9].

A. Measuring Spatial Frequency (SFM)

The Spatial frequencies (SFM) and values computed for the above set of images are given in Table 1 (16)

TABLE 1 spatial frequency measure of images

	Lena	*Baboon*	*Peppers*	*Goldhill*	*Barb*
SFM	*14.0421*	*36.5146*	*15.8446*	*16.1666*	*29.4567*



Lena *Baboon* *Peppers*

Goldhill *Barb*

Figure 1. Image Database (size of 512×512 pixels).

Test image Baboon has a lot of details and consequently large SFM. Large value of SFM means that image contains components in high frequency area. It returns that Baboon presents low redundant image, which is difficult for compression. Test image Lena are images has low details and consequently small SFM. Small value of SFM means that image contains components in low frequency area. It returns that Lena presents high redundant image, which is easy for compression than Baboon.

B. Evaluating Perceptual Quality

To compare between the used compression methods, four parameters were calculated. These are BR, PSNR, wPSNR, and SSIM when a block size is 8*8. These values are listed in Table 2.

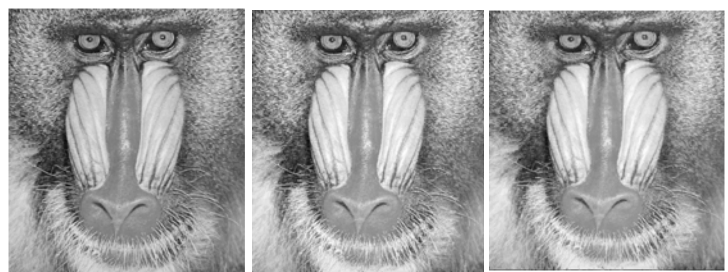
Table 2 BTC and AMBTC parameters

		BR	*PSNR*	*WPSNR*	*SSIM*
Lena	*BTC*	1.25	29.5552	34.6005	0.8741
	AMBTC	1.25	29.9419	34.9786	0.8821
Babbon	*BTC*	1.25	24.7720	33.0637	0.8264
	AMBTC	1.25	25.1861	33.7929	0.8277
Peppers	*BTC*	1.25	29.0598	34.1210	0.8628
	AMBTC	1.25	29.4614	34.6366	0.8718
Goldhill	*BTC*	1.25	29.5163	33.5522	0.8459
	AMBTC	1.25	29.9311	34.0911	0.8529
Barb	*BTC*	1.25	28.2149	33.7120	0.8613
	AMBTC	1.25	28.5985	34.0669	0.8667

The above tables assure that the image compression using AMBTC provides better image quality than image compression using BTC at the same bit rate. Moreover, the AMBTC is quite faster compared to BTC. Figure 2,3,4,5 and Figure6 shows the original and compressed images using BTC and AMBTC.

(a) (b) (c)

Figure 2. (a)Original image, (b), (c) compressed images using BTC and AMBTC respectively



(a) (b) (c)

Figure 3. (a)Original image, (b), (c) compressed images using BTC and AMBTC respectively

(a) (b) (c)

Figure 4. (a)Original image, (b), (c) compressed images using BTC and AMBTC respectively

(a) (b) (c)

Figure 5. (a)Original image, (b), (c) compressed images using BTC and AMBTC respectively

(a) (b) (c)

Figure 6. (a)Original image, (b), (c) compressed images using BTC and AMBTC respectively

VII. Conclusions

In this paper, image compression using block truncation coding has been investigated. Two algorithms were selected namely, the original block truncation coding (BTC) and Absolute Moment block truncation coding (AMBTC). The two algorithms are based on dividing the image into non overlapping blocks and uses a two-level quantize. The two techniques were applied to different grey level test image each contains 512×512 pixels with 8 bits/pixel (256 grey levels). The reconstructed images have a bit rate of 1.25 bit/pixel. This corresponds to 85% compression. Objectives measures were used to evaluate the image quality such as: Peak Signal to Noise Ratio (PSNR), Weighted Peak Signal to Noise Ratio (WPSNR), Bit Rate (BR) and Structural Similarity Index (SSIM).The results have shown that the ATBTC algorithm outperforms the BTC. It has been show that the image compression using AMBTC provides better image quality than image compression using BTC at the same bit rate. Moreover, the AMBTC is quite faster compared to BTC.

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