Multi-level Block Truncation Code Algorithm for RGB Image Compression

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Abstract - *The purpose of this paper is continuous compression of multi-level block truncation code (BTC) based image compression to achieve low bit rate and high quality of image. The algorithm is proposed by combining bit map and quantization. The algorithm has been proposed based on the assumption that computing power is not a limiting factor. The parameters considered for evaluating the performance of the proposed methods are compression ratio and subjective quality of the reconstructed images.The performance of proposed algorithm including color image compression, progressive image transmission is quite good. The effectiveness of the proposed schemes is established by comparing performance with existing methods.*

Key Words: *Image Compression, Block Truncation Code (BTC), Bit Map, Multi-level, Quantization*

1. INTRODUCTION

With the advent of the multimedia era and the development of digital packet networks, the total image data accessed and exchanged by users has reached a gigantic value of several terabytes. Therefore, the need for compression of continuous vowel still images has increased considerably. Image compression maps an original image into a bit stream suitable for transmission and storage. The number of bits required to represent a compressed image must be smaller than that required for the original image. Compression per pixel (BPP) or compression ratio (CR) [1] is specified in terms of the number of bits. The subjective quality of the compressed image is specified by the peak signal to noise ratio (PSNR). Digital image compression methods can be divided into two broad categories: 'lossless' and 'lossy' compression methods. Lossy compression methods are necessary to achieve high compression ratios. In a lossy compression system, the reconstructed image is not the same as the source image and a much higher compression ratio is possible at the cost of loss of visual quality [2]. Lossy compression algorithms are based on the principle of removing subjective redundancy and are extremely important in applications such as the transmission of still images over the Internet where certain distortion can be tolerated. Traditional image compression techniques such as run length coding, arithmetic coding, and Huffman code are lossless coding schemes. The statistical redundancy present in the image can be effectively compressed using such lossless compression but the compression achieved is low [3–4]. The best compression ratio that can be achieved with current lossless compression standards such as the Joint Photographic Expert Group (JPEG) is around 3 to 4. Harmless is a widely applied method for image compression. The image beautifies the pixels effectively so that pixels representing similar events in the image can be grouped together according to their spatial or spectral properties. After transformation, useful information is concentrated in some low frequency coefficients and the human visual system is more sensitive to such low spatial frequency information than high spatial frequency [5]. This is achieved through some conservative transformations such as Karhunen – Loew transform (KLT), distress cosine transform (DCT), discrete sign transform (DST), Walsh headmard transform, etc. One of the best known coding techniques currently known. A primary example of change coding is the DCT-based JPEG image compression standard formulated by the ISO / IEC / JTC1 / SC2 / WG10 committee popularly called the Joint Photographic Expert Group. It performs lossy compression of still images. However, it suffers from defects of blocked artifacts. Recently, the application of discrete wavelet transform (DWT) in image compression has received significant attention and several wavelet based image compression algorithms have been proposed. The wavelet transform decomposes a signal into its various frequency components. In the case of natural images, one obtains several small or zero-valued coefficients corresponding to the high frequency components of the image. Due to the large number of small coefficients, the converted signal is easier to code than the original signal [6]. The JPEG 2000 standard is based on changing the coding employed to DWT. It achieves higher compression ratios and better subjective quality, especially at lower bit rates than previous DCT-based JPEGs [7].

2. ELEMENTS OF LOSSY IMAGE COMPRESSION SYSTEM

In transform-based image compression, the image is subjected to transformation and then the transformed data is encoded to produce a compressed bitstream. The general structure of a transformation-based image compression system is shown in Fig. 1. There are two versions of change coding. One is frame-based and the other is block-based. The block-based approach requires less computation and allows adaptive quantization of coefficients.

In Figure 1, X represents the original image pixel values; Yi denotes the transformed values of the original image. All transformed coefficients are then quantized and entropy coded as indicated by CI. These compressed bit streams are either transmitted or stored. Reconstructed images can be obtained by decomposing the coded signal. The goal is to design a system so that the coded signal CI is represented with fewer bits than the original image X [8].

In the 1980s, almost all transform based compression approaches using DCT. Later, the trend moved to compression schemes based on DWT. DWT eliminates the effect of blocking artifacts associated with DCT. Perhaps the most significant improvement in traditional coding comes from the use of arithmetic coders rather than ordinary Huffman coders, which increases the compression ratio by 5–8%. However, multimedia content is growing rapidly in daily life; Therefore, a performance gain of around 10% over ten years does not meet demand. Therefore, researchers have looked for new solutions that can solve the problem of static image compression performance.

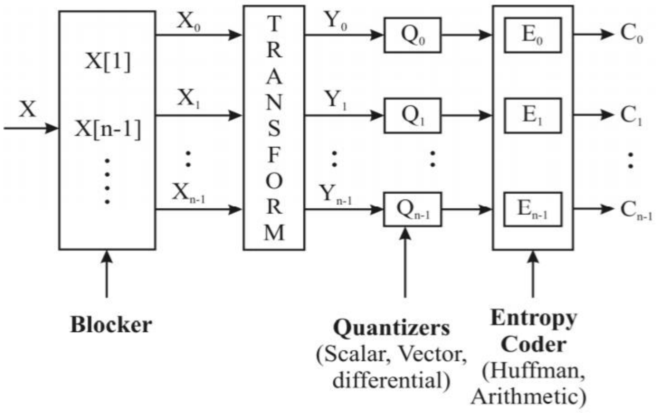


Fig -1: Transform-based image compression system

Finally, the magnitude coefficient is coded to produce a compressed bitstream. The coding process typically exploits a statistical model to code symbols with fewer bits for symbols in which the probability of occurrence is higher. In doing so, the size of the compressed bitstream is reduced. Assuming that the planned change is indeed the inverse, the only possible cause of information loss is coefficient quantification, as quantitative coefficients are coded losslessly [9]. The dissolution process simply reflects the process used for compression. The compressed bitstream is decoded to obtain the compressed transformation coefficient. Then, the inverse reconstruction of the transverse used during compression is employed to obtain the reconstructed image.

3. IMAGE QUALITY MEASURES

Evaluating the image quality of an image compression system is a major task to describe the amount of degradation in a reconstructed image. In the case of lossy compression, the reconstructed image is only an approximation of the original. The difference between the original and the reconstructed signal is called an approximation error or distortion. Typically, performance is evaluated in terms of compression ratio and image fidelity [10]. A good image compression algorithm results in a high compression ratio and high fidelity. Unfortunately, both requirements cannot be obtained simultaneously. Although several matrices exist to determine the distortion, it is commonly expressed as the squared error (MSE) or peak-signal-to-noise ratio (PSNR). The performance of image compression systems is measured by the metrics defined in equations (1) and (2). It is based on the assumption that the digital image is represented as $N_1 \times N_2$ matrix, where N_1 and N_2 denote the number of rows and columns of the image respectively. Also, $f(i, j)$ and $g(i, j)$ denote pixel values of the original image before compression and degraded image after compression respectively.

Mean Square Error (MSE)

$$= \frac{1}{N_1 N_2} \sum_{j=1}^{N_2} \sum_{i=1}^{N_1} (f(i, j) - g(i, j))^2 \tag{1}$$

Peak Signal to Noise Ratio (PSNR) in dB

$$= 10 \times \log_{10}\left(\frac{255^2}{MSE}\right) \quad (2)$$

Smaller MSE and larger PSNR values correspond to lower levels of distortion. While these metrics are often employed, it can be seen that MSE and PSNR metrics do not always correlate well with image quality as perceived by the human visual system. For this reason, it is preferable to supplement any objective lossy compression performance measurement by subjective testing such as objective scores (MOS) to ensure that objective results are not misleading [11].

Sometimes compression is determined by stating the bit rate (BR) achieved by the compression algorithm expressed in bpp (bits per pixel). Another parameter that measures the amount of compression is the compression ratio (CR) defined

$$CR = \frac{Original\ image\ size}{Compressed\ image\ size} \quad (3)$$

4. PROPOSED METHODOLOGY

The proposed encoder and decoder block of the multi-level block truncation code algorithm is denoted if figure 2. The encoder part of the proposed algorithm shows that the original image is divided into three parts namely R component, G component and B component. Each R, G, B component of the image is divided into non-overlapping blocks of equal size and a threshold value is being calculated for each block size.
Threshold value means the average of the maximum value (max) of ‘k × k’ pixels block, minimum value (min) of ‘k × k’ pixels block and m_1 is the mean value of ‘k × k’ pixels block. Where k represents block size of the color image. So threshold value is:

$$T = \frac{\max + \min + m_1}{3} \quad (4)$$

Each threshold value is passing through a quantization block. Quantization is the process of mapping a set of input fractional values to a whole number. Suppose the fractional value is less than 0.5, then the quantization is replaced by the previous whole number and if the fractional value is greater than 0.5, the quantization is replaced by the next whole number. Each quantization value is passing through a bit map block. A bit map means that each block is represented by means 0 'and' 1 'bit map. If the threshold value is less than or equal to the input image value then the pixel value of the image is represented by '0' and if the threshold value is greater than the input image value then the pixel value of the image is represented by '1'.
The bit map is directly connected to the high and low components of the proposed decoder multi-level BTC algorithm. The high (H) and low (L) component is directly connected to the bit map, the bitmap changed the '1' and to 0 'pixel value to high and low pixel value and arranged the entire block.

$$L = \frac{1}{q}\sum_{i=1}^{p} W_i \quad W_i \le T \quad (5)$$

$$H = \frac{1}{p}\sum_{i=1}^{p} W_i \quad W_i > T \quad (6)$$

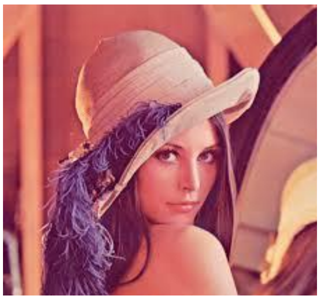
W_i represents the input color image block, Q is the number of zeros in the bit plane, P is the number of people in the bit plane. In the joint block of the decoder, the values obtained from the pattern fitting blocks of the individual R, G, B components are combined then all the individual joint blocks are merged into one block. Finally, a compressed image and all parameters relative to that image will be obtained.

5. SIMULATION RESULT

Figure 2; shows the Lena image of 2×2 block pixel. In this figure 2 (a) show the random image of the Lena image and resize the image of the 512×512 in the Lena image shown in figure 2 (b). The compressed image is 2×2 block pixel of Lena image shown in figure 2 (c) respectively.

(a) (b)

(c) (d)



(e) (f)

Fig -2: Multi-level BTC Algorithm applied on Satellite Image of block size 4×4

The peak signal to noise ratio (PSNR) and computation time are derived from the proposed multi-level block truncation code algorithm, as shown in Table 1. The value obtained for different block sizes is the average value of the red, blue, and green components of the image.

Table -1: Comparative Study of Proposed Method on different images

Image		MSE	PSNR
Flower Image	Previous	498.52	38.15
	Proposed	479.12	40.21
Baboon Image	Previous	458.25	41.62
	Proposed	439.98	43.21
Lena Image	Previous	501.326	36.91
	Proposed	489.278	39.87

Table -2: PSNR Calculate of R, G, B channel refinement

Image	Red channel	Green Channel	Blue Channel
Baboon Image	35.1957	35.1401	34.8256
Lena image	36.6889	36.4779	36.8824
Bike Image	33.1614	33.2006	33.1019

6. CONCLUSION

The proposed method improved the quality of de-noised images, especially for random-valued impulse noise. The proposed method is evaluated on standard images such as flower, lena, and baboon images. Peak signal noise to ratio and square error-value mean that the proposed method outperforms the existing method.

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