Quality of Image Compression of Block Adaptive Models for FPGA Implementation

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Abstract— With the intention of resolving this issue, image compression has become very important for efficient archiving and transmission of images. Compression is the process of coding that will effectively reduce the total number of bits needed to represent certain information. Currently, research in medical image compression concentrates on the implementation of methods such as Run length coding, Lempel-Ziv Welch (LZW), Huffman coding, Vector Quantization (VQ) and so on for improved quality of image. Among the various spatial domain image compression techniques, multi-level Block partition Coding (ML-BTC) is one of the best methods which has the least computational complexity. The parameters such as Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE) are measured and it is found that the implemented methods of BTC are superior to the traditional BTC. This paves the way for a nearly error free and compressed transmission of the images through the communication channel.

Keywords—Multi-level Block Truncation Code (ML-BTC), Bit Map, Multi-level Quantization (MLQ), Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE)

I. INTRODUCTION

With the improvement of digital technology, it would be essential to safeguard image data. Because of the increment in transfer demand and data storage of compressed image turn into a vital in the research field. Image compression goes for diminishing the measure of information required to specify digital image. It is a procedure that yields a reduced image representation. It reduces image transmission bandwidth and storage requirements. At the point when image size is decreased, it enables more images to be stored in the given amount of memory space [1, 2].

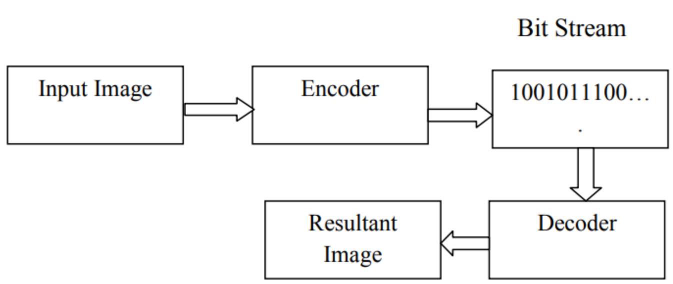

Fig. 1: Basic Flow of Image Compression

It likewise lessens the time required for images to be sent over the Internet. Fundamental flow of image compression is outlined in Figure 1. Image is given to encoder which changes images into bit streams. When decoder gets these encoded bit streams, it interprets it and the resultant images are acquired from the output of decoder. Image compression occurs when the overall data quantity of the input image is greater than that of the attained bit stream [3, 4].

In a raw state, images can occupy a large amount of memory both in RAM and in storage. Image compression reduces the storage space required by an image and the bandwidth needed when streaming that image across a network. It is clearly the need for adequate storage space, large transmission bandwidth and long transmission time for image. In the present state-of-art in technology, the only answer is to compress the image. Decreasing the irrelevance or redundancy of an image is the fundamental aim of the image compression techniques to provide the facility for storing and transmitting the data in an effective manner [5, 6].

II. LOSSY AND LOSSLESS IMAGE COMPRESSION SYSTEM

In transform based image compression, the image is subjected to transformation and then the transformed data are encoded to produce the compressed bit stream.

An image reconstructed following lossy compression contains degradation relative to the original. Often this is because the compression scheme completely discards redundant information. However, lossy schemes are capable of achieving much higher compression. Lossy methods are especially suitable for natural images such as photos in applications where minor (sometimes imperceptible) loss of fidelity is acceptable to achieve a substantial reduction in bit rate. The lossy compression that produces imperceptible differences can be called visually lossless [7, 8].

In lossless compression schemes, the reconstructed image, after compression, is numerically identical to the original image. However lossless compression can only achieve a modest amount of compression. Lossless compression is preferred for archival purposes and often medical imaging, technical drawings, clip arts etc. whereas lossy compression methods, especially when used at low bit rates, introduce compression artifacts.

Lossy and lossless transform based image compression system is shown in figure 1. In figure 1, the original image X is passed through the partition block then partition method divide the original image into X_0, X_1,………..X_{n-1} sub part. All sub part is passed through the transform block then transform block change the X_0, X_1,………..X_{n-1} to Y_0, Y_1,………..Y_{n-1} domain.

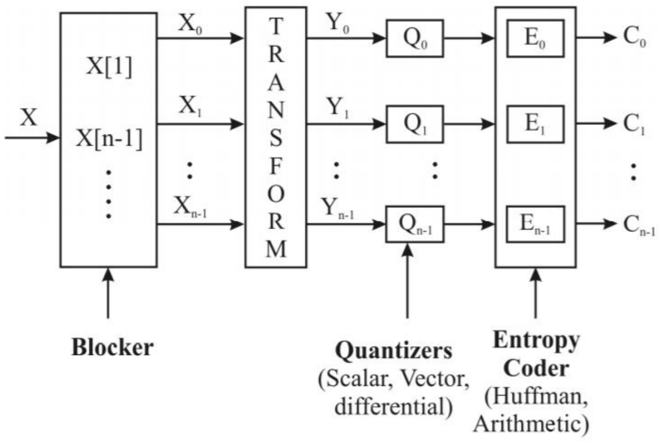

Fig. 2: Transform-based image compression system

Finally, the quantized coefficients are coded to produce the compressed bit stream. The coding process typically exploits a statistical model in order to code symbols with fewer bits for symbols that has higher probability of occurrence. In doing so, the size of the compressed bit stream is reduced. Assuming that the transform employed is truly invertible, the only potential cause for information loss is in the coefficient quantization, as the quantized coefficients are coded in a lossless manner [9]. The decompression process simply mirrors the process used for compression. The compressed bit stream is decoded to obtain the quantized transform coefficients. Then, the inverse of the transform used during compression is employed to obtain the reconstructed image.

III. BLOCK ADAPTIVE (BA)

The Next proposed work is to accomplish alterations in SPIHT calculation. SPIHT is broadly utilized in picture pressure and alteration of SPIHT calculation has an zone of fascination for some scientists to improve its effectiveness to the most extreme degree. The other proposed work is Lossless Efficient Run Length Coding for grayscale picture. The E-RLC strategy performs block insightful pressure of the entire picture for better pressure proportion. The proposed E-RLC calculation is most useful asset to utilize TIFF, GIFF, JPEG and printed which makes out of proficiency what's more, better pressure. The E-RLC technique will appropriate for grayscale, monochrome pictures [10, 11].

Oddity of the proposed lossless prescient coding based BA is to give the high CR without bargaining demonstrative data. The proposed lossless prescient BAAE based model includes expectation to eliminate between pixel excess followed by expulsion of coding excess from the picture by separating the lingering picture into little estimated blocks prior to encoding.

The initial step of the proposed method is to eliminate between pixel excess is talked about in the section 3. The RIGED indicator is limit based and proposed for the effective forecast of picture pixel esteem for 8-digit profundity information. RIGED is moreover stretched out for higher piece dept pictures as current imaging methods create high nature of pictures having high piece profundity i.e., 16-digit. The RIGED16 determines the ideal T-esteem for 16-digit picture expectation with least remaining entropy. Ideal limit values are gotten for 8-bit and 16-digit profundity clinical picture datasets for viable [12].

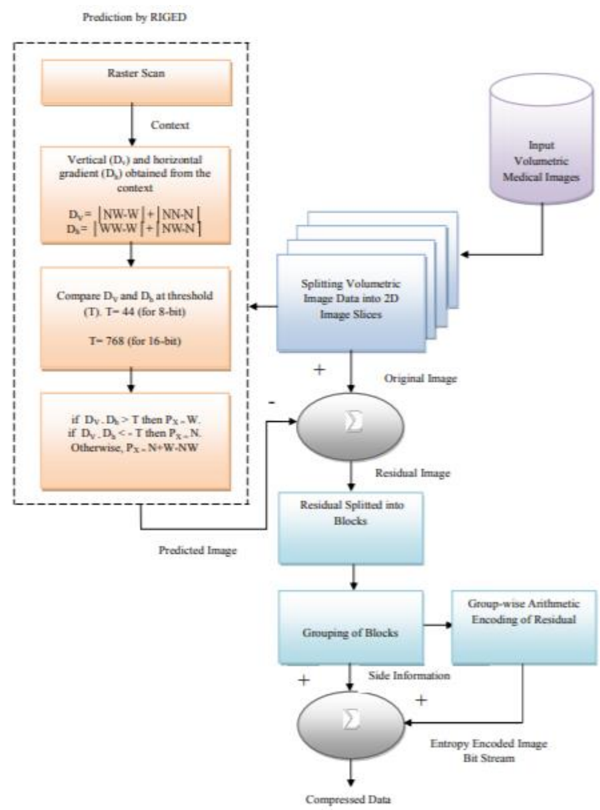

Fig. 3: Proposed predictive model employing BA

In this section, a square based blunder encoding method for viable lossless coding of clinical picture dataset is proposed. This method encourages the lossless coding of volumetric clinical pictures with less computational intricacy. After RIGED expectation, the remaining is isolated into little squares and observational experimentation is accomplished for various square size from more modest to bigger square size to locate the ideal square size [13].

The various squares are gathered based on mean total blunder and afterward encoded each gathering by using number juggling encoder. An exact experimentation was finished with various square sizes and the BPP is determined. Overhead BPP is needed for decompress the pictures. The square size differs from 4×4 to 128×128 as appeared in Fig. 4. Experimentation is accomplished for the square size beginning from 2×2 yet in this section results are appeared from the square size 4×4 as there is irrelevant contrast between the block sizes 2×2 and 4×4 regarding BPP.

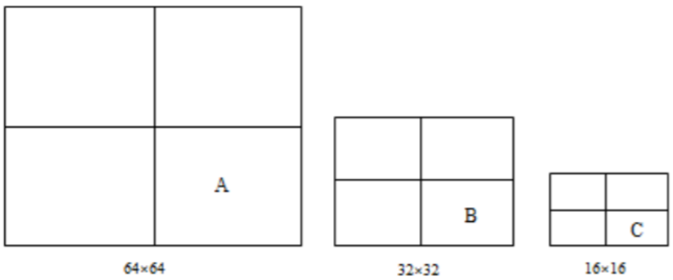

Fig. 4: Adaptive blocks with different sizes. Block A: 32×32, block B: 16×16 and block C: 8×8

For the picture size of 512×512, block size can be up-to 256×256 and for the picture size of 256×256, block size can be doing 128×128. There is no huge distinction between the square sizes 128×128 and 256×256. The proposed expectation model with the ideal T-esteem indicator and the square based encoder eliminates IPR and coding repetition to accomplish high pressure.

IV. PROPOSED METHODOLOGY

The best possible solution to the problem is to use compression methods where the compression of data on digital images are made to reduce irrelevance and redundancy of the image data to be able to efficiently store or transmit data. Most of the existing compression techniques employed have their negatives and an enhanced technique which is faster, effective and memory efficient can definitely satisfy the requirements of the user.

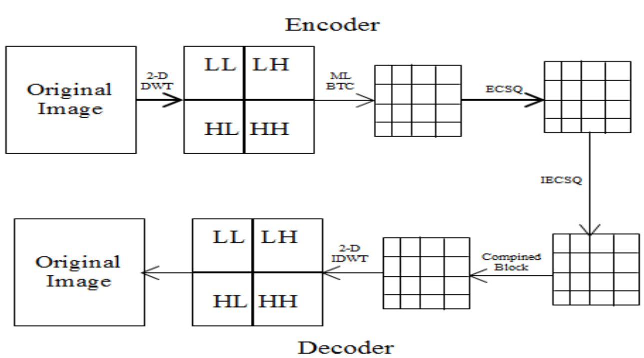

Fig. 5: Proposed Methodology

Image compression thrives to store or transmit the data in a proficient mode as well as to offer a best image quality at a specified bit-rate. Image compression can be done in lossy or lossless mode. Lossless compression is preferred for archival objectives and mainly used in medical imaging, technical drawings, clip art, or comics. This is due to the introduction of compression artifacts, low bit rates and also because the resources cannot be considerably saved by using image compression method. Lossy methods are especially suitable for natural images such as photographs in applications where negligible loss of fidelity is tolerable to attain a considerable reduction in bit rate. Here conciliated ensuing image quality devoid of much perception by the viewer is achieved.

Proposed Encoder and decoder block of the multi-level block partition code technique is shown in figure 3. Encoder part of the proposed technique shows that the original image is divided into three parts i.e. R component, G component and B component. Each R, G, B component of the image is divided into non overlapping block of equal size and threshold value for each block size is being calculated.

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:

$$T = \frac{\max + \min + m_1}{3}$$

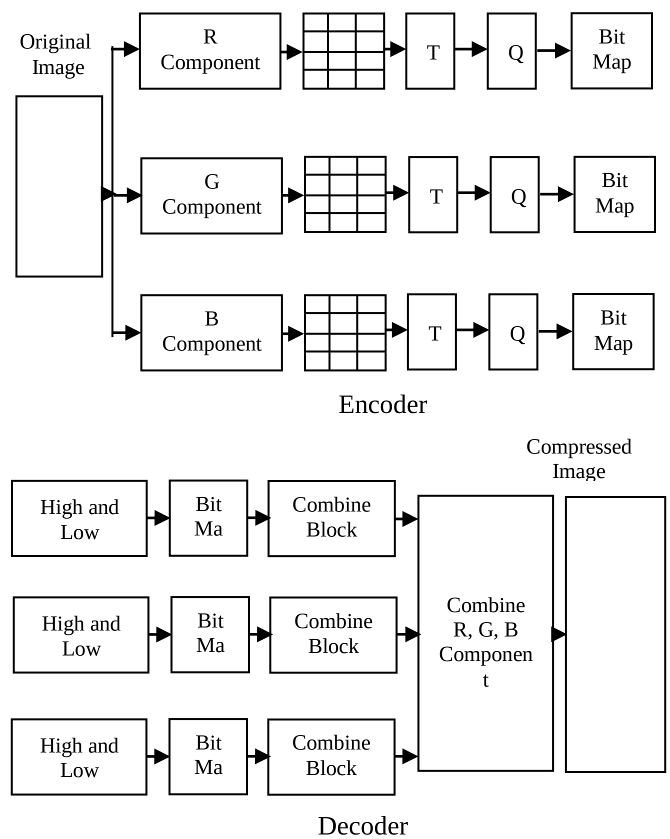

Fig. 6: Block Diagram of ML-BTC Algorithm

Each threshold value is passing through the 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 previous whole number and if the fractional value is greater than 0.5, then the quantization is replaced by next whole number. Each quantization value is passing through the bit map block. Bit map means each block is represented by ‘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 represent 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’.

Bit map is directly connected to the high and low component of the proposed decoder multi-level BTC algorithm. High (H) and low (L) component is directly connected to the bit map, bitmap converted the ‘1’ and ‘0’ pixel value to high and low pixel value and arrange the entire block.

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

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

W_i represent the input color image block, q is the number of zeros in the bit plane, p is the number of ones in the bit plane. In the combine block of decoder, the values obtained from the pattern fitting block of individual R, G,B components are combined after that all the individual combined block are merged into a single block . Finally compressed image and all the parameter relative to that image will be obtained.

FPGA:-

The initial FPGAs didn't have internal memories but now a day's all new FPGAs have internal memories with that internal memory a lot of real time applications may implement. Generally the FPGA internal structure block illustrations are available to count the number of divide address buses going to the RAM. Every manager has a dedicated address bus and in addition each manager has also a read, a write or both information data buses. If having both information data user always mean and manager can read and write at the same time. Writing and reading to the RAM is usually done synchronously but can also 20 from time to time be done asynchronously. Xilinx has a group of flexibility in the RAM distribution for the reason that it also allows using the logic cells.

V. SIMULATION RESULT

The proposed multi-level block truncation code algorithm gives a higher PSNR 36.7432 dB (4×4 Block Pixel), 34.0577 dB (8×8 Block Pixel) and 32.3318 dB (16×16 Block Pixel), for Lena image as compared with 25.31 dB for previous block truncation code algorithm. Similarly, proposed Multi-level block truncation code algorithm gives a higher PSNR for Cameraman image and Bird image is compared with previous block truncation code algorithm.

Figure 7 shows the graphical illustration of the performance of different methods discussed in this research work in term of peak signal to noise ratio. From the above graphical representation it can be inferred that the proposed Multi-level BTC algorithm gives the best performance for Lena, Cameraman and Bird images.

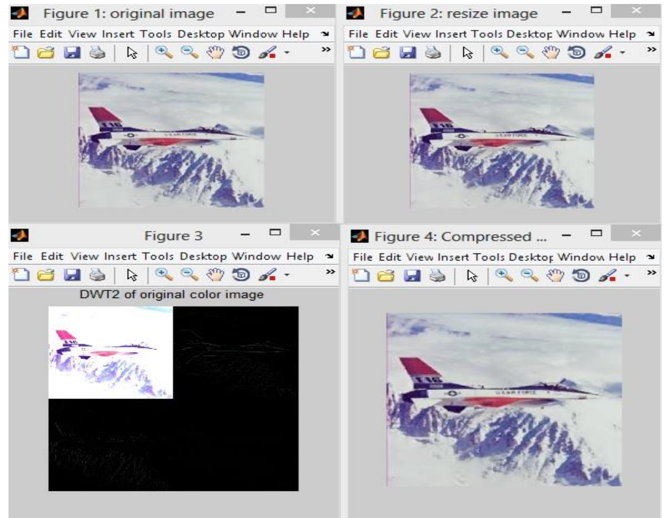

Fig. 7: Experiment Result for Airplane Image

Figure 7; show the Airplane image of 4×4 block pixel. In this figure 7 (a) show the random image of the Airplane image and resized the image of the 512×512 in the Airplane image is shown in figure 7 (b). The resize image is passed through 2-D DWT and present in 7 (c). The compressed image of 4×4 block pixel of Airplane image is shown in figure 7 (d) respectively.

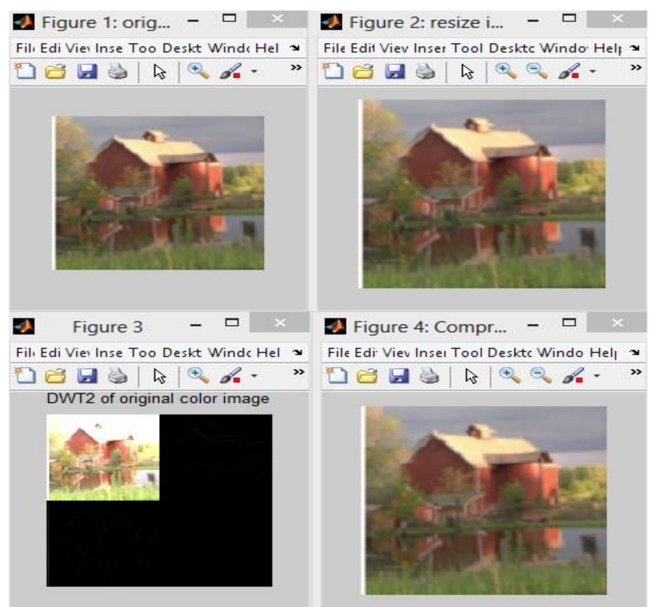

Fig. 8: Experiment Result for House Image

Figure 8; show the House image of 4×4 block pixel. In this figure 8 (a) show the random image of the House image and resized the image of the 512×512 in the House image is shown in figure 8 (b). The resize image is passed through 2-D DWT and present in 8 (c). The compressed image of 4×4 block pixel of House image is shown in figure 8 (d) respectively.

As shown in table 1 the mean square error (MSE) result are obtained for the proposed Multi-level BTC and DWT algorithm and previous Enhance block truncation code algorithm. From the analysis of the results, it is found that the proposed Multi-level BTC and DWT algorithm gives a superior performance as compared with previous Enhance block truncation code algorithm.

Table I: Experimental Results for Mean Square Error (MSE)

Image of Size 512×512	**4×4 Block Pixel**	**8×8 Block Pixel**	**16×16 Block Pixel**	**32×32 Block Pixel**
Airplane Image	9.431	17.338	29.672	44.543
House Image	4.929	6.136	15.342	23.953
Peppers Image	8.753	18.543	28.553	42.107
Flower Image	4.657	14.556	22.554	37.834
Parrot Image	10.257	21.001	33.512	47.353
Butterfly Image	26.914	33.882	45.771	57.441

Table II: Experimental Results for Mean Square Error (MSE)

Image of Size 512×512	**4×4 Block Pixel**	**8×8 Block Pixel**	**16×16 Block Pixel**	**32×32 Block Pixel**
Airplane Image	44.44 dB	41.79 dB	38.25 dB	36.50 dB
House Image	50.96 dB	46.32 dB	38.57 dB	40.42 dB
Peppers Image	44.82 dB	42.10 dB	39.86 dB	37.96 dB
Flower Image	47.51 dB	44.56 dB	41.43 dB	38.41 dB
Parrot Image	44.08 dB	42.05 dB	38.89 dB	37.44 dB
Butterfly Image	39.89 dB	38.79 dB	37.95 dB	36.62 dB

VI. CONCLUSION

In this paper a spatial domain technique for image data compression, namely, the multi-level block truncation coding (ML-BTC) has been considered. This technique is based on dividing the image into non overlapping blocks and uses a two-level quantize. The ML-BTC technique has been applied to different grey level test image each contains.

The multi-level block partition encoder and decoder technique is presented. Such method is suitable in situations where image or image is compressed once but decoded frequently. It is clear that the decoding time due to spatial domain based compression is much less than that of the sub-band compression techniques. The developed technique is increase 27.22% PSNR for ocean image, 28.57% PNSR for building image, 27.57% PSNR for lighthouse and 24.65% PSNR for sailing image compared to previous technique.

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