IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.-6, Issue-6, June 2018 E-ISSN: 2347-2693

Design Image Compression for Fractal Image using Block Code Algorithm

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Available online at: www.ijcseonline.org

Accepted: 17/Jun/2018, Published: 30/Jun/2018

Abstract- This paper aims to proposed multi-level block code based image compression of continuous tone still image to achieve low bit rate and high quality. The algorithm has been proposed by combining fractal image and block code algorithm. Fractal image compression (FIC) is a new compression technique in the spatial domain. It is based on block based image compression technique which, detects and codes the existing similarities between different regions in the image. 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 the performance with that of the existing methods.

Keyword- Block Code, Bit Map, Fractal Image Compression, Quantization, MRI Image

1. INTRODUCTION

Abnormality detection in Magnetic Resonance (MR) brain images is a challenging task. The difficulty in brain image analysis is mainly due to the requirement of detection techniques with high accuracy within quick convergence time. The detection process of any abnormalities in the brain images are a twostep process. Initially, the abnormal MR brain images are classified into different categories (image classification) since treatment planning varies for different types of abnormalities. Further, the abnormal portion is extracted (image segmentation) to perform volumetric analysis which verify the success rate of the treatment given to the patient. Conventionally, the detection process is performed manually which is highly prone to error because of the intervention of human perception. Several automated techniques are developed to overcome this drawback. Among the automated techniques, Artificial Neural Networks (ANN) and Fuzzy techniques are found to be highly efficient in terms of the performance measures. But, the major factor is that the merits are not simultaneously available in the same ANN or the fuzzy technique. In this research work, several modified ANN and fuzzy techniques are proposed for image classification and segmentation applications. The focus of this research work is to develop automated techniques with simultaneous merits of high accuracy and convergence rate. Few conventional ANN and fuzzy techniques are also implemented to show the superior nature of the proposed approaches. This chapter specifically focuses on the significances of the various aspects of the automated abnormality detection process.

Modern medical imaging technology has given physicians a non-invasive means to visualize internal anatomical structures and diagnose a variety of diseases. Among the imaging techniques, Magnetic Resonance Imaging is found to be much superior to other techniques especially for brain tissues. This type of scan uses magnetism to build up a picture of the internal parts of the body. The main advantage is that the soft tissue differentiation is extremely high for MRI which is essential for brain imaging. Compared to other techniques, MRI has high spatial resolution and contrast. Other advantages of MRI scans are that they are devoid of X-ray radiation and a single scan can produce many pictures. MRI is also better than Computer Tomography (CT) at showing how deeply the tumor has grown into body tissues. It can be particularly useful for showing whether tissue left behind after treatment is tumor or non-tumorous tissue. These MR images are used to find the different stage of tumor. The MRI scanner can be also used for cross section views of the body. Thus, these factors have motivated the usage of MR brain images for the abnormality detection process in this research work. These MR images can be collected from scan center or can be downloaded from publicly available database. Both these options are tried in this work for image classification and image segmentation applications.

2. BASIC CONCEPTS OF FRACTAL IMAGE ENCODING

Here the neural network is trained with the Domain blocks and Range blocks of an MRI image. Initially FIC is applied to a single MRI image with the optimized sizes of range and domain blocks. Based on the performance measures, the optimum values of sizes of range and domain blocks are chosen. The designed intelligent system has been tested and evaluated with the help of MRI images. The fractal coefficients of the MRI image are further compressed by using the Huffman coding and stored. The decoding algorithm first converts the Huffman codes into equivalent fractal coefficients and then the decompression algorithm applies these coefficients to any starting image to a final attractor of the MRI image. The experimental results illustrate the effectiveness of the designed intelligent system for MRI images, in speeding-up the fractal image encoding. The IFIC is applied to brain MRI images. During the training phase, a single brain MRI image (MRI 12) was chosen as input image and is partitioned into:

1. A collection of non-overlapped sub image blocks called RBs and
2. A collection of possibly larger sub image blocks called DBs.

Subsequently the neural network is trained based on the properties of the domain and range blocks. The neural network classifies these blocks into two classes. FIC is now used to search for the best match among the domain blocks for each range block that belongs to the same class. Thus the search space is reduced which leads to subsequent reduction of encoding time. The same neural network is used for classification of other brain MRI images and FIC is used for best match of domain blocks for all the range blocks.

3. IMAGE QUALITY MEASURES

It is a major task in evaluating the image quality of an image compression system to describe the amount of degradation in the reconstructed image. In the case of lossy compression, the reconstructed image is only an approximation to the original. The difference between the original and reconstructed signal is referred to as approximation error or distortion. Generally, the 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 achieved simultaneously. Although many metrics exist for quantifying distortion, it is most commonly expressed in terms of means squared error (MSE) or peak-signal-to-noise ratio (PSNR). The performance of image compression systems is measured by the metric 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)

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

Peak Signal to Noise Ratio (PSNR) in dB

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

Evidently, smaller MSE and larger PSNR values correspond to lower levels of distortion. Although these metrics are frequently employed, it can be observed that the 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 tests such as the Mean Opinion Score (MOS) to ensure that the objective results are not misleading [11].

Sometimes compression is quantified by stating the Bit Rate (BR) achieved by compression algorithm expressed in bpp (bits per pixel). Another parameter that measures the amount of compression is the Compression Ratio (CR) which is defined as

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

4. PROPOSED METHODOLOGY

Proposed Encoder and decoder block of the multi-level block code algorithm is shown in figure 1. Encoder part of the proposed algorithm 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 FIC technique for each block size is being calculated.

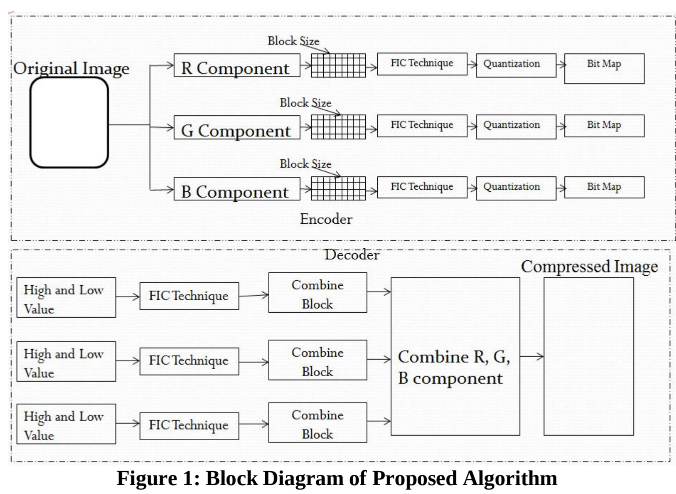


Figure 1: Block Diagram of Proposed Algorithm

FIC technique 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 FIC value is:

$$T = \frac{\max + \min + m_1}{3} \tag{4}$$

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 FIC 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.

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

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

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.

Algorithm for fractal Image Compression (FIC) technique:-
Read any input image and resize it to a standard size. Convert it to gray and normalize the image.
Partition the image into non-overlapping blocks of any desired size, called Range blocks.
Partition the image into non-overlapping blocks of any desired size, called Domain blocks. The size of range blocks can be less than or equal to the domain blocks.
Compute the eight orientations of all the domain blocks.
Determine the block parameters like mean, skewness and standard deviation for all range and domain blocks.
Initialize the targets based on some criteria.
Initialize neural network and set the training parameters.
Train the net with the domain and range blocks with targets as output.
Simulate the net with domain and range blocks as input. Save the neural net.
Initialize a, b and j coefficients to zero.
Compute the best values of a, b and j for all range blocks in all domain blocks that belong to the same class, based on minimum distance metrics.
Save these coefficients, a, b and j. Using Huffman coding converts these coefficients into Huffman codes and save.
Compute Compression Ratio.
Note the encoding time for computing the execution time for this algorithm.

Step 1: Input random image

Step 2: Rearrange the random image

Step 3: Partition the color Image into set of non-overlapping block

If

Image resize / Block Size = = 0 then

Calculate threshold value of each block

Else

Partition the color Image into set of non-overlapping block

End if;

Step 4: Calculate Quantization

Step 5: Design bit map according to the multilevel BTC

If

Bit map / Block Size = = 0 then

Calculate high and low component

Else

Design bit map according to the multilevel BTC

End if;

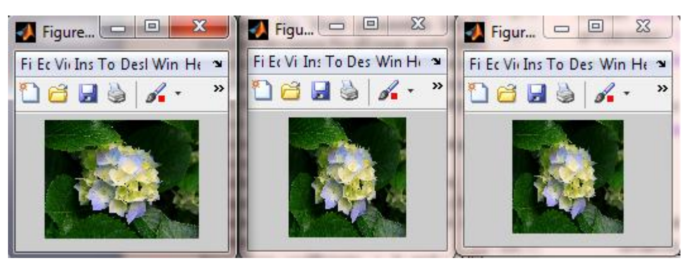
Step 6: Combined all block

Step 7: Combined R, G, B Image

Step 8: Output Compressed Image

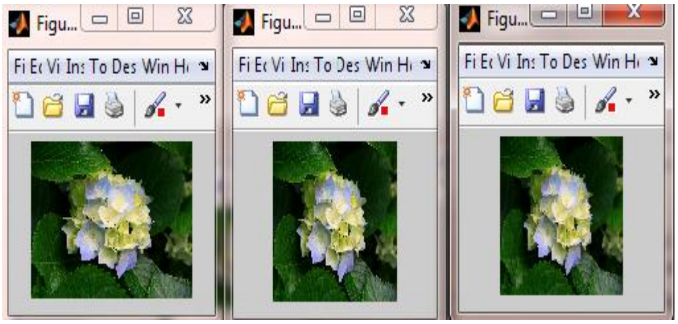
5. SIMULATION RESULT

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



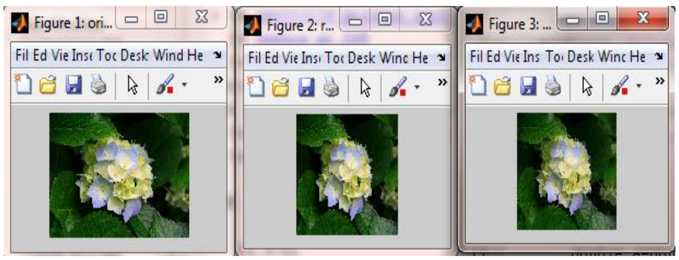
(a) (b) (c)

Figure 3: FIC and Block Code Algorithm applied on Hydrangeas Image of block size 4×4



(a) (b) (c)

Figure 4: FIC and Block Code Algorithm applied on Hydrangeas Image of block size 8×8



(a) (b) (c)

Figure 5: FIC and Block Code Algorithm applied on Hydrangeas Image *of* block size 32×32

Figure 6 shows the graphical illustration of the performance of different block size discussed in this research work in term of MSE. From the above graphical representation it can be inferred that the proposed FIC and block code algorithm gives the best performance for 4×4 Block Pixel.

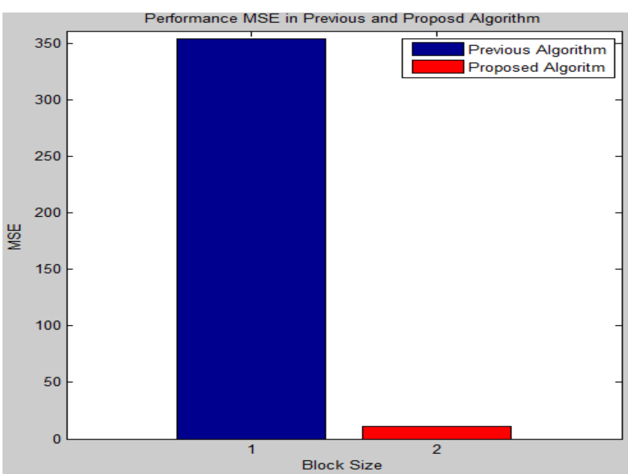


Figure 6: MSE for Different Block Size using Hydrangeas Image

Figure 7 shows the graphical illustration of the performance of different block size discussed in this research work in term of PSNR. From the above graphical representation it can be inferred that the proposed FIC and block code algorithm gives the best performance for 4×4 Block Pixel.

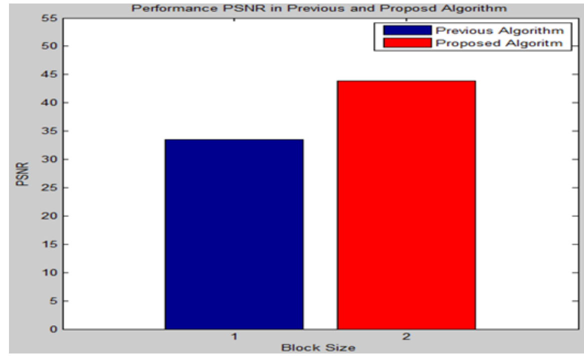


Figure 7: PSNR for Different Block Size using Hydrangeas Image

Figure 8 shows the graphical illustration of the performance of different block size discussed in this research work in term of CT. From the above graphical representation it can be inferred that the proposed FIC and block code algorithm gives the best performance for 4×4 Block Pixel.

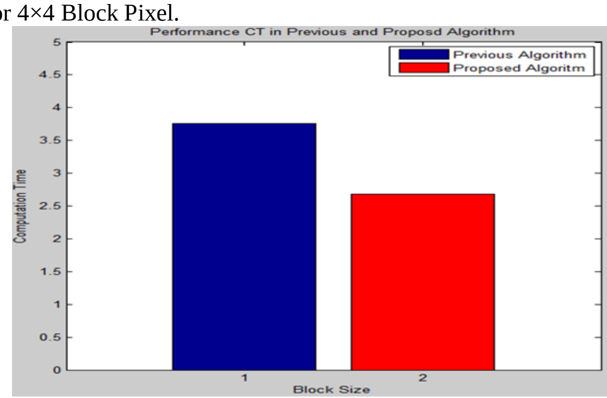


Figure 8: CT for Different Block Size using Hydrangeas Image

Figure 9 shows the graphical illustration of the performance of different block size discussed in this research work in term of CR. From the above graphical representation it can be inferred that the proposed FIC and block code algorithm gives the best performance for 4×4 Block Pixel.

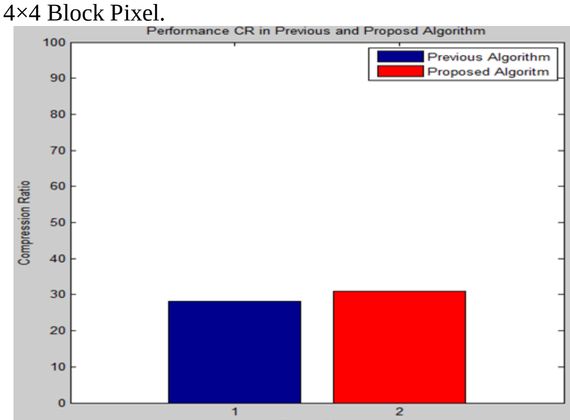


Figure 9: CR for Different Block Size using Hydrangeas Image

Table 1: Experimental Results MSE, PSNR and CT for Hydrangeas Image

	Previous Algorithm			Propose algorithm		
Block Size	MSE	PSNR (dB)	CT (sec)	MSE	PSNR (dB)	CT (sec)

2×2	349.08	34.17	3.76	2.323	50.538	2.345
4×4	353.87	33.45	3.76	8.942	44.680	2.683
8×8	363.19	32.90	3.74	15.910	42.173	3.219
16×16	368.89	31.98	3.71	24.958	40.215	3.332
32×32	373.63	29.05	3.84	35.475	38.688	3.399

As shown in table 1 the peak signal to noise ratio (PSNR) and computation time are obtained from the proposed FIC using block truncation code algorithm. The values obtained for various block sizes is the average value of red, blue and green component of the image.

As shown in table 2 the compression ratio is obtained from the proposed FIC using block truncation code algorithm. The values obtained for various block sizes is the average value of red, blue and green component of the image.

Table 2: Experimental Results CR for Hydrangeas Image

	Previous Algorithm	Propose algorithm
Block Size	CR (%)	CR (%)
2×2	2.45	4.48
4×4	28.07	31.028
8×8	46.14	56.074
16×16	62.77	71.215
32×32	72.04	79.626

6. CONCLUSION

In the proposed method compression ratio for block size (2×2) is 45.31%, block size (4×4) is 9.5%, block size (8×8) is 17.71%, block size (16×16) is 11.85%, block size (32×32) is 9.5%, for Hydrangeas Image. It is clear that by increasing block size, compression ratio also increases and image quality degrades for Hydrangeas Image.

7. REFERENCE

[1] G.V. Maha Lakshmi, "Implementation of Image Compression Using Fractal Image Compression and Neural Networks for MRI Images", 978-1-5090-1987-8/16/$31.00 ©2016 IEEE

[2] Prashanth N and Arun Vikas Singh, "Fractal Image Compression for HD image with noise using Wavelet Transform", 978-1-4799-8792-4/15@2015IEEE.

[3] Aanestad A., Edwin B. and Marvick R. (2003) 'Medical image quality as socio -technical phenomenon', Journal of Methods Information in Medicine, Vol. 4, pp. 302-306. 2.

[4] Abdou Youssef, 'Medical Image Compression and Quality Testing', http://hissa.nist.gov/rbac/proj/abdou.html

[5] Adrian Munteanu, Jan Cornelis and Paul Cristea (1998) 'Wavelet lossy and lossless image compression techniques - use of the lifting scheme', International Workshop on Systems, Signals and Image Processing IWSSIP'98, pp. 12-19.

[6] Adrian Vanzyl (1995) 'Increasing Web Bandwidth through Image Compression: An overview of GIF, KPEG and Fractal Compression Techniques', Proc.AusWeb95.

[7] Ahmed N., Natarajan T. and Rao K.R. (1974) 'Discrete Cosine Transform', IEEE Transactions on Computers, Vol.23, pp. 90-93.

[8] Ahmet Eskicioglu M., Fisher and Paul S. (1993) 'A Survey of Quality measures for Gray Scale Image Compression', Space and Earth Science Data Compression Workshop, NASA CP-3191, pp. 49-61.

[9] Ahumada A.J. Jr. and Rensheng Horng (1994) 'De-blocking DCT Compressed Images' Human Vision, Visual Processing, and Digital Display V, SPIE Proc. Vol. 2179, pp.109-116.

[10] Ahumada A.J. Jr. and Rensheng Horng (1995) 'Smoothing DCT Compression Artifacts', SID Digest, Vol. 25, pp. 708-711.

[11] Alexandre Krivoulets (2003) 'Design of Efficient Algorithms for Image Compression with Application to Medical Images', Ph.D. dissertation, The IT University of Copenhagen, Denmark .

[12] Ali M. and Clarkson T.G. (1991) 'Fractal Image Compression', Information Technology and its Applications (ITA 1991), pp. 1-12. 173.

