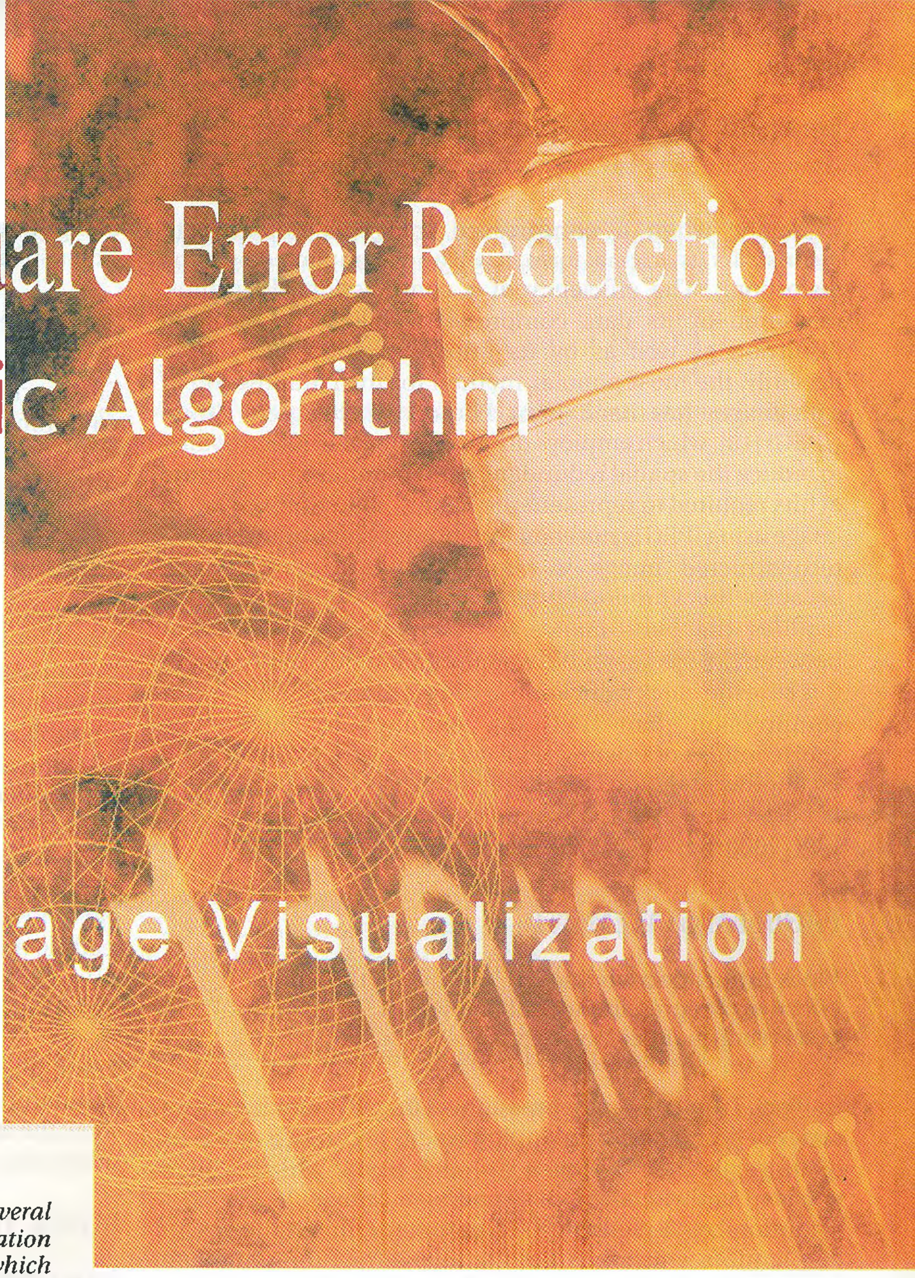


Mean Square Error Reduction Using Genetic Algorithm

An Error Image Visualization

Ms. Madhu Shandilya, Dr. R.P. Singh
& Mr. Rajesh Shandilya

ABSTRACT

This work is devoted to design and analysis of several aspects of image compression, specially quantization and coding. Here we utilize a coding technique, which not only preserves some of the statistical characteristics of the block during quantization, but also giving a fixed bit rate with very easy hardware implementation. Though the approach is very simple but due to limited quantization levels does not perform equally well in every region, resulting in ragged edges and introduced noise at edges.

This work stands in contrast to the above algorithm and implemented an idea based on mean square error criteria, which reduces the above artifacts to a great extent. A natural processing concept called genetic algorithm: a stochastic global search and optimization approach that mimic the metaphor of natural biological evolution, has been applied to find out the optimal solution in a multimodal search space.

The multilevel quantization is modeled as optimization problem and an attempt is made for selecting the better thresholds using GA in order to reduce mean square error. The simulations results indicate that both the computational complexity and the reconstructed image quality achieved have been improved as a outcome of this work.

INTRODUCTION

Compression is the coding of data to minimize its representation, which in tern conserve space in storage media and save bandwidth in communication. Many image compression techniques have been developed to suit different requirements of reconstruction. They are broadly classified as loss less (reversible or noiseless) and lossy compression (irreversible or noisy). In loss less compression the reconstructed image is identical to the original but can achieve low compression factors. While lossy image compression techniques can provide high compression ratios but will produce some compression errors. In application where the pictures are subjected to further processing e.g. for the purpose of extraction of specific information like medical imaging, image archival systems, precious artworks and remote sensing, lossless compression is preferred. Huffman coding, arithmetic coding etc. are the techniques of loss less compression, while vector quantization (VQ), transform coding, block truncation coding (BTC) etc. are the examples of lossy compression techniques.

Typically, when a compressed image is decoded to reconstruct its original form, it will be accompanied by some distortion. The efficiency of a compression algorithms, measured by its data compression ability, the resulting distortion as well as by its implementation complexity. Recently, the most popular method for the compression of still images has been Joint Photographic Expert Group (JPEG) [13], which employs discrete cosine transform coding to reduce the spatial redundancy and minimize the number of bits required to represent the image. The compression of image using JPEG is not economical if very high quality of the reconstructed image is required after decompression, because the computational complexity of JPEG, which requires the performance of discrete cosine transform between the spatial and frequency domains, is very high. In this case the block truncation coding is more appropriate for compression than JPEG [6]. Although to correct the shortcomings of existing JPEG its committee initiated work on another standard commonly known as JPEG 2000, which is based on wavelet decomposition. There is much about JPEG 2000 that is yet to be determined.

PROBLEM STATEMENT

Block truncation coding [1] is one of the simplest and effective compression technique, with a single bit moment preserving quantizer to quantize each individual block.

In Block Truncation compression an image is divided into a series of n x n non-overlapping blocks of pixels, a two level quantizer is then designed for each block, which is then encoded individually. For coding a single block, BTC algorithm consists of three separate steps, first is the design of quantizer which includes the selection of threshold and quantization levels, second is the coding of quantization data and the third is coding of bit plane [4].

In original BTC, the two level quantizer quantizes 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 preserves the edges and having low computational complexity. However, due to limited number of quantization levels, it does not perform equally well in every region, resulting in staircase artifact, ragged edges and also introduces noise at edges. Thus, it is necessary to develop a version of BTC with more number of quantization levels to improve the quality of the image. Many multilevel BTC algorithms have been proposed. The major problem with multilevel BTC lies in the search for an optimal set of code words to quantize the pixels in the block. With the original BTC proposed in [1,3] an optimal quantization can be obtained by selecting the thresholds with an exhaustive search [10]. However this requires an enormous amount of computation and is thus impractical when we consider an exhaustive search for multilevel BTC.

AN APPROACH TOWARDS SOLUTION

This work is devoted to the design and implementation of an optimum algorithm, which is capable of giving a high quality reconstruction with less computational complexity. The multilevel quantization is modeled as optimization problem and an attempt is made for selecting the better thresholds in order to design an optimum quantizer to improve the image quality. The process of threshold selection is, carried out by using genetic algorithms. The genetic algorithms (GAs) [4] are stochastic global search and optimization methods that mimic the metaphor of natural biological evolution. GAs operates on a population of potential solutions applying the principal of survival of the fittest to produce better and better approximations to a solution. At each generation a new set of approximations is created by the process of selecting individuals according to their level of fitness in the problem domain and breeding them together using operators borrowed from natural genetics. This process leads to the evolution of populations of individuals that are better suited to their environment than the individuals that they were created from just as in natural adaptation.

These methods are rooted in the mechanism of evolution and natural genetics. The main objective of this work is to show the applicability of GAs in finding the globally optimal solution in a multimodal search space.

BLOCK TRUNCATION COMPRESSION

An extensive study of block truncation compression with a moment preserving quantizer was done by E.J. Delp in August 1979 and was applied to still image by Delp and Mitchell [1]. It is a compression technique that processes data in the spatial domain itself.

The basic idea is to split the image into a number of small m (=n x n) non overlapping small blocks of pixels, and than each block which independently needs a two level quantizer, is quantized in such a way that each resulting block has the same sample mean and sample variance as the original one. The quantizer threshold and two reconstruction levels are varied in response to the local statistics of a block. The two output levels l1 and l2 from the quantizer for each block are computed by

$$l_1 = \bar{x} - \bar{\sigma}\sqrt{\frac{q}{m-q}}$$

$$l_2 = \bar{x} + \bar{\sigma}\sqrt{\frac{m-q}{q}}$$

Where $\bar{x}$ – mean of the block.

$\bar{\sigma}$–deviation of the block.

q–the number of the pixels whose value are greater than or equal to $\bar{x}$

m–the total number of pixels in the block.

BTC also gives good reconstructed images since the method preserves local characteristics of spatial blocks of the image important to the human observer. Other advantages of this technique are that it is easy to implement and a fixed bit rate can be obtained using this. In general, the bit rate for BTC requires 2 bits per pixel.

Other than ragged edges, stair case artifact and noise at edges BTC quantizer has another disadvantage that it needs squaring and square root operations and increases the computation complexity.

An improvement in BTC can be obtained by preserving absolute moments rather than standard moments. This method is called absolute moment block truncation coding or AMBTC [7].

It gives simpler equations, which leads to faster computation and smaller mean square error than BTC.

This technique has the same general characteristics as BTC, which includes low storage requirements and an extremely simple coding and decoding technique. In AMBTC the two-quantization output levels for each block are given as:

$$a = \frac{1}{m-q}\sum_{j=1}^{n} x_j \; ; \; x_j \le x_{th}$$

$$b = \frac{1}{q}\sum_{j=1}^{n} x_j \qquad ; \; x_j > x_{th}$$

Where x_{th} is quantizer threshold value.

In AMBTC the first absolute central moment is defined as

$$\alpha = \frac{1}{m}\sum_{j=1}^{m} \left| x_j - \bar{\eta} \right|$$

Where

$$\bar{\eta} = \frac{1}{m}\sum_{j=1}^{m} x_j$$

A similar iteration algorithm, which produces the quantization levels and threshold of the Lloyd quantization is proposed by Efrati et al. [8] and Hui [9]. The only difference between two algorithms exists only because of the way of selection of the initial threshold values. Efrati takes the mean as the threshold and Hui defines it as the average of minimum and maximum pixel values of the block. To improve the performance of quantizer H.B. Mitchel and M. Dorfan [10] suggested a Hopfield neural network.

The performance measure of the effectiveness of a quantizer can be taken as mean square error (MSE), given by

$$MSE = \frac{1}{MN} \sum \sum \left[I(x,y) - I'(x,y) \right]^2$$

Where M,N are number of rows and column respectively in a particular block.

I (x,y) represents the original image.

I'(x,y) represents the reconstructeid image.

One way to obtain the optimal quantization s to select the quantization threshold such that it minimize MSE or MAE, which is a exhaustive search requires a large amount of computation if the number of the quantization levels are greater than 2.

In a 3-level BTC scheme proposed by Ronson and Dewitte, two threshold values for 3-level quantization given below are generated from the output of 2-level AMBTC.

$t_{th1} = (3b_2 + a_2) / 4$

$t_{th2} = (3a_2 + b_2) / 4$

Where a_2 and b_2 are the two outputs of 2 level AMBTC. The final outputs are a_3, $(a_3 + b_3) / 2$ and b_3

Where a_3 = mean of pixels $\le t_{th2}$ and

b_3 = mean of pixel $> t_{th1}$

Here only a_3, b_3 and the bitmap will be transmitted.

Many multilevel BTC algorithms were proposed to improve the image quality e.g. Efrati et al. [8] Mor et al. [10] 3-level BTC algorithm, Wu and Coll [15], 4-level BTC algorithm, which minimizes the maximum quantization error in each block and have much better MSE Performance than max quantizer.

Kuo and Chen [7] presented a nearly optimum multilevel BTC with an iterative techniques. The concept behind their algorithms is to find a better MAE by iteratively moving the threshold based on matching criterion. Their proposed methods can obtain a nearly optimum MAE and MSE progressively, when the number of iterations is increased.

BTC IMPLEMENTATION USING MATLAB [11]

In this work the design and implementation is done for two, three & four quantization levels, which can be extended up to n levels. Several numbers of (512 X 512) images has been tested.

The algorithms are coded in MATLAB ® version 6.5, executed on Pentium III. In order to evaluate the performance of multilevel Block Truncation Coding, several test images has been utilized for the simulation of this work. The block size taken is 4 X 4 pixels. PSNR (Peak signal to noise ratio) is taken as a measure of reconstructed image quality. Mean square error (MSE) between original and reconstructed image has been computed. Comparison of results obtained for 2 level, 3 level and 4 level BTC shows that as we increase the quantization levels, mean square error between original and reconstructed image will be reduced as indicated in table 1.

Table 1
The comparisons of test images with 4x4 block size for 2-level, 3- level and 4- level BTC based on mean square error

Image	2 Level BTC		3 Level BTC		4 Level BTC	
	MSE	PSNR	MSE	PSNR	MSE	PSNR
Lena	28.2058	33.62	11.599	37.4863	6.1291	40.2568
Pepper	25.8799	34.0012	10.9489	37.7371	5.8937	40.4269

PROPOSED ALGORITHM TO REDUCE MEAN SQUARE ERROR

An optimal design for quantization can be obtained by selecting the quantization threshold with an exhaustive search. However, this requires an enormous amount of computation and is thus impractical when we consider an exhaustive search for multilevel BTC. In order to get better results, in this work we have applied genetic algorithm (GAs) to find a better threshold so that the average mean square error between the original and reconstructed images is a minimum. Initially, we have applied GAs to design a two level quantizer; here we used the bit map of BTC to form the initial population of chromosome directly to obtain the nearly optimum solution.

This approach works well in case of 2 level BTC but has a problem in the case of 3 level BTC in that there is a null state. In 3 level BTC, the bit map needs 2 bits to represent 3 states including high, medium and low intensity. We can consider the problem from another angle, for that we extended our work for multilevel block truncation coding, where we searched the better thresholds to obtain a good reconstructed image. A genetic algorithm based searching is proposed. Here we code the index of threshold(s) as a chromosome in the sorted data. The length of the chromosome is 8 bits for the three level BTC and 12 bits for four level BTC with block size chosen as 4 x 4.

Computation of Fitness Value

A fitness value f is computed for each chromosome. The fitness value can be regarded, as a measure of the ability to solve a given problem i.e. a chromosome with a higher fitness is more suitable for solving a given problem. When a genetic algorithm is applied to data compression, the performance measure may be the quality of the reconstructed signal, defined in this work as the reciprocal of MSE between the original block and the reconstructed block. The performance measure of this representation is

$$f = \frac{1}{MSE}$$

A population of chromosomes is combined according to their fitness values and selecting the chromosomes with higher fitness value forms a new generation. Then selected chromosomes are evolved by cross over and mutation until an acceptable solution appears in one of the generations.

Threshold(s) Selection [14]

By studying image statistics, many pixel distributions are found biased in some block. We assume that the position of optimal threshold(s) are also be biased, but lie around the mean of the block. The initial thresholds of n level BTC are computed by

$$t_i = x_{\min} + \frac{x_{\max} - x_{\min}}{n} \times i$$

xmin, xmax represents the minimum and maximum intensity of the block, respectively. For the design of a three level quantizer (can be extended for n levels) first the value of two thresholds t1 and t2 calculated using above formula The indexes of the initial thresholds are 4 and 9.

We can create an initial population of chromosomes by randomly selecting around the index of initial threshold e.g

Random Selection	Initial Population
(4,9)	(01001001)
(3,9)	(00111001)

Stopping Criterion

Stopping criterion can be a check that the fitness function value of the best chromosome between the two consecutive iterations cannot be further improved or a predefined number of generations have been reached. Here 30 GA generations has been set as the stopping criteria.

Practical Implementation

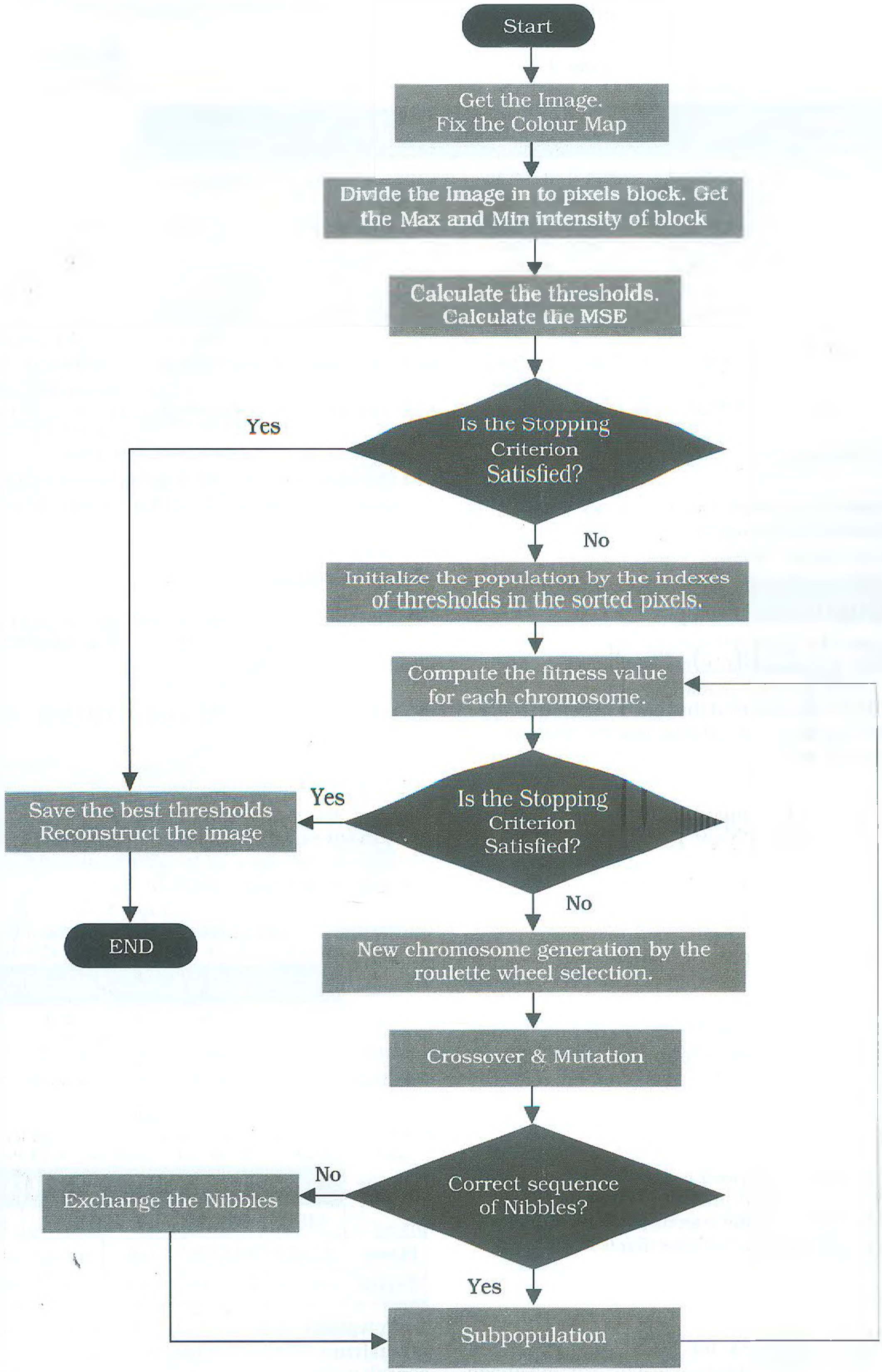
The initial work is done on 2 level BTC, where we applied genetic algorithm directly on bit map and initial population of chromosomes for first generation has been set. After that we switched over to multilevel GABTC to further improve the image quality.

RESULTS

The algorithm has been tested on a series of different types of images such as Lena, Baboon, Elaine, Boat, Flower, Pepper and Tissue to check its effectiveness. In visual image form here we are presenting image LENA only. According to several test runs with different parameters, the crossover probability is set as 0.8, and the mutation probability is set as 0.002.

The population size for all simulation results is 8 for the 4 X 4 block. The work is done for 2 level, 3 level and 4 level GABTC and performance is checked for 10,20 and up to 30 GA generations.

Flow Chart


Start
Get the Image.
Fix the Colour Map
Divide the Image in to pixels block. Get the Max and Min intensity of block
Calculate the thresholds.
Calculate the MSE
Is the Stopping Criterion Satisfied?
Yes
No
Initialize the population by the indexes of thresholds in the sorted pixels.
Compute the fitness value for each chromosome.
Is the Stopping Criterion Satisfied?
Yes
No
Save the best thresholds
Reconstruct the image
END
New chromosome generation by the roulette wheel selection.
Crossover & Mutation
Correct sequence of Nibbles?
No
Yes
Exchange the Nibbles
Subpopulation

Observations and Plots

The results obtained by using GA based technique for image LENA are given below in table 2

Table 2
Image LENA block size 44

Image	Quant. Level	Chromo. Generation	MSE	PSNR	Processing Time	Method	Matlab File
Lena	3	10	10.6068	37.875	0:05:47	GA10Generation	GA10gentest
Lena	3	20	10.5069	37.9161	0:14:47	GA20Generation	GA20gentest
Lena	3	30	10.4288	37.9485	0:23:47	GA30Generation	GA30gentest
Lena	4	10	5.564	40.677	0:06:51	GA10Generation	GA10gen4test
Lena	4	20	5.4607	40.7583	0:17:17	GA20Generation	GA20gen4test
Lena	4	30	5.3631	40.8366	0:28:53	GA30Generation	GA30gen4test

Performance Evaluation

Following parameters has been taken into account while measuring performance of proposed algorithm:

MSE

Mean square error between the original image and reconstructed image is calculated by

$$MSE = \frac{1}{MN}\sum\sum\left[I(x,y)-I'(x,y)\right]^2$$

Lower value of MSE indicates that the reconstructed image is closer to original image. For various images the value of MSEs has been computed.

PSNR

As a measure of reconstructed image quality, the peak signal to noise ratio (PSNR) presented in table 2 is defined as

$$PSNR = 10\log_{10}\left[\frac{255^2}{MSE}\right]$$

Where 255 is the maximum intensity.

The Search Points

For the proposed algorithm (GABTC) the maximum number of search points (SP) has been computed as 240 for GA generation 30.

Bit Rate

Number of bits required per pixel is called bit rate, for the proposed algorithm it is computed as 2-2.5 bits / pixel in case of multilevel GABTC, While transmitting original block without compression requires 8 bits per pixel.

Compression Ratio

Compression ratio computed for GABTC is 75%, with reconstructed image quality compatible with existing image compression algorithms with much less computational complexity.

Reconstructed Image Quality

The reconstructed image obtained by using GABTC algorithm is much better than the image obtained by utilizing other existing BTC algorithms.

We have also observed that as the number of quantization levels and number of GA generations increased, the quality of reconstructed image will improve in the same manner.

In our case we have got a good quality image very close to original one, with 4 quantization levels and 30 GA generations.

The Error Image

The quality of reconstructed image can also be measured by observing the error between original and reconstructed image shown in fig. 1

COMPARISON WITH TRADITIONAL ALGORITHMS

Comparison of BTC with proposed GABTC algorithm is presented here in tabular as well as in graphical forms. Various images has been tested to check the algorithm's effectiveness. An improvement in image quality by applying GABTC can be visualize by reconstructed image as well as by the error image LENA shown in fig. 1

Table 3
Performance comparison of results obtained by using GA based and exhaustive search with block size 4X4 for 4 level BTC.

Image	4 Level GA			4 Level Exhaustive search		
	MSE	PSNR	SP	MSE	PSNR	SP*
Lena	10.4288	37.9485	160	11.599	37.4863	256
Pepper	9.5027	38.3523	160	10.9489	37.7371	256

Table 4
Performance comparison of results obtained by using GA based and exhaustive search with block size 4X4 for 4 level BTC.

Image	4 Level GA			4 Level Exhaustive search		
	MSE	PSNR	SP	MSE	PSNR	SP*
Lena	5.3631	40.8366	240	6.1291	40.2568	4096
Pepper	4.9119	41.2183	240	5.8937	40.4269	4096

Search point value for 3,4 level exhaustive search has been taken from [15] for comparison the reduction of MSE and search points by applying GABTC can be clearly seen from the tables (3,4). Therefore, the same quality of reconstructed image can be obtained by using GABTC with very less computational efforts.

CONCLUSIONS

This paper describes an image encoding approach thatpreserves the spatial details in digital images and is specifically designed for the transmission of high-resolution to obtain higher fidelity. Later, the approach is combined with genetic algorithm in order to get optimum quantization (based on nonexhaustive search) and to improve the image quality. The performance analysis is done by using mean square error, peak signal to noise ratio obtained and by visualizing error image for various different types of images. Integration of genetic algorithm with BTC opens our path to select better and better threshold(s) for multilevel quantization. The idea implemented, leads us towards getting a reconstructed image, which is a close replica of the original one. Finally designed and implemented algorithm shows better performance than other existing multilevel BTC algorithms with significant reduction in mean square error and computational requirements.

Image Comparison

Lena GABTC Image Magnified View

Fig. 1 Error Image Comparison

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