

Recent Image Compression Algorithms: A Survey

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Abstract: This paper presents the short survey on some of the recent non transformation based image compression algorithms. It covers the different techniques for the purpose. Paper describes harmony search, various algorithms on block truncation coding and fractal compression techniques. These algorithms are based on the lossy compression of images. Paper also gives the overview regarding some traditional techniques used for image compression. Compression refers to the reduction of the size of the data that images contain. Redundant data can be considered as repeated or irrelevant information. Eliminating statistically redundant data often yields reversible or lossless compression while eliminating visually irrelevant data inflicts losses on the reconstructed image, which is the method implemented by lossy compression techniques.

Keywords: image compression, lossless compression, lossy compression, PSNR, HSA, BTC, quantization, fractal.

I. INTRODUCTION

Image compression softwares are constantly used to store or transmit information with methods that try to reduce redundant information in file content and thus minimizing their physical space. Since various amounts of data can be used to represent the same amount of information, the principle approach in compression is the reduction of the amount of image data (bits) while preserving information (image details). Image can be classified as vector or raster image. Raster images are made up of array of pixel while vector image is made up of lines and curves that are results of mathematical calculations from several points, thus forming an object image [1]. All compression algorithms are applied to raster or bitmap image as their size is comparatively very large as compare to vector image. Thus when we talk about image here it should be considered as raster. Images generally consist of redundant information which can be classified as *statistically redundant* or *visually irrelevant*. Targeting these areas defines the type of technique to be used for compression [2-4].

In this paper we first describe various algorithm based on three techniques i.e. HSA, BTC and fractal compression. Later we give an overview regarding some traditional techniques being used followed by conclusion.

II. HARMONY SEARCH ALGORITHM

In 2001, Geem *et al.*[5] developed an optimization algorithm called harmony search algorithm (HSA). It's a music-inspired algorithm that mimics the approach of musicians in searching for harmony when playing music. Basic steps of algorithm are as follows:

A. Initialization

In this phase, program parameters are defined.

- Maximum improvisation (MI): the termination criterion of the optimization process.
- Harmony Memory Size (HMS): determines the number of solution vectors handled simultaneously by algorithm.
- Harmony Memory Consideration Rate (HMCR): refers to the rate at which a solution from the memory is considered as a component in the new solution being created.
- Pitch Adjustment Rate (PAR): refers to the rate of adjusting a value from the harmony memory by adding certain value.

B. Harmony Improvisation

Here, a new solution is created. The three methods viz. playing from memory; pitch adjustment; and randomization are used to decide what value will be assigned to each decision variable in the solution.

C. Selection

In The best harmony or solution is selected when the termination condition is satisfied.

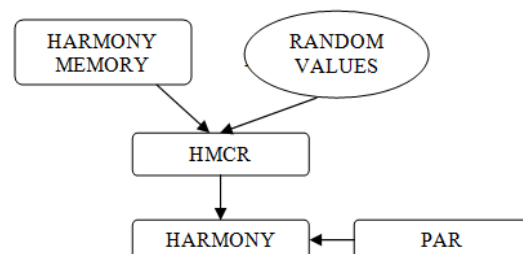


Fig. 1 Harmony formation using HMCR and PAR



Harmony can be formed using memory or thinking randomly by the musician. When to chose it from memory is determined using HMCR and whether to perform pitch adjustment to instrument is determined by PAR which modifies the harmony.

Before applying this method to an image some pre-processing is required in which red, green and blue component (RGB component) of image is separated to calculate the variance of each component using Eq. 1.

$$\sigma^2 = \frac{\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (x_{ij} - \mu)^2}{n} \quad (1)$$

Component with least variance is selected for manipulation[7-8].

Next, harmony memory is initialized with harmonies which can be obtained as, given an $n \times n$ image, harmony will have size of $(n \times n)/4$ elements, where an element in the harmony represents a 2×2 pixel block of the selected RGB component. Each element is initialized with an RGB value ranging from 0 to 255. Algorithm then attempts to optimize the selected RGB component without changing the RGB values of the other two RGB components. Original RGB values in each of the 2×2 pixel block of the selected RGB component will be substituted with the corresponding RGB values in the harmony.

This new RGB component is used to create compressed image. It is then combined with the other two RGB components whose RGB values were unaffected, producing new image.

The quality of this image produced using the said harmony will be evaluated using the Peak Signal-to-Noise Ratio (PSNR) and is measured in decibels (dB). A high PSNR value indicates that there is less visual degradation in the compressed image.

$$PSNR = 10 \log_{10} \frac{255^2}{MSE} \quad (2)$$

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2 \quad (3)$$

The fitness of the newly generated harmony will be compared to the fitness of the other harmonies in the harmony memory. If the newly generated harmony obtains a higher PSNR value compared to the worst harmony in the harmony memory, then the worst harmony will be replaced by the newly generated harmony.

When the termination criterion is satisfied, the best harmony (best solution) is determined. The best harmony contains the new RGB values for the selected RGB component. These new RGB values will be used to create the compressed image.

Algorithm requires harmony memory to be initialize first with random values and operates on small block (2×2 pixels)

of image to improvise quality through iterations. But, if image size is large, for both memory initialization and manipulation on small blocks, time requires and quality will be important issues of concern. However experiments conducted on both color and grayscale images shows its feasibility [7].

III. BLOCK TRUNCATION CODING ALGORITHMS

Block truncation coding (BTC) developed by Delp and Mitchell [20] is a simple and fast lossy compression technique for gray scale images and achieves 2.0 bits per pixel (bpp) with low computational complexity [10]. In BTC, an image is first segmented into small blocks of pixels of size is 4×4 , but we can choose other size as 8 and so on. Many techniques with modifications to BTC have been proposed to reduce the bit rate obtained with normal BTC. More interested reader can refer [11-14],[18].

A. Standard BTC

Standard BTC works by dividing the image into small blocks of pixels and then reducing the number of gray levels within each block. This reduction is performed by a quantizer that adapts to the local image statistics. The basic form of BTC divides the whole image into N blocks and codes each block using a two-level quantizer. These two levels are selected using the mean (μ) and standard deviation (σ) of that block. Each pixel value within the block is then compared with the mean and then is assigned to one of the two levels, maintaining the same mean and standard deviation [9]. If the pixel value of each block is greater than or equal to mean, it is represented by 1 and if it's less, it is represented by 0 in bit plane, allowing single bit to represent pixel. Thus for 4×4 pixel block 16 bits are used. Two statistical moments a and b are computed using the Eq. 4 and Eq. 5 are preserved along with the bit plane for reconstructing the image. The compressed image is transmitted or stored as a set $\{B, a, b\}$ rather than a bitmap.

$$a = \mu - \sigma \sqrt{\frac{q}{p}} \quad (4)$$

$$b = \mu + \sigma \sqrt{\frac{p}{q}} \quad (5)$$

Where p and q are the number of 0s and 1s in the compressed bit plane. Image can be reconstructed using bit plane, the 0 in the bit plane is replaced by a and the 1 is replaced by b . Algorithm is asymmetric because the decoder is simply replacing 1's and 0's whereas the encoder is also required to calculate the mean, standard deviation and the

Input image block bit plane reconstructed

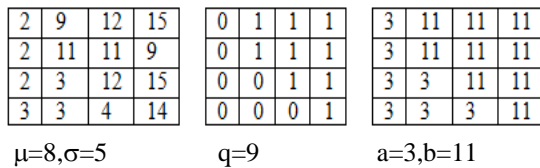


Fig. 2. Encoding and decoding of image block

two values a and b to use [19]. PSNR is then used to evaluate the quality of image produced.

B. Absolute Moment Block Truncation Coding (AMBTC)

It's the variant of BTC. In this method, two statistical moments a (lower mean) and b (higher mean) calculated using the Eq. 6 and Eq. 7 respectively, are preserved along with the bit plane.

$$a = \frac{1}{p} \sum_{x_i < \mu} x_i \tag{6}$$

$$b = \frac{1}{p} \sum_{x_i \geq \mu} x_i \tag{7}$$

Processes of coding and decoding are fast for AMBTC because the square root multiplications are omitted [16].

C. Minimum Mean Square Error (MMSE)

MMSE is the iterative process of AMBTC. This technique is used to reduce MSE value. In this method, the threshold value is initialized by the average of minimum and maximum values of each block as shown in Eq. 8. The threshold value thus calculated is optimized through iterations. The optimization process is terminated when the threshold values of consecutive iterations converge [14].

$$Th = (Xl + Xh) / 2 \tag{8}$$

D. Adaptive Block Truncation Coding (ABTC)

ABTC uses multi level quantizer [17]. The input blocks are categorized into three groups viz. (1) Low activity blocks - where all the pixel values inside the block are approximately the same and visually represent a flat area of gray, (2) Medium activity blocks - small transitions between pixels but do not represent any contrasting edges, and (3) High activity blocks - contain big pixel value changes with contrasting edges. Three set of quantizers are used for these blocks. a 1-level quantizer for low activity blocks, a 2-level quantizer for the medium activity blocks, and a 4-level quantizer for the high activity blocks. These blocks can be mathematically classified using σ (std. deviation). class 1 contains all low (σ) blocks, class2 with medium (σ) and class 3 with high (σ) blocks.

The output equation of the 1-level quantizer can be simply described using sample mean of the block. The bit-rate of

these blocks will be $8/16 = 0.5$ bits per pixel (bpp) when 8 bits are used to represent mean value. For medium activity blocks, the standard BTC method is best designed. The bit-rate for this class is 2 bpp. In 4-level MMSE quantizer, the raggedness produced by standard BTC in the high activity edge blocks can be smoothed using four levels. Output levels of the quantizers a , b , c and d . can be calculated using following equations.

$$\begin{aligned} a &= \min. \\ b &= (2\min + \max) / 3 \\ c &= (\min + 2\max) / 3 \\ d &= \max \end{aligned} \tag{9}$$

Iterative process is used to optimize the thresholds $t1$, $t2$ and $t3$ for the output levels a , b , c and d and vice versa. The results of the quantization will be a bit plane whose individual elements are of size 2 bits and the output levels are a , b , c and d . Hence, the bit-rate for this quantizer is 4 bpp [17].

E. Improved Adaptive Block Truncation Coding (IABTC)

This method is based on ABTC and is used in further reducing the bit rate and to improve image quality [14]. Blocks are categorized into three groups based on sum value (S) which is calculated using Eq. 10.

$$S = \sum_{i=1}^m abs(x_i - \mu) \tag{10}$$

Blocks then categorized based on this S value as, low detailed block, if $S \leq t1$, medium detailed block, if $S > t1$ and $S \leq t2$, high detailed block, if $S > t2$ and $S \leq t3$. The threshold values $t1$, $t2$ and $t3$ are 50,170 and 256 respectively.

$$thr = \min + ((\max - \min) r / n)$$

where, thr represents the r th value of threshold and n is the number of quantization levels and the four quantizing levels a , b , c and d are computed using the Eq. 12. \min and \max are the minimum and maximum intensities of the block respectively.

Compression is performed in two levels. In first level input the image of size $n \times n$ pixels is divided into small blocks, each of size 4×4 pixels. Blocks are then categorized into low, medium or high detailed block using their mean and S value and stored as set $\{B, \text{statistical moments}\}$. The number of statistical moments (quantizers) depends on the type of input block.

In the second stage, all the statistical moments are divided by 4. Generally a statistical moment requires a maximum of 8 bits ($\log_2 256$) to get stored. But, when divided by 4, it requires only a maximum of 6 bits ($\log_2 64$). While reconstructing the image, the statistical moments are



multiplied back by 4 to get the approximate original values ranging from 1 to 256.

Experiments were carried out on images uses PSNR value as a measure of the quality of the reconstructed image. All block truncation coding algorithms exploits the feature of inter-pixel redundancy to reduce the bpp to significant level[14].

F. BTC for colour image

true color digital image, consist RGB color components. Straightforward way to compress color image is to compress each of the color components separately using gray-scale compression technique. But this class of method does not use the correlation between the color planes. Alternative is to convert RGB to less correlated YIQ, YUV, YCbCr, etc. color space and then to apply gray-scale image compression method on each of these components A single-bit-map BTC (SBBTC) method, developed by Wu and Coll [21], exploits the inter-color correlation by using a single bit map to quantize all three color planes. Here two color vector $C1 = (R1, G1, B1)$ and $C2 = (R2, G2, B2)$ and a bit pattern are needed to reconstruct the block. In SBBTC method bit rate is 4 bits/pixel if block size is 4×4 , while the bit rate for color BTC (CBTC), i.e., BTC method applied to each color plane separately, is 6 bits/pixel. Kurita and Otsu [22] suggested another SBBTC method which generates the single bit-map by employing an adaptive one-bit vector quantization based on the principle score of each pixel in the block. The SBBTC method proposed by Tai et al. [23] uses Hopfield neural network (HNN) to generate the single-bit-map of a block. Yang et al. [24] suggests another single bit map method, called CICMPBTC method, based on moment preserving principle. Various other methods for color image compression using BTC are proposed ref [25-26].

IV. FRACTAL COMPRESSION TECHNIQUES

Fractal image compression is a relatively recent image compression method which exploits similarities in different parts of the image. The technique works on the basis of the observation that as fractals can produce fairly realistic images, then, it must be probable to store a given image as just a few basic fractal patterns, coupled with the specification of reconstructing the image from those fractals. The algorithm initially begins with the complete image, and partitions the image into a number of smaller blocks [27].

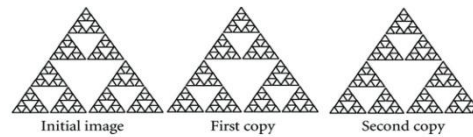


Fig. 3. First three copies generated using fractals

Observe in second example that all the copies seem to converge to the same image as original. Thus storing images as collections of transformations could lead to image compression is the idea behind fractal compression. It exploit the self-similarity property between objects within natural images and express them as similar repeating patterns, to reduce the image's file size. Basically it consist of three parts [34].

- Range block partition: The original image is partitioned into non-overlapping sub-blocks called range blocks, R_i
- Domain Block selection: parts of original image with double size of range block are chosen to form the searching pool of domain blocks, D_i Harmony Memory Consideration Rate (HMCR): refers to the rate at which a solution from the memory is considered as a component in the new solution being created.
- Mapping: domain blocks are mapped to range blocks by an affine transformation as $W_i : D_i \rightarrow R_i$

Affine transformation includes isometrics (rotation, reflection, etc.), grey level scaling and shift operation. In general, this transformation can be given by Eq. 11.

$$D_i = \alpha D_i + \Delta \tag{11}$$

Where α is scale factor and Δ is the luminance shift factor. The best estimate can be obtained by minimizing the distance between D_i and R_i . The mapping relationships, which are called fractal codes, are recorded as compressed data [29][34].

Since the introduction of fractal-based image coder, several variations of fractal coders have been proposed.

A. FIC Using Artificial Neural Networks.

The main objective of this FIC Using ANN was to develop a neural network in order to classify the domain pool objects of a gray level image, thus improving the encoding time and quality of the image. Initial step involves clustering of the image. To reduce that encoding time an efficient classification algorithm is utilized. Classification of domain and ranges is performed to reduce the number of domain-range match computations. Domain-range matches are then performed for those domains that belong to a class similar to the range. In classification feature extraction is an important



process, because in classification feature vectors are utilized as an input to the classifier.

classification is based on the back-propagation algorithm and input to this classifier (Standard deviation and Skewness) are extracted from the domain cells obtained from the arbitrary images[28]

B. FIC Based on Hybrid Particle Swarm Optimization with Genetic Algorithm

This FIC technique has proposed an SCPSOGA for reduce the time and improve the compression ratio. In FIC techniques spent more time to search the best-match blocks in a large domain pool. To reduce such more time on the best match block they have use of spatial correlations in images.

This method performs the compression process in two stages. The first stage makes full use of spatial correlations in images to exploit local optima. It can reduce the searching space of the similar matching domain pool, and shorten the optimal searching time. The second stage was operated on the whole image to explore more adequate similarities if the local optima are not satisfied [28].

C. Other FIC techniques

FIC techniques take more time to perform encoding and global search processes. These processes are extremely computationally intensive and time consuming. Thus several algorithms are being developed to reduce this time. Fractal image compression by fast convolution [35] is lossless FIC method. It's based on codebook coherence characteristics to FIC using fast fourier transformed based convolution to reduce the time complexity

Fast fractal image coding [34] analyzes the distance between the range block and best matched domain block. It works on the idea that most of the best matched domain block can be found close to the range block. The searching region is restricted to a five neighbor area around the range block.

V. TRADITIONAL TECHNIQUES

Conventional standard of image for eg.JPEG uses transformation based compression scheme namely DTC. The DTC is a technique for converting a signal into elementary frequency components. The image is decomposed into several blocks, and for each block, DCT is mathematically expressed as a sum of cosine functions oscillating at different frequencies [29]. Wavelet was developed to overcome the weakness of the short time Fourier transform and to enhance DCT features, such as localization in time and frequency. The DWT is a non-block-based transform allows avoiding blocking artifacts introduced by the DCT transform within the reconstructed image. Moreover, it has a good localization in both time (space) and frequency domains [30]. A variety of wavelet-based image compression schemes have been developed [30-33].

VI. CONCLUSION

In this paper, we provided a short survey on recent lossy image compression algorithms. We have mainly discussed three coding techniques viz. Harmony search, Block truncation coding and Fractal compression. Many algorithms are developed by performing some variation on basic ideas of these techniques to provide better result and or performance. All of them use PSNR value as a quality measure for image constructed. When to prefer a certain technique is heavily depends on context in which its used based on complexity and time requirement

ACKNOWLEDGMENT

I am thankful to my guide prof. Shweta Jain for her noble guidance and support. Her valuable suggestions and timely advices inspired me towards sustained efforts for my concerned work.

Special thanks to Prof. Wanjari Co-ordinator M.tech. CSE for his timely guidance.

And finally I am grateful to our Head Of Department Dr. Chandak and entire Computer Science and Engineering Department of RCOEM for their assistance.

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