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Review Paper on Fractal Color Image Compression using Lossy Compression Technique

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ABSTRACT: In the present multimedia age there is continuous demand for large image information storage and transmission. This necessitates storing of large images in limited memory space and faster transmission for communication. These requirements justify the development of more efficient image compression algorithms. Fractal image compression (FIC) is a novel technique which promises higher compression efficiency for large scale images. FIC is a lossy compression method for digital images based on fractals. The method is best suited for natural images relying on the fact that parts of an image resemble other parts of the same image. Fractal algorithms convert these parts into mathematical data called fractal codes which are used to recreate the encoded image. With fractal image compression, encoding is computationally expensive because of the search methodology to find the self similarities but decoding process is fast.

KEYWORDS: Discrete Wavelet Transform, Discrete Cosine Transform, Compression Ratio, Fractal Color Image

I. INTRODUCTION

The vast quantity of data as medical images demands considerable data storage capacity and powerful means of data processing and data analyzing. Despite rapid progress in mass-storage density, processor speed, and digital communication system performance, demands for larger data storage capacity and data transmission bandwidth continue to outstrip the capabilities of available technologies, it is more and more difficult to store, process, and transfer them [1]. It is desirable to represent the image information with fewer storage bits and whenever needed, to reconstruct the original image so that it will facilitate to transfer them as compressed images. Image compression is minimizing a graphics file in size without significant degradation in the quality of the image. The image decompression, or restoration, is the inverse procedure of compression, the compressed images are converted back to the original one, or the best approximation of the original images.

Image compression is applied to obtain an image representation while reducing the amount of memory needed as much as possible to encode the image [2]. Image compression is possible because images, in general, are highly coherent (non-random), which means that there is repetitive information. Compression methods try to eliminate repetitiveness, thus producing a more compact code that preserves the essential and accurate information contained in the original image. Natural images have local and global redundancy. Local redundancy causes a given neighbourhood in the image to exhibit coherence or correlation (smoothness of data). Schemes are more effective in preserving the local redundancy of the image and are expected to yield better compression when coupled with coding scheme that can take advantage of local redundancy [3, 4]. Global redundancy is caused by patterns repeated over the image, in other words, the same brightness pattern gets repeated with statistic similarity [5]. Two fundamental components of compression are redundancy and irrelevancy reduction. Redundancy reduction aims at removing duplication from the signal source (image/video). Irrelevancy reduction omits parts of the signal that are not noticed by the signal receiver, namely the Human Visual System (HVS). In general, three types of redundancy can be identified:

- Spatial Redundancy or correlation between neighboring pixel values.
- Spectral Redundancy or correlation between different color planes or spectral bands.
- Temporal Redundancy or correlation between adjacent frames in a sequence of images (in video applications). Image compression aims at reducing the number of bits needed to represent an image by removing the spatial and spectral redundancies as much as possible.

For still image compression, temporal redundancy need not be considered [6]. Image compression techniques are classified as either lossless (reversible) or lossy (irreversible) compression methods.

II. FRACTAL IMAGES

The term fractal was derived by Benoit Mandelbrot in 1975 from the Latin fractus meaning "broken" or "fractured." Mathematically explained as a fractal is based on an equation that undergoes an iteration in the form of feedback based on recursion. A fractal is a fragmented geometric shape that can be split into parts, each of which is approximately a reduced-size copy of the whole, this property called self-similarity. Fractals are easily found in nature and anobjects display self-similar structure over an extended, but finite scale range. Examples include clouds, snowflakes, crystals, mountain ranges, lightning, river networks, cauliflower or broccoli, systems of blood vessels and pulmonary vessels etc. Coastlines may be also considered as fractal in nature. Trees and ferns are fractal in nature and can be modeled on a computer by using a recursive algorithm [7]. This recursive nature is obvious in these examples, a branch from a tree or a frond from a fern is a miniature replica of the entire not identical, but similar in nature. Imagine a special type of photocopying machine that decreases the image to be copied by half and reproduces it three times on the copy in Fig. 1. Fig. 2 demonstrates several iterations of this process on several input images. It can be observed that all the copies appear converge to the same final image. Since the copying machine reduces the input image, any initial image placed on the copying machine will be reduced to a point as the process is repeated again and again. In fact, it is only the position and the orientation of the copies that determines the final image.

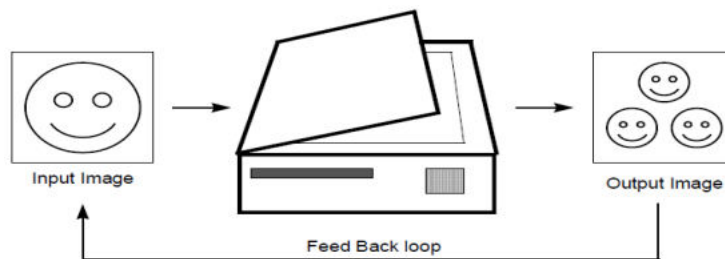


Fig. 1: A Copy Machine that Makes Three Reduced Copies of the Input Image

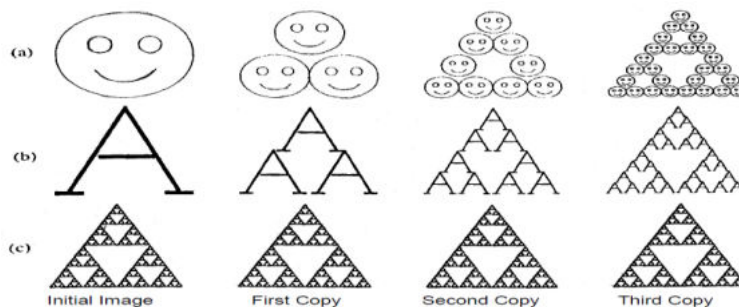


Fig. 2: The First Three Copies Generated on the Copying Machine of Fig.1

Fig 1.1 and Fig 1.2 depict two major features, the first is that the number of copies of the original pasted together to form the output and the second is that setting of position and scaling, stretching, skewing, rotation, contrast and brightness adjustment for each copy [1]. The way the input image is transformed determines the final result when running the copy machine in a feedback loop. These transformations must be constrained such that the transformations must be contractive that is, a given transformation applied to any two points in the input image must bring them closer in the copy.

III. LITERATURE SURVEY

Abdul-Malik et al. [1], the well-known fractal compression method encodes an image by mapping the image inside of itself, which necessitates a massive and repetitive search. As a result, the fractal algorithm's main issue is the excessive encoding time. Several hardware implementations have been developed to speed up the encoding process. However,

they are typically designed for grayscale images, and encoding color images requires at least a doubling of the encoding time when using them. In order to encode RGB images quickly, a brand-new high-speed hardware architecture is proposed in this paper. The proposed method encodes two of the color components by mapping them directly to the most correlated component using a searchless encoding scheme, while the third component is encoded using a search-based scheme. This is in contrast to the conventional method, which encodes the color components separately and similarly as a grayscale image. Encoding time is reduced, and compression rate is increased as a result. The processing time has been significantly cut down thanks to the use of parallel and deep-pipelining techniques. In addition, the image is partitioned so that half of the matching operations use the same data retrieved for processing the other half in order to reduce memory access to half. As a result, with a compression ratio of 46.5 and a minimum time of 12.2 milliseconds, the proposed architecture can encode a 1024 x 1024 RGB image. As a result, the proposed architecture outperforms the most recent designs even more.

M. Ahadullah et al. [2], benoit Mandelbrot came up with the concept of a natural fractal entity, an entity that could be described by those fundamentals, by combining the fundamentals of self-similarity, scaling correlation, and statistical components. Fractal image codings are already being used in a wide range of important applications, including image compression, image signature, watermarking, attribute extraction, and even texture segmentation. As a result, despite its relative newness in the field of image encoding, fractal image coding is rapidly gaining widespread acceptance. These applications are conceivable due to its advantageous properties, including its independence of resolution at any size, rapid decomposition, and high compression ratio. However, the high cost and time complexity of fractal image coding, in comparison to its benefits, restrict its use. This issue was caused by a large hunting domain for the relevant range blocks. In this paper, we made a number of changes to the Jacquin design. To test the block's edge textures' value, we first utilized max-pooling as an alternative for the medium bonding of spatial contractions. Second, in order to validate the symmetric central pixel (CP), we construct an odd-size pixel block as an alternative to an even-size pixel block. Finally, prior to beginning the search, we suggested reducing block space by converting each eight-bit pixel into a two-bit one by using the block's central pixel. Consequently, the edge pixel selection, block space reduction, and symmetrical CP of odd pixels block all resulted in faster coding and comparable image quality to that of existing exhaustive search algorithms.

A.-M.-H. Y. Saad et al. [3], due to its simplicity and superior performance, fractal image compression (FIC) is a widely used method in image compression applications. However, the lengthy encoding time is a major drawback. This is because encoding each tiny part of the image necessitates a huge similarity search. As a result, a current research topic is how to keep the quality of reconstructed images at an acceptable level while simultaneously reducing FIC's search time. As a result, the search problem of the conventional full-search FIC algorithm and the effects of employing a spatial dynamic search method in addition to the matching threshold strategy have been the primary topics of investigation in this paper. The dynamic search method is based on starting the search from the closest domain block to the range block that needs to be encoded. This is in contrast to the conventional full-search method, which is spatially static and starts from a fixed position (typically from the top-left corner of the image to the bottom-right corner) regardless of the position of the range block being encoded. The search is terminated whenever a domain block with an acceptable matching level is found under the different matching threshold values that these two search strategies are tested under. The test is carried out for a variety of image sizes and types, range block and partitioning step sizes, and quantization levels in order to complete the investigation. When the threshold is high, the experimental results demonstrate that using the dynamic search method rather than the conventional search method has a significant impact. The improvement that can be made is close to 90% in terms of search reduction and 1.6 dB PSNR in terms of image quality for the best encoding parameters.

PoonlapLamsrichan et al. [4], new block truncation coding-based color image compression is proposed. The new method for effectively encoding all four RVs in the 4-level BTC is applied to the Y component following integer color transformation. The chromatic components are encoded with 2-level BTC and down-sampled. The encoder and decoder can determine the number of levels in each block by making a simple level adjustment. A bitmap with variable length raises the compression ratio and adapts to the current level number. The new BTC coder can achieve 12 dB higher PSNR than some published BTC-based coders using true means as RVs without approximation.

Haichuan et al. [5], end-to-end optimized image compression, which is based on deep networks, has made significant progress over the past few years. A compressive auto-encoder, in which the encoder first converts the image into latent features and then quantizes those features before encoding them into bits, is typically used in previous research.

Information is lost during the conversion and quantization, making it difficult to achieve an ideal compression ratio. As a new end-to-end optimized image compression method a trained wavelet-like transform, to transform images into coefficients with no loss of information. After that, the coefficients can be quantized or encoded into bits. Unlike the previous methods, By simply adjusting the quantization scale, a single model can achieve any compression ratio and support both lossless and lossy compression.

Fabian Mentzer et al. [6], In order to create a cutting-edge generative lossy compression system, we extensively investigate how to combine learned compression with generative adversarial networks. Normalization layers, generator and discriminator architectures, training strategies, and perceptual losses are among the topics we focus on. In contrast to previous work, we can use our method on high-resolution images, operate in a wide range of bitrates, and produce visually appealing reconstructions that are perceptually similar to the input. By evaluating our method quantitatively using a variety of perceptual metrics and in conjunction with a user study, we bridge the gap between rate-distortion-perception theory and practice. Even if they use more than twice the bitrate, the study demonstrates that our method is superior to previous methods.

Emiel Hoogeboom et al. [7], using a statistical model, lossless compression methods reduce the expected representation size of data without sacrificing information. In this context, flow-based models are appealing because they permit exact likelihood optimization, also known as reducing the expected number of bits per message. However, when quantized for compression, conventional flows assume continuous data, which may result in reconstruction errors. As a result, we present Integer Discrete Flow (IDF), a flow-based generative model for ordinal discrete data: a bijective integer map that is capable of learning complex transformations on data with high dimensions. We introduce integer discrete coupling, a flexible transformation layer, as the foundation for IDFs. IDFs compete with other flow-based generative models, as demonstrated by our experiments. In addition, we demonstrate that lossless compression rates on CIFAR10, ImageNet32, and ImageNet64 can be achieved with IDF-based compression. We are aware of no other lossless compression techniques that make use of invertible neural networks.

S. Liu et al. [8], medically, magnetic resonance imaging (MRI) has a lot of value because it helps doctors figure out the expected surgical range and clinical staging. In offline storage and remote diagnosis, a lot of MRI images need a lot of storage space and the PACS system's transmission bandwidth. As a result, MRI image compression of high quality is very research-oriented. The loss of information regarding lesions caused by current compression techniques for MRI images with a high compression ratio results in misdiagnosis; Low compression ratio compression techniques for MRI images do not produce the desired effect. As a result, this paper offers a fast MRI image compression algorithm based on fractals. Initial, three-layered (3D) X-ray pictures are changed over into a two-layered (2D) picture grouping, which works with the picture succession in light of the fractal pressure technique. The inherent spatiotemporal similarity of 3D objects is then used to classify range and domain blocks. The proposed method's matching speed is increased by reducing the number of blocks in the matching pool through the use of self-similarity. Finally, in order to compress MRI images with high decompression quality, a residual compensation mechanism is implemented. The results of the experiments indicate that the PSNR is nearly 10 times higher and compression speed is two to three times faster. It demonstrates that the proposed algorithm is efficient and resolves the contradiction between MRI medical images of high quality and high compression ratio.

IV. METHODOLOGY

- **Discrete Wavelet Transform**

Wavelets are signals which are local in time and scale and generally have an irregular shape. A wavelet is a waveform of effectively limited duration that has an average value of zero. The term 'wavelet' comes from the fact that they integrate to zero; they wave up and down across the axis. Many wavelets also display a property ideal for compact signal representation: orthogonality. This property ensures that data is not over represented. A signal can be decomposed into many shifted and scaled representations of the original mother wavelet. A wavelet transform can be used to decompose a signal into component wavelets. Once this is done the coefficients of the wavelets can be decimated to remove some of the details. Wavelets have the great advantage of being able to separate the fine details in a signal. Very small wavelets can be used to isolate very fine details in a signal, while very large wavelets can identify coarse details. In addition, there are many different wavelets to choose from. Various types of wavelets are: Morlet, Daubechies, etc. [6].

This technique first decomposes an image into coefficients called sub-bands and then the resulting coefficients are compared with a threshold. Coefficients below the threshold are set to zero. Finally, the coefficients above the

threshold value are encoded with a loss less compression technique. The compression features of a given wavelet basis are primarily linked to the relative scarceness of the wavelet domain representation for the signal. The notion behind compression is based on the concept that the regular signal component can be accurately approximated using the following elements: a small number of approximation coefficients (at a suitably chosen level) and some of the detail coefficients.

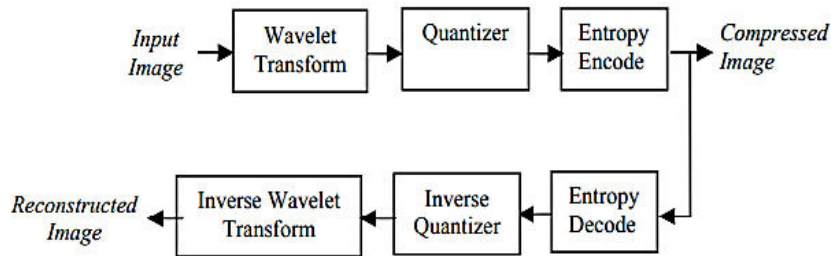


Figure 3: The structure of the wavelet transform based compression.

The steps of compression algorithm based on DWT are described below:

- I. Decompose Choose a wavelet; choose a level N. Compute the wavelet. Decompose the signals at level N.
- II. Threshold detail coefficients For each level from 1 to N, a threshold is selected and hard thresholding is applied to the detail coefficients.
- III. Reconstruct Compute wavelet reconstruction using the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N.

• **Multi-level Block Truncation Code**

The Encoder and decoder block of the multi-level block truncation code algorithm is shown if figure 2. 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 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:

$$(1) \quad T = \frac{\max + \min + m_1}{3}$$

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.

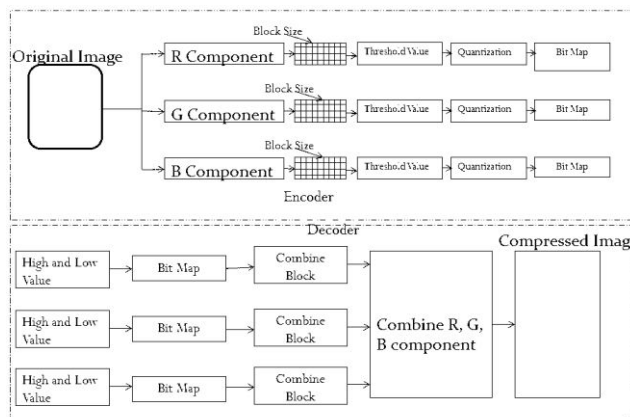


Figure 4: Block Diagram of Proposed Algorithm

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.

$$(2) \quad L = \frac{1}{q} \sum_{i=1}^p W_i \quad W_i \leq T$$

$$(3) \quad H = \frac{1}{p} \sum_{i=1}^q W_i \quad W_i > T$$

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.

- **Discrete Cosine Transform**

A discrete cosine transform (DCT) express a finite sequence of data points in expressions of a sum of cosine functions oscillating at different frequencies. DCTs are mainly important to numerous applications in science and engineering, from lossy compression of audio(e.g.-MP3) and image(e.g. JPEG) (where small and high frequency components can be rejected), to spectral method for the numerical solution of partial differential equations. The use of cosine function instead of sine is critical for compression, since it turns out (as explained below) that fewer cosine functions are required to approximate a typical signal, where for differential equations cosines function express a particular choice of boundary conditions.

- **Error-compensated scalar quantization**

The application of ICDF in the TDDC-based coding aims at a better interpolation and a lower compression cost. However, when the compression happens, the interpolation efficiency as well as the coding efficiency will be limited by the distortion occurring on those filtered pixels (denoted as $\sim x$) that will be used for interpolation. To solve this problem, we purpose to reduce the sum of square error (SSE) distortion of $\sim x$ as much as possible via controlling the quantization error of the transformed macro-block based on an error-compensated scalar quantization (ECSQ).

IV. CONCLUSION

Fractal image compression has numerous aspects of fast developing technology. There are many opportunities to develop the concepts further and improve upon the methodology. Below are a few areas which could be explored. Finding suitable partitioning scheme for the range block to match with domain blocks. The geometry of the range block and domain blocks is square or rectangle. This was just an imposition made to keep the problem tractable. Other geometries which might yield less blocks could be considered. The size of range blocks, size of domain blocks and the number of allowable Affine transformations to be optimized could be investigated. Quadrees techniques could be used with different size range blocks and multi-level image partitions.

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