PERFORMANCE EVALUATION OF IMAGE QUALITY BASED ON FRACTAL IMAGE COMPRESSION

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ABSTRACT

Fractal techniques for image compression have recently attracted a great deal of attention. Fractal image compression is a relatively recent technique based on the representation of an image by a contractive transform, on the space of images, for which the fixed point is close to the original image. This broad principle encompasses a very wide variety of coding schemes, many of which have been explored in the rapidly growing body of published research.Unfortunately, little in the way of practical algorithms or techniques has been published. Here present a technique for image compression that is based on a very simple type of iterative fractal. In our algorithm a wavelet transform (quadrature mirror filter pyramid) is used to decompose an image into bands containing information from different scales (spatial frequencies) and orientations. The conditional probabilities between these different scale bands are then determined, and used as the basis for a predictive coder.

We undertake a study of the performance of fractal image compression. This paper focuses important features of compression of still images, including the extent to which the quality of image is degraded by the process of compression and decompression.The numerical experiment is done by considering various types of images and by applying fractal Image compression to compress an image. It was found that fractal yields better

result as compared to other compression techniques. It provide better peak signal to noise ratio as compare to other techniques, but it take higher encoding time.The numerical results are calculated in Matlab.

Keywords- Image Compression, Fractal Image Compression, Compression ratio (CR), Peak Signal to Noise Ratio (PSNR), Encode Time, Decode Time.

1. INTRODUCTION

Multimedia data requires considerable storage capacity and transmission bandwidth. The data are in the form of graphics, audio, video and image. These types of data have to be compressed during the transmission process. Large amount of data can't be stored if there is low storage capacity present. The compression offers a means to reduce the cost of storage and increase the speed of transmission. Image compression is used to minimize the size in bytes of a graphics file without degrading the quality of the image. There are two types of image compression is present. They are lossy and lossless [1]. In lossless compression, the reconstructed image after compression is numerically identical to the original image. In lossy compression scheme, the reconstructed image contains degradation relative to the original. Lossy technique causes image quality degradation in each compression or decompression step. In general, lossy techniques provide for greater compression ratios than lossless techniques i.e. Lossless compression gives good quality of compressed images, but

yields only less compression whereas the lossy compression techniques [2] lead to loss of data with higher compression ratio. The approaches for lossless image compression include variable-length encoding, Adaptive dictionary algorithms such as LZW, bit-plane coding, lossless predictive coding, etc. The approaches for lossy compression include lossy predictive coding and transform coding. Transform coding, which applies a Fourier-related transform such as DCT and Wavelet Transform such as DWT are the most commonly used approach [3]. Over the past few years, a variety of powerful and sophisticated Fractal image compression schemes for image compression have been developed and implemented. The iteration function system provides a better quality in the images.

In this paper, we will evaluate result of fractal image compression based on different performance measure such as Peak to Noise Ratio (PSNR), Mean Square Error (MSE) and Compression ratio.

The paper is organized as follows: Section 2 explains image compression; Section 3 explains fractal image compression; Section 4 gives experimental results; Section 5 explains Conclusion; Section 6 gives numerical result of images.

2. IMAGE COMPRESSION

Image compression means minimizing the size in bytes of a graphics file without degrading the quality of the image to an unacceptable level. The reduction in file size allows more images to be stored in a given amount of disk more memory space. It also reduces the time required for image to be sent over the internet or downloaded from web pages. The recent growth of data intensive multimedia based web application have not only sustained the need for more efficient ways to encode signals and images but have made compression of such signal central to storage and communication technology.

The principle behind image compression is that the neighboring pixels are correlated and therefore contain redundant information. The foremost task then is to find less correlated representation of the image.

Two fundamental components of compression are redundancy and irrelevancy reduction.

- Redundancies reduction aims at removing duplication from the signal source (image/video).
- Irrelevancy reduction omits parts of the signal that will not be noticed by the signal receiver, namely the Human Visual System.

In digital image compression, three basic data redundancies can be identified and exploited:

- Coding redundancy
- Inter pixel redundancy
- Psycho visual redundancy

Data compression is achieved when one or more of these redundancies are reduced or eliminated.

2.1 Coding Redundancy

Use shorter code words for the more common gray levels and longer code words for the less common gray levels. This is called Variable Length Coding. To reduce this redundancy from an image we go for the Huffman technique where we are assigning fewer bits to the more probable gray levels than to the less probable ones achieves data compression.

2.2 Inter pixel Redundancy

Another important form of data redundancy is inter pixel redundancy, which is directly related to the inter pixel correlations within an image. Because the value of any given pixel can be reasonable predicted from the value of its neighbors, the information carried by individual pixels is relatively small. Much of the visual contribution of a single pixel to an image is redundant; it could have been guessed on the basis of its neighbor's values. A variety of names, including spatial redundancy, geometric redundancy, and interframe Redundancies have been coined to refer to these interpixel dependencies.

2.3 Psycho visual Redundancy

Human perception of the information in an image normally does not involve quantitative

analysis of every pixel or luminance value in the image. In general, an observer searches for distinguishing features such as edges or textural regions and mentally combines them into recognizable groupings. The brain then correlates these groupings with prior knowledge in order to complete the image interpretation process. Thus eye does not respond with equal sensitivity to all visual information. Certain information simply has less relative importance than other information in normal visual processing. This information is said to be psycho visually redundant. To reduce psycho visual redundancy we use quantizer. Since the elimination of psycho visually redundant data results in a loss of quantitative information [5].

3. FRACTAL IMAGE COMPRESSION

Fractal is one effective method to describe natural modality in the process of transformation and iteration. In 1973, Benoit Mandelbrot firstly brought forward the idea of fractal geometry, Infinity self-similarity is the soul of fractal. It was Michael Barnsley and his research group who first give out the method of fractal-based image compression, via IFS (Iterated Function Systems), according to the local and global self-similar principle. In 1989, Amaud Jacquin and Michal Barnsley realized a first automatic fractal encoding system [7].

Fractal parameters, including fractal dimension and iterated function systems, have the potential to provide efficient methods of describing imagery in a high compact fashion for both communication and storage applications [6].
Fractal image compression is also called as fractal image programming because compressed images are represented by contractive transforms. These transforms are composed of group of a number of affine mappings on the whole image, known as Iterated Function System (IFS). Contractive transformation is applied to the IFS's called Collage theorem. This theorem is the technique core of the fractal coding [8]. Fractal

image compression is a modern image compression technique based on self similarity.
In FIC the image is decomposed two times, into overlapping domain blocks with size D*D to make a domain pool. Then we decompose the image again into non-overlapping range blocks with size R*R, and usually D=2*R. This type of decomposition is closely related to quad–tree (parent child relationship) where domain block forms parent and small four range block forms children.The whole process of fractal image encoding is shown in Fig. 1 [9].

Partition Scheme   Virtual Codebook
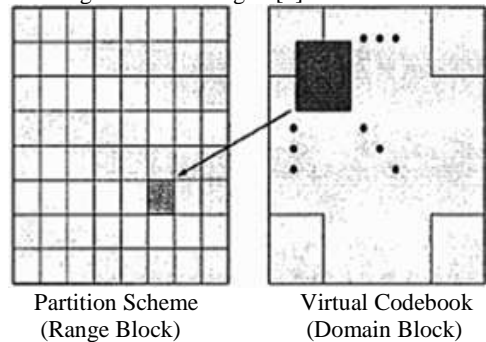(Range Block)   (Domain Block)
Fig 1: Encoding in FIC

After decomposition, for each range block we search for best matched domain block in the domain pool with a contractive affine transformation W_i, which can be defined by the following function

$$W_i \begin{pmatrix} x \\ y \\ p_{xy} \end{pmatrix} = \begin{pmatrix} a_i & b_i & 0 \\ c_i & d_i & 0 \\ 0 & 0 & s_i \end{pmatrix} \begin{pmatrix} x \\ y \\ p_{xy} \end{pmatrix} + \begin{pmatrix} u_i \\ v_i \\ o_i \end{pmatrix}$$

Fig 2: Affine transformation

Where x and y are the spatial coordinates of the image block and $p$xy is the pixel value at the position (x,y); a_i, b_i, c_i and d_i denote the combinations of some of the eight symmetrical transformations; u_i, v_i are the location luminance values; s_i is the scaling coefficient; o_i is the luminance offset [10].
Finally the best matched domain block can be found for each range block in the original image

3.1 Iterated Function Systems

The major tool used in describing images with iterated function systems is the affine transformation. This transformation is used to express associations between different parts of an image. Affine transformations can be described as combinations of rotations, scaling and translations of coordinate axes in n-dimensional space [11]. For example, in two dimensions a point (x, y) on the image can be represented by (xn, yn) under affine transformation. This transformation can be described as follows (figure 2):

The parameters a, b, c and d perform a rotation, and their magnitudes result in the scaling. For the whole system to work properly, the scaling must always result in a decrease of the distances between points, otherwise repeated iterations will result in the function blowing up to infinity. The parameters e and f cause a linear translation of the point being operated upon. If this transformation is applied to a geometric shape, the shape will be translated to a new location and there rotated and shrunk to anew, smaller size. In order to map a source image onto a desired target image using iterated function systems, more than one transformation is often required and each transformation, i, must have an associated probability, p_i, determining its relative importance with respect to the other transformations. The random iteration algorithm given by Barnsley [11] can be used to decode an IFS code in order to reconstruct the original image.

The coding-decoding system shown in figure 3 is based on partitioning the original image into non-overlapping squares of two different sizes forming a two-level square partition as shown in figure 3. To encode an image, for each small size block a set of affine transformation are applied to a selected set (codebook) of the large size blocks and the one which produces the minimum error is selected with its transformation to be used in the reconstruction of a particular small block.
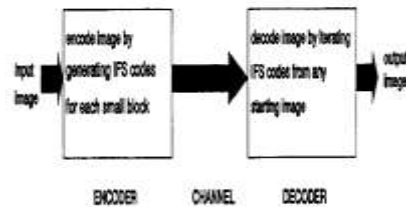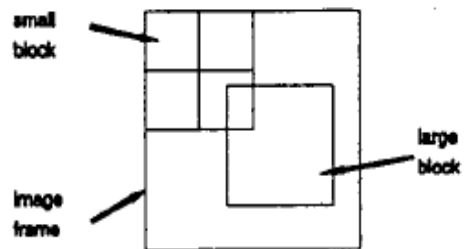

Fig 3: Fractal encoding/decoding systems

Fig 4: Image partitioning.

3.2 Vector Quantization

Vector quantizers map an input signal onto a set of finite reproduction vectors, known as the codebook. In image compression, each input signal is a 2D k x l image patch. Once the codebook is constructed, pattern matching occurs between the input vector and the codebook entries. The algorithm iterates by replacing the two "nearest neighbor" vectors in the codebook by a vector which optimally encodes their constituency. Codebook distance is measured using mean squared error and vectors are weighted by the number of samples which depend on them.

3.3 Fractal-Based Encoding

The output of the VQ stage is a set of codes for each of the horizontal, vertical and diagonal subbands within each of the scales included in the wavelet transform. The codes for a lower frequency subband will contain one-fourth the numbers of entries contained by the next-higher frequency subband. The goal of our fractal-based encoding scheme is to first estimate the conditional probabilities between various subbands codes, and then use these statistical

relationships in a predictive coding algorithm. As images are coded, the mappings between the VQ codes for each subband and the next-higher frequency subband are tallied to obtain a histogram of the frequency of each of the mappings. Separate histograms are required for each of the four lower-to-higher frequency mappings. These histograms are called the prediction lookup tables. Once this frequency histogram is constructed, the conditional probabilities between the various subband coding can be analyzed to determine an optimal lossless (with respect to the VQ coding) encoding scheme. In this scheme each VQ-coded entry of each band is re-coded by comparing it to the codes most frequently associated with the VQ code at the corresponding location in the next-lower frequency band. Typically the higher frequency band's VQ code is one of the 2" - 1 code found most frequently in the prediction lookup table associated with the lower frequency band's VQ code. The VQ code for the higher frequency band can then be re-coded by use of an n bit index into that prediction lookup table.

4. EXPERIMENTAL RESULTS

In this paper two 8bits images are selected jetplane.gif (298097 bytes) and house.gif (298097 bytes) to stimulate and evaluate result of fractal image compression. The simulation result has shown in TABLE I, TABLE II, figure 5 and figure 6. TABLE I, TABLE II show compressed size, Compression Ratio, Peak to Noise Ratio (PSNR), encode time, decode time, Mean Square Error (MSE) for image at different search block size. Figure 5 shows images of Jetplane.gif at different size of search block. Figure 6 shows images of house.gifat different size of search block. It can be seen from Figure 5 and figure 6 that quality of reconstructed image is much closer to the quality of the original image. It has been analyzed that result obtained from the Fractal image compression provide good visual quality and PSNR value and compression ratio. Figure 7 show reconstruction of image woman_darkhair.tif (262750 bytes) at different iteration of decoding process. It was found that with increase of iteration quality of image increases.

5. CONCLUSION

In this paper, the results of different images are compared which are obtain from fractal image compression. The effects of image contents and compression ratios are examined. This compression algorithm provides a better performance on picture quality at higher compression ratio. This technique is successfully tested on jetplane.gif and house.gif images. It is observed that fractal image compression provide better result because of high psnr values and also compression ratio is also very high. The main drawback of this algorithm is that it takes long encoding time which is not tolerable. The above algorithm can be used to compress the image that is used in the web applications.

6. EXPERIMENTAL RESULTS

TABLE I PERFORMANCE EVALUATION OF FRACTAL IMAGE COMPRESSION ALGORITHM ON

Increases of value of search block	Compressed Size	MSE	PSNR	Encode time(Sec)	Decode time(Sec)	CR
1	189552	146.3160	74.6765	241.7890	19.1860	1.5726
2	156611	233.7032	72.6428	163.3160	18.9120	1.9034
3	152717	248.3464	72.3789	177.5630	19.1450	1.9520
4	157610	246.5669	72.4101	207.8770	18.5000	1.8914
5	151181	250.5155	72.3411	149.6700	18.2180	1.9718

"JETPLANE.GIF" (298097 BYTES)

TABLE II PERFORMANCE EVALUATION OF FRACTAL IMAGE COMPRESSION ALGORITHM ON

Increases of value of search block	Compressed Size	MSE	PSNR	Encode time(Sec)	Decode time(Sec)	CR
1	205871	177.0884	73.8476	202.1530	20.9670	1.4480
2	179484	257.2029	72.2267	153.2950	19.0830	1.6609
3	174498	287.0878	71.7493	172.4120	18.9350	1.7083
4	174641	303.6448	71.5058	229.0850	18.9870	1.7069
5	173028	276.6069	71.9108	202.9010	18.0220	1.7228

"HOUSE.GIF" (298097 BYTES)

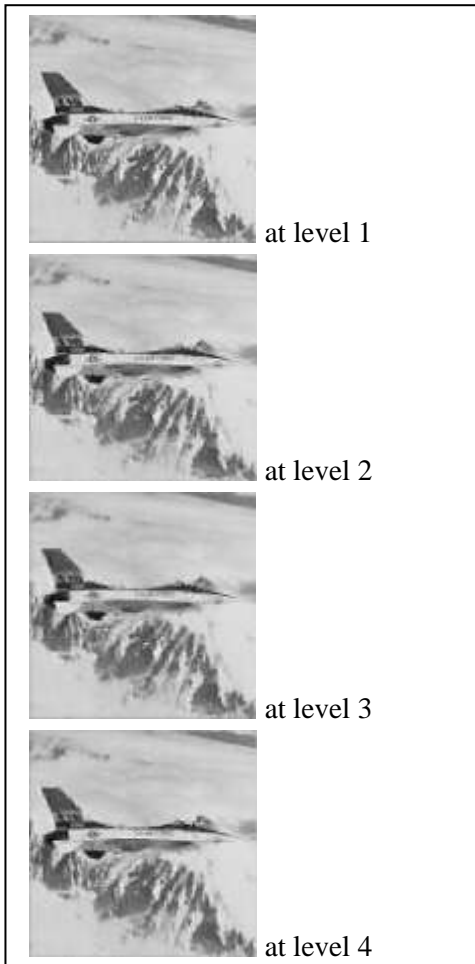## RESULT ON IMAGES

Original Image
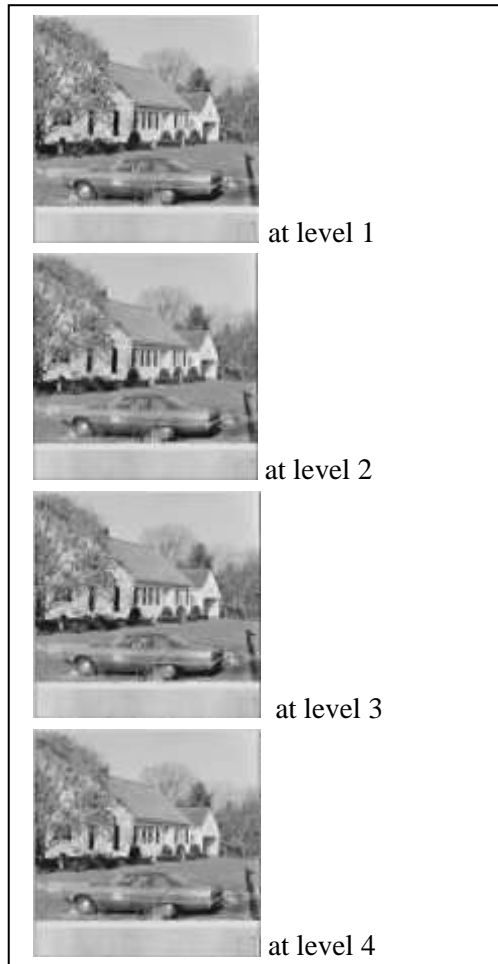

Original Image

Figure 5

Figure 6

Fig 5: Shows images of "JETPLANE.gif" at different size of search block.
Fig 6: Shows images of "HOUSE.gif" at different size of search block.

IMAGE DECODING PROCESS

TABLE III PERFORMANCE EVALUATION OF FRACTAL IMAGE COMPRESSION ALGORITHM ON "WOMAN_DARKHAIR.TIf"

Compressed Size (Original size 262750 bytes)	MSE	PSNR	Encode time(Sec)	Decode time(Sec)	CR
232752	62.6419	78.3608	155.8480	18.4470	1.1289

Fig 7: (a) Original image (b) at iteration 1   (c) at iteration =2   (d) at iteration =5   (e) at iteration =10

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