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Encoding Time Reduction Method For The Wavelet Based Fractal Image Compression

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Abstract —In this paper we show the two implementations of fractal (Pure-fractal and Wavelet fractal image compression algorithms) which have been applied on the images in order to investigate the compression ratio and corresponding quality of the images using peak signal to noise ratio (PSNR). And in this paper we also set the threshold value for reducing the redundancy of domain blocks and range blocks, and then to search and match. By this, we can largely reduce the computing time. In this paper we also try to achieve the best threshold value at which we can achieve optimum encoding time.

Keywords: Fractal image coding; Wavelet; Iterated Function System; Wavelet; Mean Square Error; Compression Ratio.

1. Introduction

Image compression has an important application in the areas of image transmission and image storage despite the large capacity storage devices that are currently available. Therefore, an efficient method for storing and transmitting an image to reduce execution time and memory size is needed. The general principle of image compression algorithms is to transform binary digits into a new one that contains the same information but with fewer digits, so the file can be as small as possible. The efficient image compression algorithm or any data compression is chosen according to scales, such as compression size, compression ratio, and entropy. *Compression size* is the size of the new file in bits after compression is complete. *Compression ratio* is a percentage that results from dividing the original file size in bits by the compression size in bits. *Entropy* is the number that results from dividing the compression size in bits by the number of symbols in the original file and scales as bits/symbol [1].

The general idea for achieving error detection and correction is to add some redundancy (i.e., some extra bits) to a message. The receiver then uses these extra bits to the check consistency of the delivered message and to recover data that is determined to be erroneous. These detecting/correcting codes are also used in data compression. Hamming codes, BCH code, and Huffman code are all codes for detecting/correcting errors. Hamming and BCH codes are block codes that have fixed lengths, whereas Huffman code is a variable-length code [2,3 4]. Typically, a block code takes *k* bit information and transforms this into an *n* bit codeword by adding *m* redundant bits to the original data bits. The block length of this type of code would be an *n* bit and, so, there are 2^kpossiblecodewords.

Data compression is divided into two major categories, lossless compression techniques and lossy compression techniques. In lossless compression, data can be compressed and restored without any loss of information. In lossy compression, the decompressed data may be an acceptable approximation of the original uncompressed data [5]. The codeword of length *n* and *k* data bits: (*there are* 2^k *possible* code words) are compressed into a *k* bit in the compressed file using (n, k) BCH code. For a non-codeword*(there are* $2^n - 2^k$ *possible non*-code words*)* the same *n* bits are written in the compressed file. We use an indicator to determine whether or not the *n* bits in the original file are compressed into a *k* bit.

2. What is Digital Image Processing?

Pictures are the most common and convenient means of conveying or transmitting information. A picture is worth a thousand words. Pictures concisely convey information about positions, sizes and inter-relationships between objects. They portray spatial information that we can recognize as objects. Human beings are good at deriving information from such images, because of our innate visual and mental abilities. About 75% of the information received by human is in pictorial form.

An image may be defined as a two-dimensional function, *f(x, y),* where x and y are spatial(plane) coordinates, and the amplitude of *f*at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. When (x, y) and the intensity values of *f* are all finite, discrete quantities, then we call the image a digital image.

A digital image is composed of a finite number of elements, each of which has a particular location and value. These elements are called *picture elements*, *image elements*, *pels , and pixels* .In spatial domain methods we directly process the pixels of an input image. An expression for spatial domain processing is given by the equation shown below:

$$g(x,y) = T[f(x,y)] \quad (1.1\text{-}1)$$

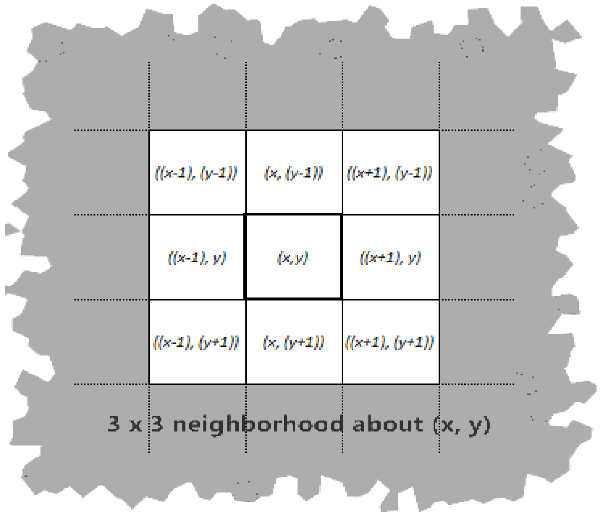


Figure 1.1 Neighborhood of pixel at point (x, y).

Here, *f(x, y)* is the original image, *g(x, y)* is the processed image and *T* is an operator over neighborhood of *(x, y).*

The principal approach in defining a neighborhood about a point *(x, y)*is to use a square or rectangular sub image area centered at *(x, y).* The center of the sub image is moved from pixel to pixel. The operator *T* is applied at each location to yield the output at that location. The process utilizes only the pixels in the area spanned by the neighborhood.

3 METHODOLGY FOR IMPROVING FRACTAL WAVELET COMPRESSION TECHNIQUE

A. Principles of improving

Energy of an image after wavelet transformed mainly concentrated in the low frequency sub image. According to the human vision mechanism, the main vision of people is sensitive to the low frequency information, but not sensitive to the high part. So we take lossless compression to the low frequency information. Previous fractal compression directly divided the original image into range blocks and domain blocks, then affine transform the range blocks and matches with domain blocks. Finally compressing and coding. However, we choose to reduce the redundancy among domain and range blocks before matching, because there are many similar blocks in the block pools. After this, less domain blocks will be left, and less time will be consumed. Here we use Mean Square Error (MSE) to judge the degree of similarity among domain and range blocks. The domain blocks' algorithm is described as follows:

- Assume threshold value= δ and assume all the flags=0.
- Set minimum value of δ, and compute the Ei, i.e. MSE of Di.
- Sequence Ei from small to large.
- Compare Ei and δ, if Ei is less than δ then delete that block, then set flag=1, And save that in affine transformation.
- If Ei is not less than δ then consider the MSE with minimum value as a best match. Then repeat the previous step.
- Further for finding out the best threshold value, first of all we set the minimum threshold value, then we vary that value in some range for getting the optimum result.

After simple screened, the representative blocks will be left, the redundancies of the pool have been removed. In the same way, the redundancy of range blocks can be removed. As range blocks are much more important than former, the initial threshold should be smaller.

- Divide a 256x256 image into 8×8 sub image blocks. If we set the step size to 8, there will be 32×32=1024 blocks. There will be more similar blocks after averaging 4 neighbor pixels, which makes this algorithm more practical and rational [49].

B. Transform the image with wavelet

First of all, decompose the image with 3scale wavelet, and then process the low frequency and high frequency data separately as below.

C. Processing of low frequency data

Low frequency sub image occupies more than 85% of the whole sub images' energy. It has a large amount of data, a big self similarity and it also contains much important information. We choose to code the low frequency sub image with lossless predictive coding. Concrete steps are as follows: Transform a image with 3scale wavelet, we'll get large low frequency coefficients, and they are very close. Then difference the coefficients of low frequency part, and code the results with Huffman coding, generating the low frequency compression data. To combine the results of low frequency and high frequency part, we will get the coding result of original image.

D. Processing of high frequency data

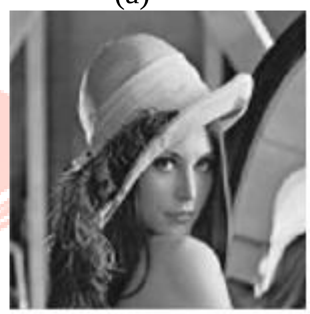
Here we choose a new method. Search and match the domain blocks and range blocks whose redundancy has been reduced. Record the position of each block when reducing the redundancy, then following the fractal coding.

4 Using Fractal Image Compression Technique in Wavelet Domain without Threshold for image of Leena

Fig 6.6 shows an image sachin.jpg of size 512x512. This image is compressed and decompressed using Fractal Image Compression Technique in Wavelet Domain. The encoding time is **110.2030** seconds and the size of the encoded text file is 351KB, and compression ratio achieved is of 85.13%. Fig. 6.7 shows the reconstructed image after 1, 3, 5 and 7 iterations.

Fig 1.2 Original Image

(a)



(b)

(c)

(d)

Fig1.2 (a)-(d) shows the reconstructed images after 1, 3,5 and 7 iteration using fractal image compression in wavelet domain.

Iteration No.	PSNR	Decoding Time (Seconds)
1	19.9637	1.3360
2	22.5996	1.9310
3	25.5867	2.1380
4	27.5050	2.6200
5	27.9747	2.9330
6	27.9747	3.3880
7	27.9747	3.9130
8	27.9747	4.3370

Table 1 PSNR, Decoding Time fordifferent Iterations for image of Leena

4.1 Histogram for Leena without threshold after 1,3,5,7 iterations

Figure 1.3 (a-d) shows the histogram for the image of Leena

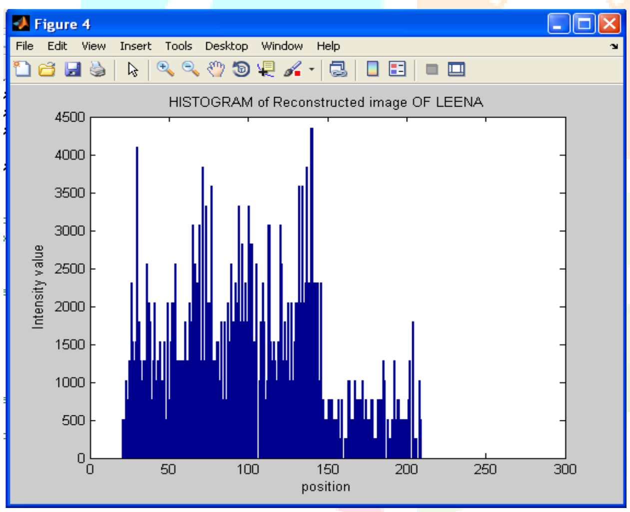


Fig 1.3(a) Histogram of Leena after iteration

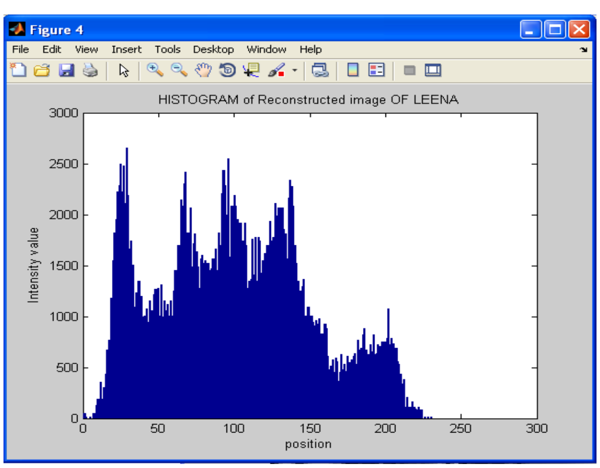


Fig 1.3(b) Histogram of Leena after iteration

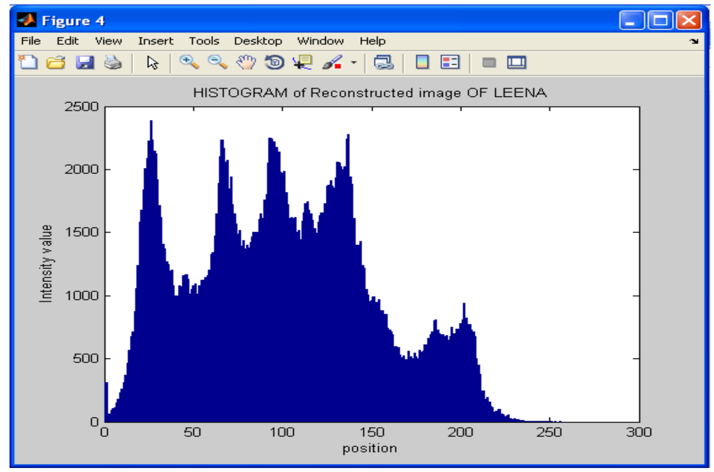


Fig 1.3(c) Histogram of Leena after iteration 5

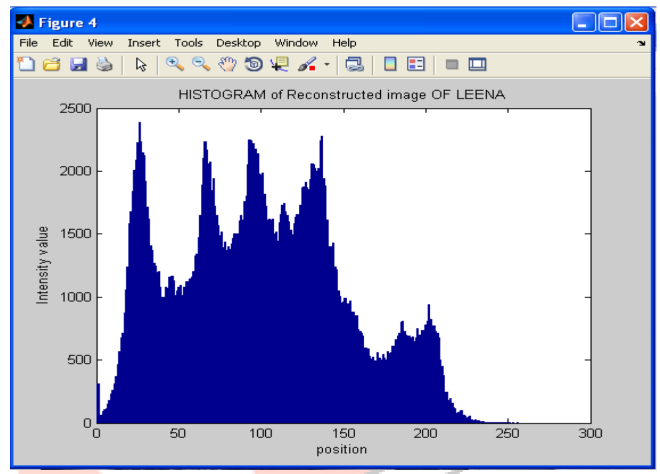


Fig 1.3(d) Histogram of Leena after iteration

4.2 PSNR and Decoding Time for Different Images without threshold

Images	PSNR	Best Decoding Time (in seconds)	Encoding Time (in seconds)
Sachin	34.7396	7.3750	109.3430
Mahi	31.3298	7.4060	110.2030
Leena	27.9747	2.9330	112.9850

Table 2

4.3 Using Fractal Image Compression Technique in Wavelet Domain with Threshold for Image of Leena

shows an image sachin.jpg of size 512x512. This image is compressed and decompressed using Fractal Image Compression Technique in Wavelet Domain. The encoding time is **6.1090**seconds and the size of the encoded text file is 351KB, and compression ratio achieved is of 85.13%. Fig. 6.12 shows the reconstructed image after 1, 3, 5 and 7 iterations.

Fig 1.4Original Image

(a)

(b)

(c)

(d)

Fig1.4 (a)-(d) shows the reconstructed images after 1, 3,5 and 7 iteration using fractal image compression in wavelet domain.

Iteration No.	PSNR (dB)	Decoding Time (Seconds)
1	19.9637	1.4230
2	22.5996	1.8160
3	23.0121	2.1800
4	23.0319	2.5700
5	23.0327	3.0050
6	23.0327	3.4560
7	23.0327	3.8470
8	23.0327	4.3040

Table 3 PSNR, Decoding Time for different Iterations for image of Leena with threshold value

5 CONCLUSION

In this Paper, we evaluated wavelet based fractal image compression technique with various threshold values to get the Encoding/Decoding process as faster as possible, that's exactly the point where it fallen below the JPEG standard.. Hence we came to conclude that a small positive value of the threshold do the needful, as the wavelet transform for a gray scale image have most the coefficients positive and near zero. Several fractal image compression algorithms in spatial and wavelet domains were implemented. In the previous work fractal-wavelet compression directly divided the original image into range blocks and domain blocks, then affine transform the range blocks and match with domain blocks. Finally compressing and coding. This work already reduced the encoding time in large amount from hours to few minutes. Now in this dissertation we further have shown the improvement on fractal-wavelet technique by setting the threshold value. By which we can reduce the redundancy of domain blocks and range blocks, the reconstructed image is not as good as the original, but the computing time is largely reduced i.e. from few minutes to few seconds. In this dissertation, we choose MSE to judge the similarity of all the blocks. As the distribution of gray is different from image blocks, there may be some residual by using MSE. In addition, we choose PSNR to judge the quality of reconstructed image. PSNR is the most common and widely used measuring method. Recent researches show that the PSNR does not always has the same visual quality as what human see.

After this we further try to find out the best result from the threshold value. Because initially we do not know that on which value we will get the best result, so for getting the best value of threshold we vary the threshold value in some range. After varying the threshold value we observe the best value.

6 FUTURE SCOPE

There are lots of schemes available for spatial fractal and fractal-wavelet image compression. There I am looking forward for some way out that the lossy fractal image compression become nearly lossless. Although the encoding time in fractal image compression is very high and it is a lossy image compression technique but it can be converted to lossless technique by maintaining the encoding time and decoding time low. Furthermore the field of research is far more being exhausted, since there are many directions that have not yet been fully investigated. The main advantages of the fractal compression scheme are its ability to provide high compression ratio for a large class of images, the speed of its decoding process and its multiresolution properties. However to arrive at an optimal algorithm which can outperform traditional techniques more attention needs to be devoted to the encoding process which is still suffers from long computation time.

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