An PSO-based Approach to Speed up the Fractal Encoding

Hsiao-Wen Tin, Shao-Wei Leu, and Shun-Hsyun Chang

***Abstract*—**Fractal block coding method is based on a large amount of self-similarity which is exhibited in the image. During the encoding phase of fractal block coding, the size of domain pool determines how much time the encoding spends on searching the best match for each range block. Therefore, most of fractal image coding researches focused on obtaining the best possible accuracy with the smallest possible domain pool.

This paper introduces three elaborative designed factors in the fitness function for particle swarm optimization (PSO) and a newly design method to obtain optimal domain blocks. The proposed method based on clustering technology and PSO method obtains the best possible accuracy with the smallest possible domain blocks in optimal pool. As a result, the proposed method greatly reduces the number of searches in the matching process. This paper experimentally demonstrates the proposed method on Java and verified with 3 medical images. By examining the experimental result, one sees that the domain blocks in optimal pool can well approximate the experimental images, and the why all natural images are rich in affine redundancy and have the property of local self-similarity. The proposed method by optimizing domain blocks achieves the image encoding that resulting in the best quality with as little searching as possible.

The experimental results also indicate that the proposed method outperforms Jacquin's method for less number of searches in matching process with the quality of image after encodes remaining acceptable. We conclude that proposed method could be obtained domain blocks in optimal pool and successfully used to image encoded and decoded with an efficient search in encoding phase and without noticeable loss of image quality.

***Keywords*—**Fitness function, Fractal block coding, Image data compression, Particle swarm optimization, Reduced domain block.

I. Introduction

In recently years, fractal-based techniques have been applied in several areas of digital image processing, such as image compression [1], image analysis [2] and image retrieval [3], [4]. A fractal is a geometric form which has self-similar irregular details. Mandelbrot suggested that the fractal is an object can be assembled by its subdivided parts similar to the whole exactly or statistically [5]. The widely used fractal block coding method is consequently based on a large amount of self-similarity which is present in the image.

The first practical block-based fractal coding method was introduced by Jacquin [6] which is based on the assumption that a large amount of self-similarity exhibits in the image at the block-image level. The Jacquin's fractal block coding method splits the image into range blocks and domain blocks at first, then searches in the collection of domain blocks (refer to as domain pool) for the best domain blocks which match the range blocks the most. Jacquin's fractal block coding achieves excellent compression result because it records only the necessary parameters of transformation in the matching process and correspondent domain blocks during encoding [6]–[8].

During the encoding phase, the Jacquin's fractal block coding is based on the self-similarity to search in the whole domain pool for finding the most similar domain block for each range block. Given a brute-force search in the matching process, the search-time complexity for search alone is the product of the number of the range blocks and the number of the domain blocks, not counting the transformation. During the encoding phase of fractal block coding, the size of domain pool determine how much time the encoding spends on searching the best match for each range block. Therefore, most of fractal image coding research focused on how to achieve the best quality after encoded with as little searching as possible. Some recent investigations have shown some improvements on the time complexity by searching for the best domain blocks in optimal pool [9]–[14]. Those studies may be classified into two categories: one is splitting the searching space into smaller spaces, such as clustering method [9], [10], PSO method [11], [12]; the other is reducing the size of search space, such as [13], [14] eliminated the domain blocks from the domain pool.

This paper proposed a newly design method to obtain the best possible accuracy with the smallest possible domain blocks in optimal pool based on clustering technology and PSO method. In the encoding phase, the proposed method uses PSO to evaluate the significance of domain blocks in each cluster and in domain pool, in which the significance is obtained by using a newly defined fitness function based on the weighting and the presence of probability of domain block in the cluster and domain pool. After PSO processing, those insignificant domain blocks are eliminated from domain pool and the significant domain blocks are kept. Meanwhile, the numbers of significant domain blocks are optimized. Consequently, the proposed

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method examines how well range blocks are approximated by significant domain blocks, and the information of successful approximation is written into the codebook.

The proposed method has been implemented in computer software and 3 medical images as the experimental data were successfully encoded and decoded without noticeable loss of image quality after encode. This paper evaluated the image quality after encode, compression rate (CR) and search-time complexity with picture signal-to-noise-ratio (PSNR), the ratio of file sizes and the searching time in match process. The experimental results indicate that the proposed method is successful in reducing the number of search in encoding phase and able to keep the great quality. We conclude that the proposed method excellently obtains the best possible accuracy with the smallest possible domain pool.

The rest of this paper is organized as follows. In the next section, the fractal block coding method, K-means, and PSO are introduced. In section III, we describe how the proposed method, based on PSO, reduces the number of domain blocks in domain pool. In section IV, we present the experiments and the results. In the final section the concluding remarks are present.

II. Related Work

This section provides the related knowledge in supporting the proposed method. The first subsection describes the Jacquin's fractal block coding context. The following subsection introduces K-means. The concept and process of PSO was introduced at the end subsection.

A. Fractal Block Coding Method

The idea of fractal image coding is based on the assumption that a large amount of self-similarity is present in the image at the microscopic or block-image level. In real world, an object can be represented by some of its subdivided parts given that the parts resemble the whole to a certain degree. This concept leads to the creation of a class of image compression methods. The first fractal image coding method was introduced by Bernesly [7] and Jacquin [6]. In what follows the basic theory of Jacquin's fractal block coding is introduced.

Jacquin's fractal block coding consists of finding a set of transformations and then generating a fractal image which is the approximation to the original image. In what follows the basic theory of Jacquin's fractal block coding is introduced.

Let I be a gray-level image. In fractal block coding, image I is partitioned into N range blocks $R_i \subseteq I$, for i = 1, 2,…, N, and M domain blocks $D_j \subseteq I$, for j = 1,2,…, M, where the size of each domain block is twice the size of each range block.

To encode an image, each range block finds a domain block most similar to itself from the domain pool, in which the finding is based on minimum mean-squared error criteria. The search for the best matching domain block D_j is performed with a local affine transformation w_i , such that $w_i : D_j \to R_i$, for i = 1,2, …, N and j = 1, 2, …, M. In theory, the union of the local affine transformations for all range blocks will form the affine transformation τ for the whole image as illustrated in following equation:

$$\tau = \bigcup_{i=1}^{N} w_i \tag{1}$$

In practice, each local affine transformation w_i is performed to find the best matched domain block D_j , such that $R_i \approx w_i\left(D_j\right)$. Image encoding is achieved by generating fractal codes for each range block R_i based on the best matched domain block D_j , then, storing the fractal code into the codebook. Fractal codes in the codebook can later be used in approximating the image with iterating process.

B. K-means

K-means is a well-known and widely used partition clustering method which will cluster n objects based on designated attributes into k partitions, where $k < n$ [15]. The K-means procedure is both easy to implement and computationally economical, therefore is suitable for processing very large data sets.

Implementation of the K-means clustering method starts from setting the number of clusters, i.e., the K-value. A brief description of the K-means method is illustrated as follows:

Step 1: Set the K-value.
Step 2: Randomly pick K data points as the first cluster centers.
Step 3: Obtain the distances between each point and the centers. Allocate the point to the nearest center to form a cluster.
Step 4: Generate new centers and new clusters.
Step 5: Repeat Steps 3 and 4 until no new centers are generated.

The center of each cluster will converge to a stable state after a number of iterations. The convergence normally does not provide an optimal partition except for some special cases, since K-means was originally developed to find feasible solution of some problem, rather than optimal partition.

C. PSO

In 1995, Kenney et al. suggested the particle swarm optimization (PSO) to resolve global optimization problem. It is one of the important techniques of swarm intelligence [16], [17].

The principle of PSO is modeled by the behavior exhibited by a flock of birds foraging for food. Assume that a flock of birds flies in an open space to seek food. At the beginning, the flock does not know where the food is. Birds fly in a certain path according to their past experience. Once a bird spots some food, it broadcasts the information to other birds around. As the message being passed on throughout the whole pack, the flock of birds quickly adjusts to a new direction leading to food. In this process, information derived from the past experience and from communication between the birds guide the flock in flight to a better foraging space.

PSO simulates the behaviors of a bird flock. Each particle in the PSO is a "bird" in the search space. A particle represents an individual solution. A fitness function generates the fitness value iteratively to be a measure of particle, in which the measure is the information guide the direction to a better search space. The next moving direction depends on the current better position found by particles. The particles continue to evolve until the preset number of iterations is reached or a termination condition is met. The final particles represent the most optimized solutions. The following steps describe the PSO method.

Step 1: Randomly initialize the location and velocity of each particle within the solution space.

Step 2: Obtain the fitness value of each particle.

Step 3: Determine the current best solution for each particle. Compare each particle's current fitness value with its best solution. If the current fitness value is better than the best solution, replace the best solution with the fitness value and the particle's current location.

Step 4: Determine the current best solution for the swarm. Compare the current fitness value of each particle with the global best solution. If the current fitness value is better, replace the global best solution with the particle's fitness value and location.

Step 5: Update the location and velocity of each particle based on the best solution obtained in Step 3, and the global best solution obtained in Step 4.

Step 6: Go back to Step 2 and repeat the process until the predefined number of iterations is finished or the termination condition is met. When the process stops, each particle has arrived at its best solution and the global best solution emerges as a result.

III. An Efficient Domain Pool Reduction Method based on PSO

In the encoding phase of proposed method, an image is partitioned into a number of non-overlap range blocks and a number of overlap domain blocks at first. Consequently, this paper uses the K-means to cluster the domain blocks at first for improving the convergence speed of PSO. The PSO method based on the newly defined fitness function, which consists of factors including weight, presence probabilities and membership, is then used to identify the most significant domain blocks for each cluster. Insignificant domain blocks of each cluster are then eliminated. At the final, the proposed method will search the significant domain blocks remaining in the domain pool for the best matching domain block to a range block. The proposed method examines how well range blocks are approximated by significant domain blocks in optimal domain pool, and the information of successful approximation is written into the codebook.

The first subsection describes the proposed fitness function. The following subsection describes the proposed reduction method based on PSO which is used to reduce the number of domain blocks in order to speed up the search.

A. *The Proposed Fitness Function*

PSO uses the fitness function to measure the particle in optimizing the particle during the particle's evolution. The particles travel through the problem space by following the current optimum particles.

This paper uses PSO to help reducing the amount of domain blocks and takes the fitness function as the measure to indicate the significance of the domain block. The more significant the domain block is, the larger the fitness value becomes. That is, the significance of a domain block is higher, and its relationship to the cluster becomes stronger. Therefore, the fitness value is bigger.

PSO might converge to a local best solution if the fitness function is not designated according to global characteristics. The local best solution might lead to eliminate insignificant domain blocks at local view but crucial at global concern. This paper designs a new fitness function for the proposed method according to both the global and local characteristics with the factors illustrated as following equation:

$$Fitness = \sum_{i=1}^{d^P} w_i \times \left(m_i + p_i^k + pg_i \right) \tag{2}$$

where d^P is the particle dimension of the particles, m_i is the membership value of the ith domain block to the cluster, p_i^k is the presence probability of the ith domain block to the kth cluster, pg_i is the presence probability of the particle to the domain pool and w_i is the weight of the ith domain block to the cluster.

1) Weight

This paper derives the weigh w_i from TF-IDF weight [18]

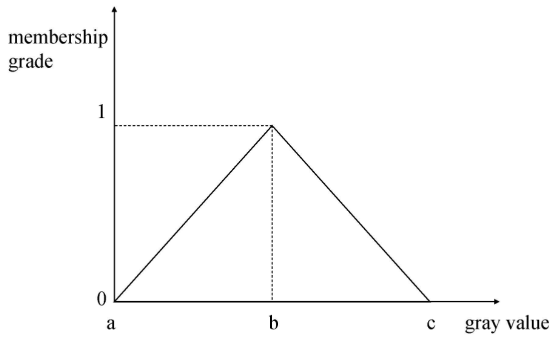


Fig. 1 graphical representation of triangular membership

method. By using the presence frequency of a domain block in the domain pool and the presence frequency of a domain block in a cluster, evaluate how critical a domain block is. The weight w_i in (2) is obtained as illustrated in (3):

$$w_i = \frac{Cnt_i^k}{N^k} \times \log \frac{TC}{C_i} \tag{3}$$

where Cnt_i^k is the presence count of the ith domain block in the cluster k and N^k is the number of domain blocks in kth cluster. TC is the number of total clusters in the domain pool. C_i is the number of clusters which contain the ith domain block.

2) The Membership Function

Fuzzy logic [19], [20] is used to deal with partial truth where the value is ranged from absolute true to absolute false. The membership function is used to measure the degree of truth of an element in a fuzzy set. The value of membership grade is normalized to a real number in the interval between 0 and 1.

This paper uses membership value to measure the degree of belonging for ith domain block to a cluster. The proposed method used triangular membership function $\mu(x)$ to evaluate the m_i in (2) as illustrated in (4):

$$m_i = \mu(x) = \begin{cases} 0, & x < a \\ \frac{(x-a)}{(b-a)}, & a \le x \le b \\ \frac{(c-x)}{(c-b)}, & b \le x \le c \\ 0, & x > c \end{cases} \tag{4}$$

where x is the gray value of ith domain block, a,b,c are the breakpoints, $a \le b \le c$ .The largest membership value would then be located at the middle. Assume the maximal gray value in the cluster where the ith domain block exhibits is $x_{\max}$ and the minimal gray value is $x_{\min}$, then, $a = x_{\min}$, $b = (x_{\max} - x_{\min})/2$, $c = x_{\max}$. Fig. 1 illustrated the relationship of a,b,c to the triangular membership function:

3) Probability of Presence

The presence of domain block is a measure of the significance of a domain block. Therefore the presences of domain block in both the cluster and the domain pool are taken into account.

The pg_i in (2) is the presence probability of a domain block in the domain pool. The function is thus:

$$pg_i = \frac{C_i}{D} \tag{5}$$

where C_i is the count of presence for the ith domain block in domain pool. And D is the number of total domain blocks in the domain pool.

The probability p_i^k in (2) is the presence probability of the ith domain block in that cluster. The function is thus:

$$p_i^k = \frac{Cnt_i^k}{N^k} \tag{6}$$

where Cnt_i^k is the count of presence for the ith domain block in cluster. And N^k is the number of total domain blocks in the k cluster.

B. The Proposed Reduction Method

In order to reduce the amount of data used in encoding phase, the proposed method uses PSO to screen out the insignificant domain blocks, then eliminates those blocks. The steps of modified fractal encode according to the proposed reduction method are described as follows:

Step 1: The image is split into D domain blocks and R range blocks for fractal encode. Consequently, separate the domain blocks into m clusters by using the K-means according to the gray value of domain block.

Step 2: For each cluster, let the maximum iteration be $g_{\max}$. Assume the particle number is N^p, allocate the domain blocks as evenly as possible into N^p particles, then the number of domain blocks of the largest particle is the particle dimension d^p . N^p particles with particle dimension d^p form a $N^P \times d^p$ matrix in each cluster. Consequently, the number N_i^p of particles in ith cluster would compliant with the following equation:

$$N_i^{DB} = d^p \left(N_i^p - 1\right) + \left(N_i^{DB} \mod d^p\right)$$

$$D = \sum_{i=1}^{k} N_i^{DB} \le \sum_{i=1}^{k} \left(d^p \left(N_i^p\right)\right)$$

where N_i^{DB} is the number of domain blocks in ith cluster.

Step 3: The location and velocity of each particle are obtained by using the uniform distribution random number function. Obtain the fitness value and location of each particle.

Step 4: Determine the local best particle. Take particle j as example. Compare the fitness value of particle j with its best fitness value in history. If the current fitness value is better than the historical best fitness value, the current fitness value replaces the previous one as the best fitness value PB_j.

Step 5: Determine the global best particle. Compare the best fitness values of particles to each others. The particle with the best fitness value is the current global best particle. Compare the fitness value of the current global best particle with the historical best value GB. If the current fitness value is better than the historical best value, the current fitness value replaces the historical value as the new GB.

Step 6: Renew the velocity and location for each particle. The next function is for calculating the velocity and location of particle j with particle dimension d^p, at iteration t:

$$\begin{aligned} v_{jd^p}(t) = w \times v_{jd^p}(t-1) + c_1 \times \varphi_1 \times \left(PB_{jd^p} - s_{jd^p}(t-1)\right) \\ + c_2 \times \varphi_2 \times \left(GB - s_{jd^p}(t-1)\right) \end{aligned} \tag{7}$$

$$s_{jd^p}(t) = s_{jd^p}(t-1) + v_{jd^p}(t) \tag{8}$$

where $v_{jd^p}(t)$ is the velocity of particle j at particle dimension d^p and at iteration t, where $1 \le t \le g_{\max}$, $s_{jd^p}(t)$ is the location of particle j at particle dimension d^p and at iteration t. c_1 and c_2 are the acceleration constants, both are defined as 1.49455. φ_1, φ_2 is a random number, between 0 and 1. w is the linear inertial weight factor, defined as 0.729 [21].

Step 7: If the maximum iteration $g_{\max}$ is met, the process stops, else go to Step 4 and repeat.

Step 8: The global best particle contains the most significant domain blocks. Keep the significant domain blocks in the domain pool, and eliminate the others.

Step 9: For each range block, the best matching domain block is searched with performing a set of affine transformations in the domain pool. Image encoding achieves by generates the fractal code for each range block and its best matched domain block, and the fractal code is stored into the codebook. Repeat this step until all of the range blocks find their best matching domain blocks.

IV. Experimental Results and Analyses

In this section, this paper introduces the computer software developed according to the proposed method. This paper uses 3 medical images as examples to verify proposed method. The experimental results and complexity analysis indicate that proposed method can speed up the search time in the encoding phase and the remaining image quality is acceptable. The following subsections introduce our system, fitness measure, and the results analysis.

A. Implementation

This paper designs and programs the system for the proposed method on Java platform. The user interface is illustrated in Fig. 2. and the flow of the coding algorithm is described as follows.

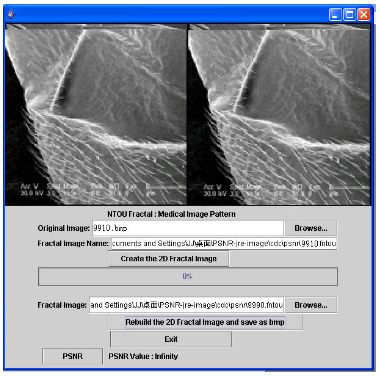


Fig. 2 the GUI

Step 1: Input the gray level image.

Step 2: Partition the image into a set of non-overlapping range blocks which size is 2×2 pixel, and a set of overlapping domain blocks which size is 4×4 pixel. The size of range block and size of domain block are as the same as those in Jacquin's experiments [6].

Step 3:Use K-means to segment the domain blocks into 2 clusters for each image. Let the number of particles is 100, particle dimension is 14 and the number of maximal iteration is 14, too. Consequently, Use PSO to evaluate the domain blocks according to the fitness value of the particle by using (2) and optimizes the particles. During the evolution, add in one domain block to each particle each time. The proposed method selects the particles in the top few from each cluster as the most significant particles. Those domain blocks in insignificant particles are then eliminated. Therefore, the search is performed in the domain pool containing the significant domain blocks.

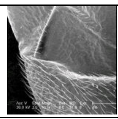
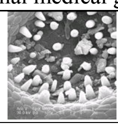
Step 4: For each range block, the best matching domain block is searched with performing a set of affine transformations in the domain pool. Image encoding achieves by generates the fractal code for each range block and its best matched domain block, and the fractal code is stored into the codebook. Repeat this step until all of the range blocks find their best matching domain blocks or reaching the maximum iteration.

Step 5: Image decoding achieves by iterating the best matched domain blocks with the affine transformations recorded in the codebook.

B. Fitness measure

This paper uses three medical gray level images from public database as examples to verify the proposed method. The images are in 150×148 pixel bmp format as illustrated in Table I.

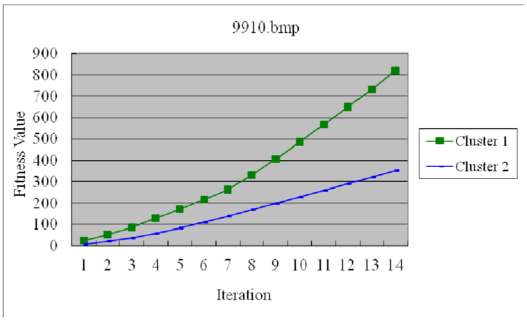
Table I. Original medical gray level images

		
9910.bmp	9934.bmp	Acdis-11.bmp

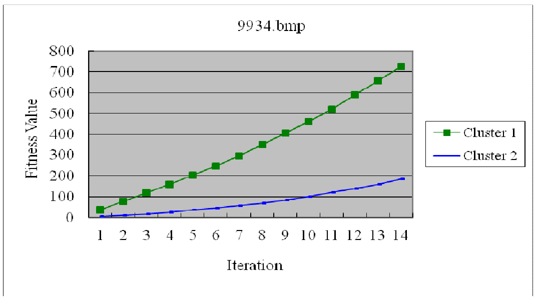
9910.bmp from: CDC/ Janice Carr
9934.bmp from: CDC
Acdis-11.bmp from: University of Alabama at Birmingham, Department of Radiology

The PSO determines the significant domain blocks according to the proposed fitness function described in section III.A. According to section IV.A, the particle with the largest fitness value is the best solution and the significant particle. In practical, this paper kept those particles on the top of best solution list and then deleted the other particles.

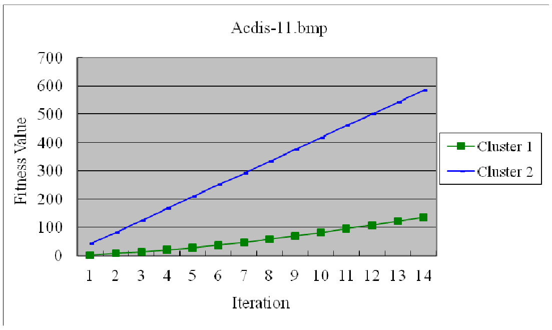
In analyzing the relationship between the iteration and the fitness value, this paper found that the number of iterations is proportional to the fitness value as indicated in Fig. 3-a, 3-b, and 3-c. Fig. 4-a, 4-b, and 4-c indicate if the iterations increase, the best particle gets closer to the best solution. In other words, when increasing the iteration number, the fitness value increased consequently, this paper obtain closer to the best solution.



(a) fitness value of each iteration of 9910



(b) fitness value of each iteration of 9934



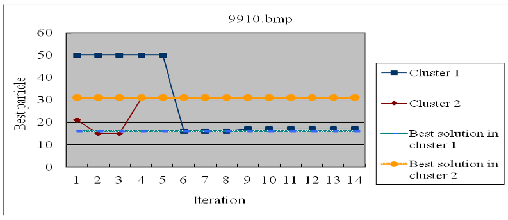
(c) fitness value of each iteration of Acdis-11

Fig. 3 iterations has positive influence on fitness value

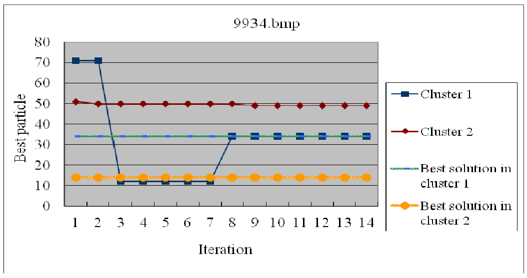
This paper uses an objective fidelity criterion, PSNR, to evaluate image quality. In general, a PSNR more than 30dB means the two images are not distinguishable to the human eyes. The PSNR method is described here. Let $A(x,y)$ be the gray value expression of the initial image, and $B(x,y)$ be the gray value expression of the decoded image. The images are of the same size $N \times M$. Let $I_{\max}$ be the maximum gray value, here it is set to be 255. After calculating the mean square error (MSE), the PSNR is obtained.

$$MSE = \frac{1}{N} \times M \times \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} \left(B(n,m) - A(n,m)\right)^2$$
$$PSNR = 10 \log_{10} \left(\frac{I_{\max}^2}{MSE} \right) \tag{9}$$

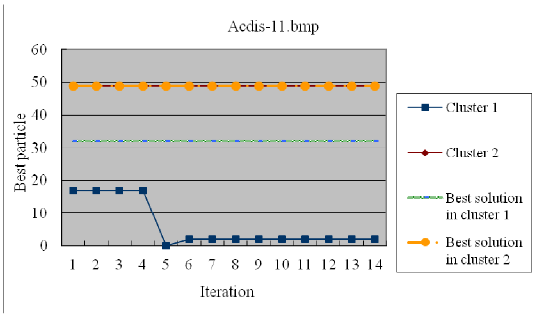
The PSNR of three images in various particle conditions is obtained and illustrated in Table II. The significant particles are from both clusters equally.



(a) number of iterations of 9910 vs. the best solution



(b) number of iterations of 9934 vs. the best solution



(c) number of iterations of Acdis-11vs. the best solution

Fig. 4 iterations has positive influence of on the best solution

Table II. PSNR by applying different number of PSO particles

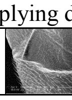
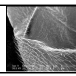
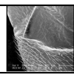
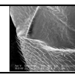
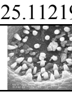
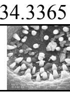
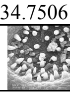
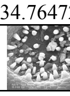
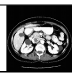
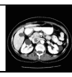
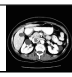
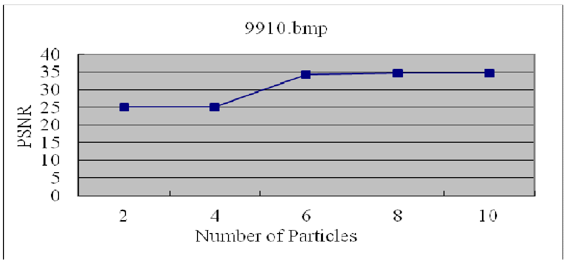
9910					
Number of particles	2	4	6	8	10
PSNR	25.07336	25.11219	34.33651	34.75061	34.76472
9934					
Number of particles	2	4	6	8	10
PSNR	25.33409	28.02051	28.05209	28.18667	34.27075
acdis-11					
Number of particles	2	4	6	8	10
PSNR	18.77283	24.46644	24.54408	24.96059	31.79177

Table II indicates if the number of significant particles is greater than 10, the PSNR would be greater than 30 dB, in which a PSNR greater than 30 dB is acceptable to the subjective evaluation. This means that keeping significant domain blocks and eliminating insignificant domain blocks can still produce a quality decoded image. Table II also indicates the number of significant particles is proportional to the PSNR of the decoded image.

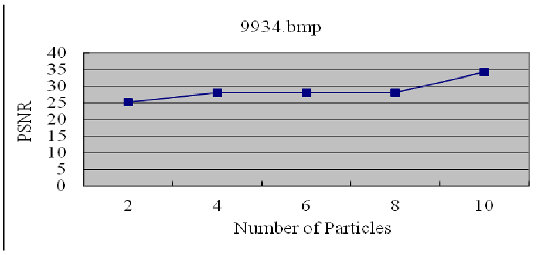
Fig. 5-a, 5-b, and 5-c indicate the quality of decoded image is proportional to the particle number. Fig. 5 also indicates more significant domain blocks are required to perform fractal encoding, a higher PSNR is obtained.

Based on the above observations, an increase of the number of significant particles would increase the domain blocks and then obtain a better image quality.

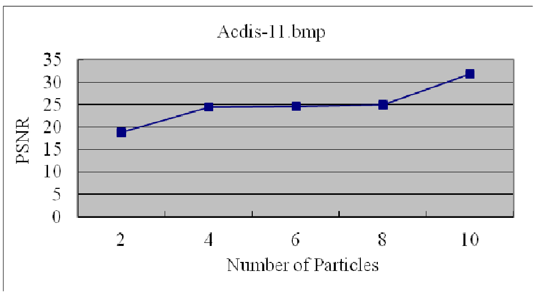
C. *Experimental Result Analysis*



(a) PSNR of 9910 vs. the number of particle



(b) PSNR of 9934 vs. the number of particle



(c) PSNR of Acdis-11vs. the number of particle

Fig. 5 number of particle has positive influence on PSNR

This paper evaluated the image quality after encode, CR and search-time complexity with PSNR, the ratio of file sizes and the number of searches. Numerical results listed in Table III indicated the proposed method performed remarkable compression rate and excellent image quality.

Table III. Resulted PSNR and CR of images

Image	9910	9934	acdis-11
PSNR (dB)	31.79177	34.27075	34.76472
CR (%)	25.7576	27.6923	16.4179

This paper compared the search numbers of matching processes in Jacquin's fractal block coding method to that of the proposed method based on brute-force search. When applying the brute-force search to encoding process, the searching time is the product of the number of range block and number of domain block without counting on the affine transformation.

In Jacquin's fractal block coding, let N_r be the number of range blocks. For each range block, a best matched domain block in a domain pool with N_d domain blocks is searched. The time complexity for every range block in searching the domain blocks is $O\left(N_r \times N_d\right)$.

In the proposed method, let N_r be the number of range blocks as the same as the one in Jacquin's fractal block coding. The number of domain blocks is the product of number N_p of particles and the particle dimension D_p. For each range block, a best matched domain block in the domain pool is searched. The time complexity for every range block searching the domain pool is $O\left(N_r \times N_p \times D_p\right)$.

The size of gray level image is 150×148 pixel in our experiment, in which the size of domain block is set to 4×4 pixel and the range block size is set to 2×2 pixel. Assume the domain blocks are not overlapping. Then, in Jacquin's fractal block coding, the number of range block would be $N_r = \frac{150}{2} \times \frac{148}{2} = 5550$, and the number of domain block would be $N_d = \frac{150}{4} \times \frac{148}{4} \approx 1388$. The number of search of the domain block would be $N_r \times N_d = 5550 \times 1388$. In the proposed method, the number of search of the domain pool will be $N_r \times N_p \times D_p = 5550 \times 10 \times 14$. The result indicates that our method may reduce the size of domain pool up to 89.91%. According to the above calculation, the proposed method has less search number than Jacquin's fractal block coding does.

V. Discussion and Conclusion

This paper presents an effective fractal block coding method which not only speeds up the matching process, but also retains the image quality after encode. Here, we would like to emphasize the following points to highlight the main contributions of this paper.

1) This paper proposed three elaborative factors in fitness function for measuring the particle, and successfully used the effective design to obtain the particle's fitness value so that the significance of the domain block manifested.
2) The proposed reduction method based on PSO with the proposed fitness function is effective to reduce the size of domain pool and still keeps acceptable image quality. The experimental result indicates that the size of the optimal domain pool decreased compared to Jaquin's fractal block coding.

Experimental results demonstrated that the proposed reduction method achieved the PSNR between 31dB and 34dB, CR between 16% and 27%. The proposed method in this paper does achieve the goal of improving the efficiency while preserving the desired image quality. The proposed method does achieve the goal of obtaining the best possible accuracy with the smallest possible domain pool. The result has encouraged us to proceed to color image study.

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