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An improved fractal image compression using wolf pack algorithm

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ABSTRACT
The fractal image compression is a recent tool for encoding natural images. It builds on the local self-similarities and the generation of copies of blocks based on mathematical transformations. The technique seems interesting in both theory and application but have a drawback renders in real-time usage due to the high resource requirement when encoding big data. By another way, heuristics algorithms represent a set of approaches used to solve hard optimisation tasks with rational resources consumption. They are characterised with their fast convergence and reducing of research complexity. The purpose of this paper is to provide, and for the first time, more detailed study about the Wolf Pack Algorithm for the fractal image compression. The whole Image is considered as a space search where this space is divided on blocks, the scooting wolves explore the space to find other smaller block which have a similarity with based on its parameters. Scooting wolfs perused the whole space a selected the blocks with the best fitness. The process will be stopped after a fixed number of iterations or if no improvement in lead wolf solution. Results show that compared with the exhaustive search method, the proposed method greatly reduced the encoding time and obtained a rather best compression ratio. The performed experiments showed its effectiveness in the resolution of such problem. Moreover, a brief comparison with the different methods establishes this advantage.

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1. Introduction

Currently, a considerable volume of information is handled and exchanged, and particularly, images have attracted great importance, especially in recognition domain. So, it becomes essential to reduce data size using compression techniques which may allow its storage charge and transfer using limited resources. Current compression tendencies trend towards the use of fractal theory algorithms which appear as a powerful tool to improve image quality performance and reduce resources' cost.

Dissimilar to text messages, images files that are involved in some particular software are characterised by huge data, pixel correlation and redundancy. In such situation, traditional compression algorithms seem not to be appropriate for this task due to their need to extensive processing time. By contrast, recently developed fractal image compression algorithms propose well compression performances (Galabov, 2003; Selim, Hadhoud, & Salem, 2009; Thanushkodi & Bhavani, 2013). They are based

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on the fact that fractals can describe natural scenes better than traditional geometrically shapes. Several techniques of fractal image compression are proposed in the literature, they involve image encoding allowing high security and reduced noise: the *Huber fractal image compression* (Jeng, Tseng, & Hsieh, 2009), *the wavelet-fractal code* (Li & Kuo, 1999) or the *fuzzy pattern classification* (Han, 2008). The most cited techniques have shown encoding flaws including loss of significant information, reduced statistical features of chaotic schemes and vulnerability to statistical cryptanalysis. By another way, heuristic algorithms are also used in this context such as *Genetic algorithm* (Mitra, Murthy, & Kundu, 1998), *ant colony* (Li, Yuan, Xie, & Zhang, 2008) and *the particle swarm optimisation* (Tseng, Hsieh, & Jeng, 2008). They are able to build a region-based partition which increases the compression ratio and preserves the decompressed image quality.

The aim of the study is to investigate for the first time, a new heuristic algorithm, namely the *Wolf Pack Algorithm* and the way in which it can be used for compression of low resolution images. The main reason for using such algorithm is its global solution finding property and its ability to produce acceptable results in a faster and cheaper way compared to similar methods. The algorithm also uses reduced number of parameters without a need to initial approximation of unknown parameters. So, this paper is organised as follows; after an introduction, a panoply of related works are presented in Section 2, an introduction of the bio-inspired heuristics, a class of heuristic algorithms and a presentation of Wolf pack algorithm is proposed in Section 3, Section 4 gives the fractal image compression definition and its beneath literature. The problem formulation is reported to Section 5, followed by some preliminary results. An analysis and a conclusion are summarised in Sections 6 and 7.

2. Related works

The fractal image compression has been the object of numerous research studies in recent years. Currently, researchers concentrate mainly on how to select and improve the classification of the range blocks of a considered image, balance the speed of compression and decompression, enlarge the compression ratio and improve the quality of the image after compression, Genetic Algorithms (GA) attempt to find near-optimal solutions without going through an exhaustive search mechanism. Thus, GA's advantage appears in reducing simultaneously the search space and compression time. (Uma, Geetha, Kannan, & Umanath, 2012)

In 2005, the *Artificial Bee Colony optimisation* (ABC), an iteration-based technique, was broadly defined by Dervis Karaboga. It is an optimisation tool, which provides a population based search procedure where each individual called food positions is altered by artificial bees with time aiming to find out the food source with large nectar amount. ABC consists of three types of bees (a) employed bee, (b) onlooker bee and (c) scout bee. The onlooker bees that are waiting in the hive receive information from the employed bees regarding the nectar sources that has been discovered before. Onlooker bees choose an exploitable food source based on the information received from the employed bees. Scout bees quest for a food source randomly within the environment in order to find nourishment (Karaboga, 2005).

In 2006, Cristian Martinez has introduced an Ant Colony Optimisation algorithm for image compression. It is based on the fact that ants find the shortest path to go from the nest to the food source. About the fractal image compression problem, Pheromone are deposited on range block *i* and domain block *j*. The pheromone matrix is rectangular (not symmetrical) where the rows indicate range blocks (image blocks) and the columns domain blocks (blocks to transform). Then, every ant constructs its path choosing one domain block *j* for every range block *i*. The solution is based on updating pheromone and heuristic information (Martinez, 2006). This solution offers images with similar quality to that obtained with a deterministic method, in about 34% less time.

In 2008, Wang and Wang (2008) have introduced a modified grey-level transform with more transform parameters than the one proposed by Tong and Pi to encode the blocks. After that they suggest a no-search fractal image coding method using two grey-level transforms, one for the large blocks and the second is used for the small ones, to improve the encoding time and the quality of the reconstructed images.

In 2009, exhibition of studies are focalised on fractal image compression:

Chakrapani and Soundara Rajan (2009) have applied a genetic algorithm to fractal image compression in order to improve the computational time with an acceptable quality of the decoded image. The results show that the GA gives better performance over traditional exhaustive search in the case of fractal image compression.

Xing-yuan, Fan-ping, and Shu-guo (2009) have proposed a spatial correlation hybrid genetic algorithm based on the characteristics of fractal and partitioned iterated function system (PIFS). It consists of two steps: the first one makes use of spatial correlation in images for both range and domain pool to exploit local optima. The second step Adopt simulated annealing genetic algorithm (SAGA) to explore the global optima if the local optima are not satisfied. In order to avoid premature convergence, the algorithm approve dyadic mutation operator to take place of the traditional one.

In 2010, we indicate also two works:

Chakrapani and Soundararajan have employed the Particle Swarm Optimisation (PSO) technique in fractal image compression (Chakrapani & Soundararajan, 2010), (PSO) is used to speed up the search of a near best match block for a given block to be encoded. PSO for fractal image compression shows that it can efficiently find the suitable domain blocks. Temporarily, the retrieved image quality can be preserved when comparing to the full search fractal image compression.

Wang and Yun (2010) modified the grey-level transform using a fitting plane. The improved grey-level transform can reduce the minimum matching error between a given range block and its corresponding domain block, and thus, it can enhance the possibility of successful domain-range matching.

In 2012, Zhang and Wang (2012) have proposed a new fractal image compression that used wavelet transform with diamond search to offer fast positioning. According to search pattern and search path of diamond search, the proposed scheme just needs to search in the domain blocks in the fixed place around the range blocks.

3. Bio-inspired heuristics

Metaheuristics represent the techniques that gratify the generation of solutions by maximising the profit and minimising the use of resources; however, the optimality of the solution cannot be guaranteed if in the exploration space a cross between the local and global solution occurs (Olamaei, Niknam, & Gharehpetian, 2008). Bio-inspired heuristics, a sub-class of heuristics, getting their inspiration from social behaviour of animals living in communities such as bird swarms, ant colonies or fish grouping are based on the principle of the populations of individuals that interact and evolve according to a common rule. Such methods appears as a well-known models that are successfully used as a powerful tools for solving complex combinatorial problems (Gandomi & Alavi, 2011) with rational consumption of resources. Many works (Blum & Li, 2008; Felix & Manoj, 2007) show that the algorithms have a successful potential to handle wide range of data and may be adapted to create solutions for a different optimisation problems.

The Wolf Pack Algorithm (WPA) (Wu & Zhang, 2014) is one of this family (bio-inspired) of algorithms that can be employed in order to approximate solutions for various optimisation problems. WPA is a population-based metaheuristic stirred by the social hunting behaviour of wolves. It consists essentially in making wolves hunt, find the trace of prey and capture it under the command of a chief wolf.

The Wolf Pack comprises a leader-wolf which is the strongest and the cleverest one. It takes on its charge the control of the pack. Its decisions are always based on the neighbouring environment: prey, wolves of pack and other predators. The pack is divided into two classes of wolves: *scoot* and *furious*. The first class moves independently in the environment and regulates its direction according to the focus of prey's odour. When a prey is located, the wolves of this class scream and report the information using sound to the lead-wolf which estimates the spatial distance, invokes the furious-wolves and moves fast toward the scream. The prey is then captured; it is distributed according to the state of each wolf: from the strongest to weakest. Hereafter, weak wolves may dead in cause of lack of food. This is how the pack remains at any moment dynamic and robust.

The WPA is realised as follows:

- In a search space $\mathbb{R}^n$, each wolf i represents a basic solution of the problem, and has a position x_i. Initially, wolves are initialised randomly in space.
- At each instant t, the wolf i move from position x_i^t to position x_i^{t+1}. The choice of the next position is updated according to the following equation:

$$x_i^{t+1} = x_i^t + \lambda \left| x_g^t - x_i^t \right|. \tag{1}$$

where λ is a random vector distributed in range [−1,1] and x_g is the position of the lead-wolf.

- After a fixed number of iterations, which corresponds to a scooting phase, the wolf of the best solution becomes a lead wolf; a given number of weak wolves (bad solutions) will be deleted and replaced by a new generation of random wolves.

4. Fractal image compression

4.1. Overview

The fractal image compression is a modern technique for lossy image compression (Lu, 1993). It was originally introduced by Hutchinson (1981) and Barnsley and Demko (1817). It explores the self-similarities between different isolated image regions (Peitgen, Jürgens, & Saupe, 2004) and store only the parameters of contract transform instead of the image pixels. This principle allows constructing an approximation of the original image by detecting the recurrence of the patterns on various scales, and tends to eliminate the redundancy from information in the source image in order that the result may accurate enough to be acceptable.

The fractal image compression is based on an Iterated function system f, a finite set of contractions defined on a metric space R^n by the relation

$$f_i: R^n \to R^n \,|\, i < N \tag{2}$$

Such contraction may take various forms according to the technical limitation, that the transformation must be contractive. It may be applied to any two or more points in the source image and bring them closer in the result image. Such idea, called *affine transformation*, allows for each sub-block of the source image to be rotated, skewed, scaled or translated according to a mathematical relation, like the following:

$$w(x) = T(x) + b \tag{3}$$

where T is a linear transformation on $R^n$and $b \in R^n$ is a vector.

In practice, the fundamental concept of fractal encoding is to find the best matching domain blocks for each range blocks in the sense of reducing the distance metric. Such concept is illustrated by the following pseudo-algorithm:

- Image input
- Partition of the image into a range blocks R
- Composition of a pool of domain blocks D for R
- Contract domain blocks to the size of R
- Extend domain blocks with symmetrical transformations
- For each range block R

Find the best matching domain block from the extended domain pool.

Store coefficients

So, the source image is divided first into a non-overlapping range blocks R_i that cover the whole image and overlapped D_i domain blocks where the size of R_i is smaller than the size of D_i. In the following step and, for each R_i, we search the D_i the most similar. When found, it must be reduced to a new block B_i with a size equal to R_i. Such process is accomplished by the following relation:

$$B_i = v\left(D_i\right) \tag{4}$$

where $v()$ is the contraction function which consists in the subsampling or averaging D_i for example.

Then, the most similar block B_i is searched for each R_i by using a metric procedure which describe the distance between B_i and R_i blocks. This operation can be accomplished by Hausdoff image distance as follows:

$$H\left(B_i, R_i\right) = \max\left(d\left(B_i, R_i\right),\ d\left(R_i, B_i\right)\right) \tag{5}$$

where $d(B,R) = max_{b \in A} min_{r \in B} ||b - r||$ or by the Euclidian distance illustrated by following equation:

$$d^2(R, B) = \Sigma^n \left(r_i, b_i\right)^2 \tag{6}$$

where n is the number of pixels in R_i and B_i blocks. The d parameter should be minimal for similar blocks.

The encoded image is then a set of information for each range block. It includes its spatial coordinates, the domain that map onto that range block and parameters that describe the transformation mapping the domain onto the range.

The conventional fractal decoding consists in the reconstruction of R_i blocks from the most similar B_i blocks by iterating the contractive transformation denoted on fractal code. In recent years, more studies focuses on developing fast decoding algorithms (Ho Moon, Soon Kim, Shin Kim, & Kim, 1999; Moon, Baek, Kim, & Kim, 1997; Øien & Lepsøy, 1994) with a goal to preserves the image quality. Their principle consists in choosing an arbitrary image as source image and performs an affine transformation such that defined by Equations (7) and (8), based on the obtained fractal codes from it. This action is proceeded recursively until the produced image meets the user satisfaction.

$$R_i = s_i \cdot D + o_i \cdot I \tag{7}$$

$$S = \cup R_i \tag{8}$$

where I is a spatial contractive or isometry transform; D, a domain block, R a range block and S the restored image.

4.2. Literature review

Currently, the fractal image compression becomes one of the most promising techniques for encoding images due to its high compression ratio and resolution preservation. Its history dates back to the 1990s where the first image compression method was proposed by Jacquin (1992, 1993); the idea consists in dividing the image onto squared domain blocks. The principle of the proposed compression is to look for the most matched domain block corresponding to each range block, determine the appropriate contract transform and store their parameters. The idea was interesting but it remains limited to domestic applications due to high time-consuming restrictions. Since that, researchers introduced new ideas in order to reduce the huge encoding time; the work of Thomas and Deravi (1995) combines range blocks and makes them more adaptive with image content by using region-growing method. A similar idea was proposed by Cardinal (2001); it is based on a geometrical partition of the greyscale image block feature space. The experimental comparisons with previously published methods show a significant improvement in speed with no quality loss. He, Xu, and Yang (2006) have the idea of using the one-norm of normalised block in order to avoid the excessive search in block matching. By another way, Tong and Pi (2001) presented a new adaptive search approach to reduce the computational complexity of fractal encoding in order to exclude a large number of unqualified domain blocks so as to speed-up fractal image compression.

However, this technique is characterised by an asymmetric process, it spends so much time in the encoding process in comparison of the decompression process, that consists in the search of the best match block, mostly on large size images; so, it is best recommended for textures and low-resolution patterns

Various other researches have introduced new concepts to improve the search quality such us the encoding via the *Fourier transform* (Hartenstein & Saupe, 2000), special image features (Zhang, Zhou, & Zhang, 2007) and DCT inner product (Truong, Jeng, Reed, Lee, & Li, 2000). Most approaches are based on matching error threshold to restrict the searching space. Recently, Lin and Wu (2011) proposed a search strategy based on image block edge property which demonstrates an acceptable performance.

Furthermore, numerous research papers have been published during the last decay; they have enhanced the quality of image without improvement in resources of coding process.

5. Fractal compression with Wolf Pack Algorithm

By assuming a plain image of m x n pixels as a space search, denoted by an array P where each pixel is represented by a cell and referenced by a byte (grey pixel). The compressed image C of $m/2 \times n/2$ pixels is obtained according to the following steps:

- Partition the image domain into small no overlapping blocks r_i of size $s \times s$ (with s << m). For simplicity, blocks are square of size of b x b and let this partition represented by $R_N = \{r_1, r_2, \ldots, r_N\}$, a range blocks.
- For each r_i, the scooting wolves explore the space to find a block d_i of size $2b \times 2b$ which have a similarity with r_i based on its parameters. Each bloc d_i will be affected with a fitness value $f(d_i)$ according to Equation (6). A d_i is considered as a prey.
- If the whole space is perused by scooting wolfs and, for each r_i, the block d_i with the best fitness is selected. It will be mapped according to Equations (4) and (5).

The process will be stopped after a fixed number of iterations or if no improvement is done on lead wolf solution.

The WPA algorithm for fractal image compression is illustrated as follows:

Algorithm 2. WPA for fractal compression

Input: Problem dimension ($N > 2, g$), objective function f.
Output: {B}
Initialization:
Generate $\boldsymbol{r}_i$, ($i = 1 \ldots N$)
For each $\boldsymbol{r}_i$, f($\boldsymbol{r}_i$) ← 0, ($i = 1 \ldots N$)
While not (*stopping criteria*)
  it←0
  While **not** ($\boldsymbol{Iter}_{scoot} < It$)
    Pick random numbers: $\lambda \in [-1,1]$
    For each r_i do
      $\boldsymbol{x}_i \leftarrow \boldsymbol{x}_i + \lambda |x_g - x_i|$
      If ($f(b_{xi}) < f(g)$) $g \leftarrow i$ Endif
    Endfor
    $\boldsymbol{r}_i \leftarrow v(\boldsymbol{d}_i)$
    Update $\boldsymbol{It}$
  EndWhile
EndWhile

6. Experiments and preliminary results

In this section and in order to show the performance of the proposed algorithm, a basic experiment is conducted to test its efficiency on the compression of standard test images: Peppers, building and a Boat (Figure 1) with low resolution of 256 grey levels. Tests were processed on an IntelCore 2.2 GHZ with RAM 4 Go. The code was implemented with Visual C++ 6.0 in Windows 7 environment.

The processing parameters are as follows: range iteration number $it \in [10,100]$; scoot wolves population is fixed to 20; range blocks in [20,50] and the random vector in range of [0.5,1]. Numerical results were averaged over 5 runs of each test.

A preliminary result is illustrated in Table 1 which demonstrates an acceptable performance of the proposed algorithm in comparison with the exhaustive search. Also, the WPA algorithm exhibits a high compression ratio and performs better than various other fractal image encoding.

Figure 2 shows the reconstructed images which appear clear and nearly close to the original ones, but they present a very interesting ratio and have been performed with a reduced time complexity with regard to various classical fractal algorithms (Table 2).

7. Results analysis

In this section, we present a brief comparison of the proposed approach with some methods.

Before making a comparison, we present our approach with different image resolutions and testing compression ratio and time.

7.1. WPA vs. PSO

From the Table 3, the PSO has better Compression ratio, but our method has close results.

7.2. WPA vs. GA

The results show that WPA is way better than GA in compression ratio (Tables 4 and 5).

7.3. WPA vs. Quadtree decomposition

As we can notice from this table, the Quad-tree has the superiority in the compression time and the compression ratio, however we are still close.

Some other methods using different ideas are resumed in the Table below.

Tested images	Methods	PSNR (db)	Time (s)	Ratio (%)
Lena	FF/FD (Wang & Lang, 2009)	29.02	17.18	/
	DWSR (Wang & Zhang, 2014)	25.8212	56.4247	15.6355
	PSO-RCQP (Xing-Yuan, Dou-Dou, & Na, 2015)	27.089	6.453	16.392
	F/MET (Wang & Zou, 2009)	32.77	30.30	/
	IFIC (Wang, Li, & Chen, 2009)	31.23	1.86	/
	HFIC (Wang, Zhang, & Guo, 2013)	27.23	13.7101	28.2941
Pepper	FF/FD	/	/	/
	DWSR	25.7231	56.4247	15.5510
	PSO-RCQP	24.983	6.750	26.292
	F/MET	/	/	/
	IFIC	/	/	/
	HFIC	26.04	15.8200	22.8886
Cameraman	FF/FD	/	/	/
	DWSR	/	/	/
	PSO-RCQP	26.686	4.281	18.212
	F/MET	/	/	/
	IFIC	/	/	/
	HFIC	24.95	8.4700	39.6993

Our method present an innovative work containing preliminary results and the analysis of the effectiveness of the algorithm will be the subject of a future study.

Figure 1. Standard test images.

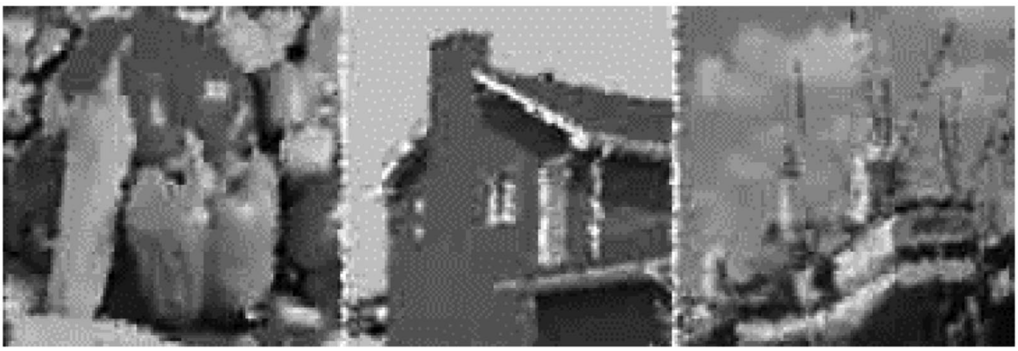

Figure 2. Image compression quality results.

Table 1. Comparison result of WPA vs. exhaustive search.

	Compression time (s)			Quality ratio (%)		
Method	Peppers	Building	Boat	Peppers	Building	Boat
Exhaustive search	3.11	2.28	3.28	9.33	9.81	8.25
WPA search	2.04	1.98	2.83	10.01	9.91	9.83

Table 2. WPA applied to different image resolution.

64×64	Ratio	Compression time
WPA		
Peppers	1.111	2.04
Building	1.110	1.98
Boats	1.109	2.83
128×128	Ratio	Compression time
WPA		
Peppers	1.231	15.32
Building	1.201	13.54
Boats	1.199	16.84
256×256	Ratio	Compression time
WPA		
Peppers	1.355	25.348
Building	1.301	20.143
Boats	1.294	27.867

Table 3. Comparison between PSO and WPA.

	Compression ratio	
Image	PSO	WPA
Lena	1.89	1.655
Barbra	1.89	1.601

Table 4. Comparison between GA and WPA.

	Compression ratio		
	GA		WPA
Image	Single level	Two Level	/
Lena	1.277	1.117	1.655

Table 5. Comparison between Quad-tree and WPA.

	Compression ratio		Compression time	
Image	Quad-tree	WPA	Quad-tree	WPA
Cameraman 64×64	2.212	1.121	0.983	1.99
Lena 64×64	1.442	1.110	0.753	2.05

8. Conclusion

The paper has investigated fractal image compression from a different view point. It focuses on how to implement and, for the first time, the use of Wolf pack algorithm for the resolution of such problem. Preliminary results prove the efficiency of the considered algorithm which can be improved by a good choice of implementation parameters. Furthermore, the approach demonstrates the ability of such algorithm to conduct the image compression and opens new issues in the investigation of more complex problems.

Disclosure statement

No potential conflict of interest was reported by the authors.

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