Fast Fractal Image Compression Scheme

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Abstract. Compression and decompression tools of digital image has become a significant aspect in the storing and transferring of digital image. Fractal image compression technique is recently used to compress images. The main problem with fractal image compression is that it takes a lot of computational time for searching blocks (domain block and range block) and then compares these blocks. There are many optimization techniques which are used to improve efficiency of fractal image compression. Some of these are particle swarm optimization, ant colony optimization and biogeography based optimization. In this paper the technique of biogeography based optimization (BBO) is applied for fractal image compression (FIC).With the help of this evolutionary algorithm effort is made to reduce the search complexity of matching between range block and domain block. The main drawback of FIC is that it involves more computational time due to global search. In order to improve the computational time and also the satisfactory quality of the decoded image, BBO algorithm is proposed. Investigational outcome show that the BBO is a better method than the traditional comprehensive search method in terms of encoding time. Results are calculated from wavelet based fractal image compression than BBO is applied over it to decrease the encode time and get better visual quality of image. In this paper compression time (encoding time) of fractal image compression is reduced.

Keywords: fractal image compression, biogeography based optimization (BBO), encoding time, suitability index variables (sivs).

1. Introduction

Compression and decompression tools of digital image has become a significant aspect in the storing and transferring of digital image. Most of the methods in use can be classified under the head of lossy compression. This implies that the reconstructed image is always an estimate of the original image. Fractal image coding introduced by Barnsley and Jacquin is the outcome of the study of the iterated function system developed in the last decade [1]. Because of its high compression ratio and simple decompression method, many researchers have done a lot of research on it. But the main drawback of their work can be related to large computational time for image compression.

The science of biogeography can be traced to the work of nineteenth century naturalists such as Alfred Wallace and Charles Darwin. In the early 1960s, Robert MacArthur and Edward Wilson began working together on mathematical models of biogeography, their work culminating with the classic 1967 publication The Theory of Island Biogeography [4].

Mathematical models of biogeography describe how species migrate from one island to another, how new species arise, and how species become extinct. The term “island” here is used descriptively rather than literally. That is, an island is any habitat that is geographically isolated from other habitats. We therefore use the more generic term “habitat” in this paper [4]. Geographical areas that are well suited as residences for biological species are said to have a high habitat suitability index (HSI) [4]. Features that correlate with HSI include such factors as rainfall, diversity of vegetation, diversity of topographic features, land area and temperature. The variables that characterize habitability are called suitability index variables (sivs). Sivs can be considered the independent variables of the habitat, and HSI can be considered the dependent variable. Habitats with a high HSI tend to have a large number of species, while those with a low HSI have a small number of species. Habitats with a high HSI have a low species immigration rate because they are already nearly saturated with species. Therefore, high HSI habitats are more static in their species distribution than low HSI habitats. By the same token, high HSI habitats have a high emigration rate; the large number of species on high HSI islands has many opportunities to emigrate to neighboring habitats. Habitats with a low HSI have a high species immigration rate because of their sparse populations. However if a habitat’s HSI remains low, then the species that reside there will tend to go extinct, which will further open the way for additional immigration. Due to this, low HSI habitats are more dynamic in their species distribution than high HSI habitats. A good solution is analogous to an island with a high HSI, and a poor solution represents an island with a low HSI. High HSI solutions resist change more than low HSI solutions. [4]

The goals of this paper is to study BBO and apply it on fractal image compression to reduce the compression time (encode time) and improve the picture quality. First give a general presentation of the new optimization method called BBO. This is done by first studying natural biogeography, and then generalizing it to obtain a general-purpose optimization algorithm. Section 2 reviews the ideas and mathematics of fractal image compression section 3 discusses biogeography and how BBO can be used to formulate a general optimization algorithm, section 4 discuss algorithm which is applied over fractal image compression to improve its efficiency(i.e. decrease encode time), section 5 and section 6 discusses experimental result calculated over image.

2. Fractal Image Compression

Fractal image compression is based on the local self-similarity property in a nature images. The fundamental idea is coming from the Partitioned Iterated Function System (PIFS). Suppose the original gray level image f is of size $m * m$. Let the range pool R be defined as the set of all non-overlapping blocks of size $n*n$ of the image f, which makes up $(m/n)^2$ blocks. For obeying the Contractive Mapping Fixed-Point Theorem, the domain block must exceed the range block in length. Let the domain pool D be defined as the set of all possible blocks of size $2n * 2n$ of the image f, which makes up $(m\text{-}2n + 1)^2$ blocks. For m is 256 and n is 8, the range pool R is composed of (256/8) *(256/8) =1024 blocks of size 8 *8 and the domain pool D is composed of (256-16 + 1) *(256-16 + 1) = 58081 blocks of size 16*16. For each range block v from the R, the fractal affine transformation is constructed by searching all of the domain blocks in the D to find the most similar one and the parameters representing the fractal affine transformation will form the fractal compression code for v. To execute the similarity measure between range block and domain block, the size of the domain block must be first sub-sampled to 8*8 such that its size is the same as the range block v. Let u denote a sub-sampled domain block. The similarity of two image blocks u and v of size $n*n$ is measured by mean square error (MSE) defined as

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\lfloor I(i,j) - K(i,j)\rfloor^2 \qquad (1)$$

The primary tool used in describing images with iterated function systems is the affine transformation. This transformation is used to express relations 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 [9]. For example, in two dimensions a point (x, y) on the image can be represented by (xn, yn) under affine transformation.

In this paper wavelet based fractal image compression is used to compute result. Wavelet transform is used to decompose the original image to various frequency subbands in which the attributes can be extracted from the wavelet coefficients belonging to different sub-bands. The distribution of wavelet coefficients can be used in context-based multi scale classification of document image [5].

3. Biogeography

Fig. 1 illustrates a model of species abundance in a single habitat [4]. The immigration rate λ and the emigration rate μ are functions of the number of species in the habitat. Consider the immigration curve. The maximum possible immigration rate to the habitat is I, which occurs when there are zero species in the habitat. As the number of species increases, the habitat becomes more crowded, fewer species are able to successfully survive immigration to the habitat, and the immigration rate decreases.

The largest possible number of species that the habitat can support is S_{max} at which point the immigration rate becomes zero. Now consider the emigration curve. If there are no species in the habitat then the emigration rate must be zero. As the number of species increases, the habitat becomes more crowded, more species are able to leave the habitat to explore other possible residences, and the emigration rate increases. The maximum emigration rate is E, which occurs when the habitat contains the largest number of species that it can support. The equilibrium number of species is S_0 at which point the immigration and emigration rates are equal. However, there may be occasional excursions from S_0 due to temporal effects. Positive excursions could be due to a sudden spurt of immigration (caused, perhaps, by an unusually large piece of flotsam arriving from a neighboring habitat), or a sudden burst of speciation (like a miniature Cambrian explosion). Negative excursions from could be due to disease, the introduction of an especially ravenous predator, or some other natural catastrophe.

It can take a long time in nature for species counts to reach equilibrium after a major perturbation [7], [8]. We have shown the immigration and emigration curves in Fig. 1 as straight lines but, in general, they might be more complicated curves. Nevertheless, this simple model gives us a general description of the process of immigration and emigration. The details can be adjusted if needed.

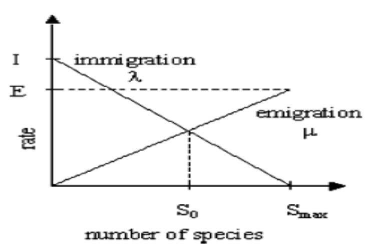

Fig. 1. Species model of a single habitat based on [6]

3.1 Biogeography-based optimization (BBO) in this section, we discuss how the biogeography theory can be applied to optimization problems with a discrete domain.

3.1.1 Migration

Suppose that we have a problem and a population of candidate solutions that can be represented as vectors of integers. Each integer in the solution vector is considered to be an SIV. Further suppose that we have some way of assessing the goodness of the solutions. Those solutions that are good are considered to be habitats with a high HSI, and those that are poor are considered to be habitats with a low HSI. HSI is analogous to "fitness" in other population-based optimization algorithms (GAs, for example). High HSI solutions represent habitats with many species, and low HSI solutions represent habitats with few species. We assume that each solution (habitat) has an identical species curve (with E=1 for simplicity), but the S value represented by the solution depends on its HSI. in Fig. 2 represents a low HSI solution, while S_2 represents a high HSI solution. S_1 in Fig. 2 represents a habitat with only a few species, while S_2 represents a habitat with many species. The immigration rate λ_1 for S_1 will, therefore, be higher than the immigration rate λ_2 for S_2 . The emigration rate μ_1 for S_1 will be lower than the emigration rate μ_2 for S2. We use the emigration and immigration rates of each solution to probabilistically share information between habitats. With

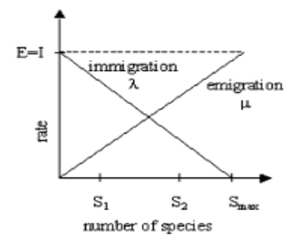

Fig. 2. Illustration of two candidate solutions to some problem. S_1 is a relatively poor solution, while S_2 is a relatively good solution [6].

probability P_{mod}, we modify each solution based on other solutions. If a given solution is selected to be modified, then we use its immigration rate λ to probabilistically decide whether or not to modify each suitability index variable (SIV) in that solution. If a given SIV in a given solution S_i is selected to be modified, then we use the emigration rates μ of the other solutions to probabilistically decide which of the solutions should migrate randomly selected SIV to solution S_i .

The BBO migration strategy is similar to the global recombination approach of the breeder GA [4] and evolutionary strategies in which many parents can contribute to a single offspring, but it differs in at least one important aspect. In evolutionary strategies, global recombination is used to create new solutions, while BBO migration is used to change existing solutions.

3.1.2 Mutation

Cataclysmic events can drastically change the HSI of a natural habitat. They can also cause a species count to differ from its equilibrium value (unusually large flotsam arriving from a neighboring habitat, disease, natural catastrophes, etc.). A habitat's HSI can, therefore, change suddenly due to apparently random events. We model this in BBO as SIV mutation, and we use species count probabilities to determine mutation rates. By looking at the equilibrium point on the species curve of Fig. 2, we see that low species counts and high species counts both have relatively low probabilities. Medium species counts have high probabilities because they are near the equilibrium point.

Each population member has an associated probability, which indicates the likelihood that it was expected a priori to exist as a solution to the given problem. Very high HSI solutions and very low HSI solutions are equally improbable. Medium HSI solutions are relatively probable. If a given solution has a low probability , then it is surprising that it exists as a solution. It is, therefore, likely to mutate to some other solution. Conversely, a solution with a high probability is less likely to mutate to a different solution.

3.2 Differences among BBO and Other Population-Based Optimization Algorithms

In this section, we point out some of the characteristic of BBO. First, we note that although BBO is a population-based optimization algorithm it does not involve reproduction or the generation of "children." This clearly distinguishes it from reproductive strategies such as GAs and evolutionary strategies.

BBO also clearly differs from ACO, because ACO generates a new set of solutions with each iteration. BBO, on the other hand, maintains its set of solutions from one iteration to the next, relying on migration to probabilistically settle in those solutions.

BBO has the most in ordinary with strategies such as PSO and DE. In those approaches, solutions are maintained from one iteration to the next, but each solution is able to learn from its neighbors and adapt itself as the algorithm progresses. PSO represents each solution as a point in space, and represents the change over time of each solution as a velocity vector. However, PSO solutions do not change directly; it is rather their velocities that change, and this indirectly results in position (solution) changes. DE changes its solutions directly, but changes in a particular DE solution are based on differences between other DE solutions. Also, DE is not biologically motivated. BBO can be contrasted with PSO and DE in that BBO solutions are changed directly via migration from other solutions (islands). That is, BBO solutions directly share their attributes (SIVs) with other solutions. It is these differences between BBO and other population- based optimization methods that may prove to be its strength.

4. Implementation of BBO algorithm in fractal image compression

The BBO algorithm in fractal image compression can be formally applied as:

1. Reduce the search space for FIC.
2. The classifier partition all of blocks in domain pool and range pool into 2 classes according to wavelet coefficient.
3. Initialize the BBO parameters. This means deriving a method of mapping problem solutions to SIVs and habitats
4. Initialize a random set of habitats, each habitat corresponding to a potential solution
5. Define HSI, Smax, immigration rate (λ) and emigration rate(μ).
6. Calculate MSE in each iteration of every range block and domain block.
7. Calculate probability of each domain block and range block based on MSE of each domain and range block.
8. If probability come above a predefined value immigrate that block in high HSI, else in low HSI.
9. Goto step 6 for next iteration.
10. If no domain is left then:
    (i) Stop the process.
    Else:
    (i) Go to step 6.

End

$$Pi(n + 1) = Pi(n) = r_1(PHSIi - Xi) + r_2((H_{hsi}) - Xi) \tag{3}$$
$$Xi(n + 1) = Xi(n) + Pi(n + 1). \tag{4}$$

The i_{th} block is represented as Xj = (x1, x2, x3, · · · , xj). The best probability of each domain and range block is recorded and represented as $PHSI_i$ = (PHSI1, PHSI2, PHSI3, · · · , PHSIj). The probability of the block among all the values in that iteration is considered as H_{hsi}. The probability for block 'i' is represented as Pj = (P1, P2, P3, · · · , Pj). Based on equation (3), (4) species(in our case domains) can migrate to habitat having high HSI. This is done on the basis of high probability value.[13]

5. Implementation of BBO based FIC

In a typical run of the BBO, for every range block, an initial population of random values which correspond to the top left coordinates of domain blocks and its isometry are generated. Each random value corresponds to the location of the domain block and is used to evaluate the domain block and find the MSE. The domain block with the minimum MSE in the BBO is identified and its coordinates are noted as PHSI values. Each Block keeps track of its coordinates in habitat which are associated with the fittest solution it has achieved so far. The P_i domain of each block at iteration is updated according to Eq.(5) .

$$P_i=\begin{cases} Xi & fi(n) < fi(n-1) \\ HSIi(n-1) & otherwise \end{cases} \tag{5}$$

Where fi(n) is the Mean Squared error (MSE) value between the range block and selected domain block in the present iteration. The probability and block value are updated using Eq. (3) and Eq. (4) in each iteration. The application of BBO involves repeatedly performing two steps:[13]

• The calculation of the objective function (MSE) for each of the block in the current population 'i'.
• The biogeography optimization then updates the block coordinates based on Eq. (3) and Eq. (4)

6. System investigated

In this paper a Gray level image of 512 × 512 size with 256 Gray levels is considered. A Range block of size 4×4 and Domain blocks of size 8×8 are considered. The domain blocks are mapped to the range block by affine transformations and the best domain block is selected. The PSNR considered in this work are given by:

Table 1 Image compressed with FIC (wavelet Based)

Image	Encode Time(sec)	Compressed image size(bytes)	Compression Ratio	MSE	PSNR(db)
Pirate	292.5440	199280	1.496	61.5985	30.2351
Mandrill	278.5600	224161	1.329	130.2591	26.9827

Table 2 Image compressed with BBO applied on FIC

Image	Encode Time(sec)	Compressed Image size(bytes)	Compression Ratio	MSE	PSNR(db)
Pirate	227.9690	208646	1.428	108.6298	27.77
Mandrill	225.0830	174377	1.709	339.3875	22.83

7. Results and discussions

This work is carried out in MATLAB 7.10.0 version on Pentium-dual core processor with 1.86 GHz and 1 GB RAM and the original image is classical 512 × 512 pirate and mandrill image coded with 8 bits per pixel. A random population of points is generated and each point is evaluated in the following manner. The point is converted into its corresponding binary value and the first 16 bits are utilized to locate the top left corner of domain block and next 3 bits are used to find the isometry to be applied to the selected domain block. Tab. 2 shows the comparison of BBO based FIC with the traditional exhaustive search method. It can be seen from the table that the visual quality and encoding time with the proposed technique has been improved as compared with the traditional method. Fig. 7 and Fig. 8 show the reconstructed images using FIC with BBO as search algorithm along with the original images of pirate and mandrill after 32 iterations.

Note down visual quality of image is much better with BBO as compared to FIC. Also encode time decreases after applying BBO optimization. Image compressed with BBO optimization is much close to original one, but with FIC distortion comes in the image.

Figure 3 and 4 original images Pirate.gif (298146) and Mandril.gif (298097 bytes)

Figure 5 and 6 images compressed with FIC pirate.gif (199280 bytes) and mandrill.gif (224161 bytes)

Figure 7 and 8 compressed images after applying BBO on FIC pirate.gif (208646 bytes) and mandrill.gif (174377 bytes)

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