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BBO Comparison with other Nature Inspired Algorithms to Resolve Mixels

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ABSTRACT: - Remote sensing is defined as a technique for acquiring the information about an object without making physical contact with that image via remote sensors. But the major problem of remotely sensed images is mixed pixel which always degrades the image quality. In this paper we attempted to present an approach for resolving the mixed pixels by using optimization/ Evolutionary algorithm i.e. Biogeography based optimization. EA's are the most well known algorithms among nature inspired algorithms, which is based on the biological evolution in nature that is being responsible for the design of all living beings on earth. A family of successful EAs comprises genetic algorithm (GA), genetic programming (GP), Differential Evolution, evolutionary strategy (ES) , Artificial Bee Colony Algorithm (ABC), Particle swarm optimization (PSO), Ant Colony Optimization (ACO). This paper also deals with the comparison of BBO and others EA's so that we can proof BBO as best algorithm for resolving MIXELS problem.

Keywords: ACO, BBO, DE, Migration, Mutation, PSO, Remote sensing.

1. INTRODUCTION

Optimization is a commonly encountered mathematical problem in all engineering disciplines. It literally means finding the best possible/desirable solution. Optimization problems are wide ranging and numerous, hence methods for solving these problems ought to be, an active research topic. Optimization algorithms can be either deterministic or stochastic in nature [1] [2]. Former methods to solve optimization problems require enormous computational efforts, which tend to fail as the problem size increases. Meta-heuristics are based on the iterative improvement of either a population of solutions or a single solution and mostly employ randomization and local search to solve a given optimization problem.

1.1 REMOTE SENSING

Remote sensing can be defined as the collection of data about an object from a distance. Humans and many other types of animals accomplish this task with aid of eyes or by the sense of smell or hearing. Geographers use the technique of remote sensing to monitor or measure phenomena found in the Earth's lithosphere, biosphere, and hydrosphere. Remote sensing of the environment by geographers is usually done with the help of mechanical devices known as remote sensors. These gadgets have a greatly improved ability to receive and record information about an object without any physical contact. Remote sensing imagery has many applications in mapping land-use and cover, agriculture, soils mapping, forestry, city planning, archaeological investigations, military observation, and geomorphologic surveying, among other uses.

1.2 MIXELS

Mixed pixels, also known as '**MIXELS**', occur where the image pixels are not homogenous, or 'pure'[7]. Instead a pixel contains a measure of the energy reflected or emitted from several different materials or land surface objects and the sensor records a composite of these responses (Fig 1).

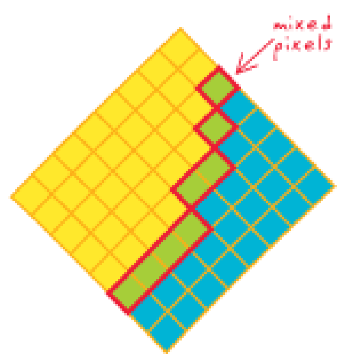

Figure 1: The mixed pixel problem

In many cases this spectral mixing can make it very difficult for the image analyst to identify the different sub-pixel components. Under these circumstances the analyst may wish to employ a finer resolution data set, in order that a greater number of 'pure' pixels may be recorded. Even with very fine resolution, however, there is still the issue of edge pixels, where pixels can show the boundaries between different land surface properties. Mixed pixels can cause great difficulties in the stages of image analysis and interpretation. One of the common tasks in this process is image classification. Classification is widely used as it allows users to easily discriminate information from images presented as a series of categories (classes) rather than raw digital number (DN) values. Images are classified on the basis of their spectral properties. Each pixel of remote sensing image contains the information from multifarious ground objects due to the difference from the resolution of remote sensing image, called "**Mixed pixel".**

To resolve these problems we proposed some optimization algorithms which are described in below section and make clear distinction between BBO and others EA's so that BBO can be used as best algorithm for resolving mixed pixel problems.

2. Biogeography- Based Optimization

Biogeography is the study of distribution of species in nature over time and space [3] [9] [11] [13]; that is the immigration and emigration of species between habitats. Each possible solution is an island and their features that characterize habitability are called suitability index variables (SIV). The fitness of each solution is called its habitat suitability index (HSI) and depends on many features of the habitat. High-HSI solutions tend to share their features with low-HSI solutions by emigrating solution features to other habitats. Low- HSI solutions accept a lot of new features from high-HSI solutions by immigration from other habitats. Immigration and emigration tend to improve the solutions and thus evolve a solution to the optimization problem. The value of HSI is considered as the objective function, and the algorithm is intended to determine the solutions which maximize the HSI by immigrating and emigrating features of the habitats .A habitat H is a vector of N (SIVs) integers initialized randomly. Before optimizing, each individual of population is evaluated and then follows migration and mutation step to reach global minima. In migration the information is shared between habitats that depend on emigration rates μ and immigration rates λ of each solution. Each solution is modified depending on probability *Pmod* that is a user defined parameter. Each individual has its own λ and μ and are functions of the number of species *K* in the habitat .Poor solutions accept more useful information from good solution, which improve the exploitation ability of algorithm. In BBO, the mutation is used to increase the diversity of the population to get the good solutions. The species model of a single habitat is shown below in Fig. 2

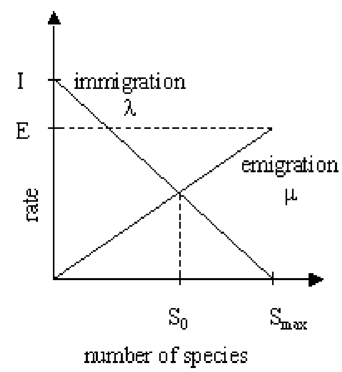

Figure: 2 Species model of a single habitat containing number of species

Fig.2 illustrates a model of species abundance in a single habitat. The immigration rate λ and the emigration rate μ are functions of the number of species in the habitat. In immigration curve, maximum possible immigration rate I to the habitat occurs when there are zero species in the habitat. As the number of species increases fewer species are able enter to the habitat and the immigration rate decreases. The largest possible number of species in habitat Smax is at which point the immigration rate becomes zero. For emigration curve, if there are no species in the habitat then the emigration rate must be zero. As the number of species increases more species are able to leave the habitat and the emigration rate increases. The maximum emigration E rate occurs when the habitat contains the largest number of species. The equilibrium number of species is So at which point the immigration and emigration rates are equal. Each individual has its own λ and μ and are functions of the number of species *K* in the habitat and is expressed by equation (1) and (2).

$\lambda = I\,(1-K/n)$………………………… (1)
$\mu=E/n$ ……………………………… (2)

Where k is the number of species of the k-th individual;
n is the maximum number of species.
E is Maximum emigration rate and
I is Maximum immigration rate.

λ = the probability that the immigrating individual's solution feature is replaced.
μ = the probability that an emigrating individual's solution feature migrates to the immigrating individual

2.1 BBO Operators

i) Migration: The BBO migration strategy in which we divide whether to migrate from one region to other or not [3] [11]. The migrate rate of each solution are used to probabilistically share features between solutions. BBO migration is used to change existing habitat. Migration in BBO is used to modify the island. The migration arises when LSI occurs. When species are less compatible with their habitat then they migrate.

ii) Mutation: The purpose of mutation is to increase the habitat among the population [2] [13]. In BBO, the mutation is used to increase the diversity of the population to get good solution.

3. Genetic Algorithm (GA)

A GA is a stochastic general search method [10]. It proceeds in an iterative manner by generating new populations of individuals from the old ones as shown in Figure 3. Every individual is the encoded (binary, real, etc.) version of a tentative solution. Figure 3 shows the selection and recombination phases of the genetic algorithm. GA is one of the most popular evolutionary algorithms in which a population of individuals evolves (moves through the fitness landscape) according to a set of rules such as selection, crossover and mutation.

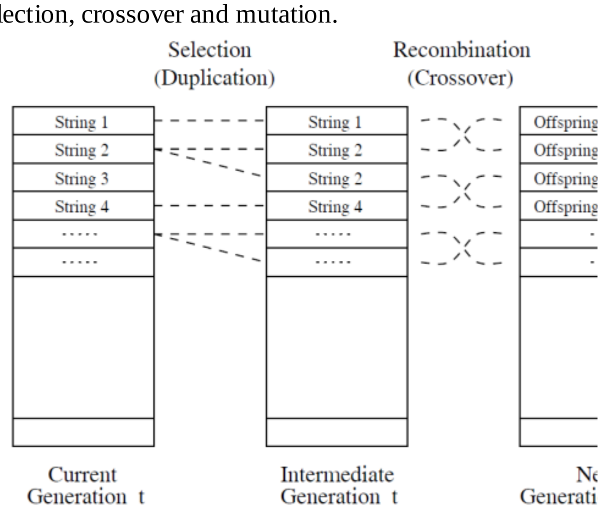

Figure: 3 Selection and recombination phase of the genetic algorithm

4. Particle Swarm Optimization (PSO)

The PSO algorithm was first introduced by Eberhart and Kennedy [5] [6]. PSO algorithm is another example of population based algorithms. PSO is a stochastic optimization technique which is well adapted to the optimization of nonlinear functions in multidimensional space and it has been applied to several real-world problems Instead of using evolutionary operators to manipulate the individuals like in other evolutionary computational algorithms, each individual in PSO flies in the search space with a velocity which is dynamically adjusted according to its own flying experience and its companions' flying experience. Each individual is treated as a volume-less particle (a point) in the D-dimensional search space as shown in figure 4.

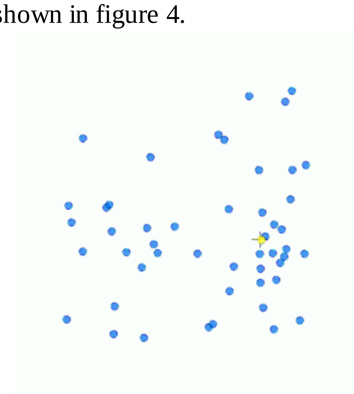

Figure: 4 Particles movement in PSO

5. Differential Evolution

Another paradigm in EA family is differential evolution (DE) proposed by Storn and Price in 1995[4] [8] [9]. DE is similar to GAs since populations of individuals are used to search for an optimal solution. The main difference between Gas and DE is that, in GAs, mutation is the result of small perturbations to the genes of an individual while in DE mutation is the result of arithmetic combinations of individuals. At the beginning of the evolution process, the mutation operator of DE favors exploration. As evolution progresses, the mutation operator favors exploitation. Hence, DE automatically adapts the mutation increments to the best value based on the stage of the evolutionary process. Mutation in DE is therefore not based on a predefined probability density function.

Advantages:

- DE is easy to implement, requires little parameter tuning
- Exhibits fast convergence

- It is generally considered as a reliable, accurate, robust and fast optimization technique.

Limitations:

- According to Krink noise may adversely affect the performance of DE due to its greedy nature.
- Also the user has to find the best values for the problem-dependent control parameters used in DE and this is a time consuming task.

6. COMPARISON ANALYSIS OF BBO WITH OTHERS

1. PSO represents each solution as a point in a space, and represents the change over time of each solution as a velocity vector. PSO do not change its solution directly.
2. DE changes its solution directly, but change in a particle DE solution is based on difference between other DE solutions. DE is not biological motivated.
3. GA and ES reproduce children by crossover, namely their solution disappear at the end of each generation, while BBO solution are not discarded after each generation, but are rather modified by migration.
4. BBO is differing from Ant colony optimization because ACO generates a new set of solution with each iteration. But in BBO, Maintains its set of solutions from one iteration of the next, relying on migration to probabilistically adopt those solution.
5. BBO has the most in common with Particle Swarm Optimization and DE In those approaches, Solutions are maintain in one iteration to the next, But each solution is able to learn from its neighbors and adopt itself as the algorithm progress.
6. BBO has low migration rate as compared to other techniques. So BBO approach evaluate more accurate and noise free images with maximum resolution of mixed pixel
7. BBO is more reliable and fast search algorithm for mixed pixel resolution and results in better optimization.
8. BBO based image segments produce different clusters of different colors at low migration rate with high computational time.
9. In BBO every pixel of particular land feature comes under the range of DN values or they are related on the basis of closeness & similarity between them.
10. Another distinctive feature is that, for each generation, BBO uses the fitness of each solution to determine its immigration and emigration rate.
11. BBO is easier to implement and there are fewer parameters to adjust.
12. BBO has a more effective memory capability than PSO & DE.

From the above comparison it is clear that BBO is the best algorithm because of its unique features for solving any complex problem as compared to others EA's. So the methodology for solving the mixed pixel problem using BBO is discussed in below section.

7. METHODOLOGY & RESULT

- Read an image and identify the data set of pure and mixed pixels.
- Initially choose a set of pure pixels and calculate the best pixel value and evaluate the fitness function.
- Now calculate HSI of each of the Habitat.
- Take one class of mixed pixel and transfer each of corresponding mixed pixel to both the Habitats to which it belongs i.e. Immigration & Emigration.
- Recalculate the HSI of those two Habitats. If recalculated HIS (A) <HIS (B) then absorb the mixed pixel in feature A otherwise in feature B.
- Repeat till all the mixed pixels of class taken are resolved.

8. CONCLUSION

As Concluded mixed pixel is a big problem in any remotely sensed imaging or high resolution image. Thus our method can resolve greater number of mixed pixels problem in effective way and also helpful in providing great accuracy in output images. BBO compare with other optimization techniques is that BBO solution are changed directly via migration from other solution. In BBO solutions directly share their attribute with other solutions. But in other optimization do not happen like this, So BBO can better to detect mixels in remote sensing images. Future work will focus on combining optimization algorithms with other algorithms like ANN's, Fuzzy algorithms to resolve mixels problem.

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