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Comparison between BBO and Genetic Algorithm

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ABSTRACT: "Segmentation**"** refers to the process of dividing a digital image into multiple segments such as sets of pixels, also known as super pixels. The main objective of segmentation is to simplify and/or change the representation of an image into meaningful image that is more appropriate and easier to analyze. "Image segmentation" is an important aspect of digital image processing. Color images can increase the quality of segmentation, but increase the complexity of the problem.

Evolutionary algorithms are well suited to optimizing complex problems such as image segmentation. In this paper two optimization algorithms are explored for image segmentation i.e Genetic algorithm and Biogeography based optimization algorithm. And then compare both these algorithm to show the better optimization and noise free color image segmentation of BBO algorithm as compared to GA. This paper also explores the limitations of GA over BBO.

KEYWORDS: Evolutionary algorithms, GA, BBO, Segmentation, Global optimization, Pixels, color images.

1. INTRODUCTION TO EVOLUTIONARY ALGORITHM

Evolutionary algorithms (EAs) are the most well known, classical and established 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, and for the strategies they use to interact with each other. EAs employ this powerful design philosophy to find solutions to hard problems. EAs are non-deterministic algorithms or cost based optimization algorithms. 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), Biogeography-Based Optimization (BBO) , Ant Colony Optimization (ACO) . EAs have been introduced to solve complex optimization problems. Each of these methods has its own characteristics, strengths, and weaknesses. The members of the EA family share a great number of features in common. They are all population-based stochastic search algorithms performing with best-to-survive criteria. Each algorithm commences by creating an initial population of feasible solutions, and evolves iteratively from generation to generation towards a best solution. In successive iterations of the algorithm, fitness-based selection takes place within the population of solutions. Better solutions are preferentially selected for survival into the next generation of solutions.

Image segmentation is an important process and its results are used in many image processing applications. However, there is no general way to successfully segment all images. Color images have more information than grey-scale images, and this information can be used to create higher quality segmentation. It does, however, increase the complexity of the problem. A way of handling this complexity is to use a directed search method, such as **genetic algorithms and Biogeography based optimization.** We start by looking at the concept and importance of image segmentation . The implication of using color in image segmentation is explored and methods for image segmentation are briefly discussed. Problems with existing image segmentation methods are mentioned. BBO algorithms are then introduced and their suitability for use in image segmentation is examined. Finally, the feasibility of the use of BBO algorithms for general color image segmentation is considered and design issues for GA algorithm are discussed.

1.1 Image Segmentation

Image segmentation is the process of dividing an image into homogeneous regions. This is equivalent to finding the boundaries between the regions. Segmentation is the first step for many higher level image processing and computer vision operations, including shape recognition, medical imaging, locating objects in satellite images, face detection and road sign recognition.

1.2 Color Segmentation

Until recently, most image segmentation has been performed on grey-scale images. Processing color images requires much more computation than the processing of grey-scale ones, but now with the increasing speed and decreasing cost of computation; color image processing has been much researched in the last decade. Color images contain far more information than monochrome images. Each pixel in a color image has information about brightness, hue and saturation. There are many models to represent the colors, including RGB (red, green, blue), CMY (cyan, magenta, yellow), HSV (hue, saturation, and intensity), YIQ, HSI and many others. Several color spaces have been used for image segmentation and no general advantage of one color space has yet been found. Many of the color image segmentation algorithms are derived from methods of grey-scale image segmentation. However, color creates a more complete representation of an image and exploiting this fact can result in a more reliable segmentation.

2. Genetic Algorithm

Genetic Algorithm GA is an evolutionary based stochastic optimization algorithm with a global search potential proposed by Holland in 1975. GAs is among the most successful class of algorithms under EAs which are inspired by the evolutionary ideas of natural selection. They follow the principles of Charles Darwin Theory of survival of the fittest. However, because of its outstanding performance in optimization, GA has been regarded as a function optimizer. Algorithm begins by initializing a population of solution (chromosome). It comprises representation of the problem usually in the form of a bit vector. Then for each chromosome evaluate the fitness using an appropriate fitness function suitable for the problem.

Based on this, the best chromosomes are selected into the mating pool, where they undergo cross over and mutation thus giving new set of solutions (offspring**).**

Genetic algorithms are an optimization technique used in image segmentation. It mimics natural selection, allowing an algorithm to adapt. Solutions are represented by a population of individual chromosomes, usually represented as binary strings. A chromosome is made up of genes, each of which can represent a particular characteristic. Each individual in the population is evaluated and given a fitness score based on how well they solve the particular problem. Higher the individual's fitness score, the greater their probability of breeding. Breeding creates the next generation through crossover and mutation. Crossover combines the chromosome of two individuals, creating a new individual which is unlike either of the parents. Mutation, which occurs only a small percent of the time, randomly alters a new individual's chromosome. Since the more optimal individuals have a greater chance of breeding, the population tends to evolve and reach an optimal solution.

Image segmentation is easily and naturally formulated as on optimization problem. It can either be seen as finding the optimal segmentation amongst all candidate segmentations, or as finding the optimal parameters for an existing image segmentation algorithm. In both cases, this creates an extremely large search space, indicating the use of genetic algorithms. Genetic algorithms are advantageous in that they are able to forego local optima in an attempt to reach the global optimum. This makes them far less likely to get caught in a local optimum than deterministic optimization techniques, such as local hill-climbing and gradient descent. Though more computationally expensive than these methods, genetic algorithms are less computationally expensive than exhaustive searches and other adaptive techniques, such as simulated annealing, which is theoretically guaranteed to find a global optimum. While, genetic algorithms cannot guarantee finding a global optimum, they usually give a good approximation.

This makes genetic algorithms a good compromise between accuracy and computational intensity. Many image segmentation problems have large search spaces but need only an approximate global optimum. In this case, genetic algorithms using a directed search have proven useful. A disadvantage of genetic algorithms is that they can take a long time to converge. Though this is the case, they are still much more efficient than performing an exhaustive search. Many images, particularly natural scenes, are complex and noisy.A characteristic of genetic algorithms is their effectiveness and robustness in dealing with uncertainty, insufficient information and noise. Combined with the fact that no matter how it is posed, the image segmentation problem involves a very large search space, making genetic algorithms well suited to the problem. One of the major challenges for designing genetic algorithms is defining a fitness function. The only information available to the population of chromosomes is the result of the fitness function evaluated every generation. This makes an appropriately defined fitness function essential for successful genetic algorithms. In the context of image segmentation, the fitness function should evaluate the resulting segmentation. There is, however, no generally accepted unsupervised method of evaluating image segmentation.

2.1 Working Principle of GA

GA begins with a set of solution (represented by chromosomes) called the population. Solution from one population are taken and used to form a new population. Solutions are selected according to their fitness to form new solutions (offspring/ children). This is repeated until some condition is satisfied like no. of population or improvement of the best solution).

1. [START] Generate random population of n chromosomes i.e. suitable for the problem.

2. [FITNESS] Evaluate the fitness f(x) of each chromosome x in the population.

3. [NEW POPULATION] Create a new population by repeating following steps until the new population is complete.

(a) [SELECTION] Select two parent chromosomes from the population according to their fitness (better the fitness, bigger the chance of selection).

(b) [CROSSOVER] with a crossover probability, cross over the parents to form new children. If no cross over was performed, children is the exact copy of his parents.

(c)[MUTATION] with a mutation probability, mutate new children at each locus (position in chromosome).

(d) [ACCEPTING] place new offspring in the new population.

4. [REPLACE] use new generated population for the further run of the algorithm.

5. [TEST] if the end condition is satisfied then stops and returns the best solution in current population.

6. [LOOP] Go to step 2.

2.2 OPERATORS OF GA

1. Reproduction (Selection): Selection is usually the first operator applied on the population. From the population, the chromosomes are selected to be parents to crossover and produce offspring.

Methods for selecting chromosomes for parents to crossover are:

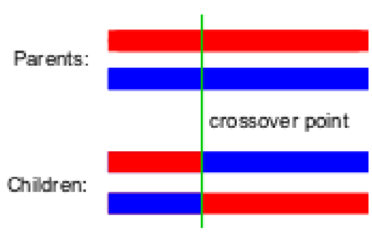
1. Roulette wheel selection
2. Tournament selection
3. Steady state selection
4. Boltzmann
5. Rank selection
6. Truncation

2. Crossover (Recombination): crossover is a genetic operator that combines (mates) two chromosomes (parents) to produce a new chromosome (offspring). The idea behind crossover is that the new chromosome may be better than both of the parents if it takes the best characteristics from each other of the parents. Crossover occurs during evolution according to user definable crossover probability. Crossover selects genes from parent chromosomes and creates a new offspring.

Methods for Crossover:

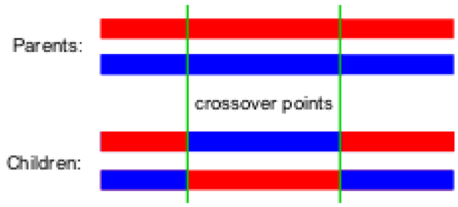
1. **one-point crossover**

A single crossover point on both parents' organism strings is selected. All data beyond that point in either organism string is swapped between the two parent organisms. The resulting organisms are the children:



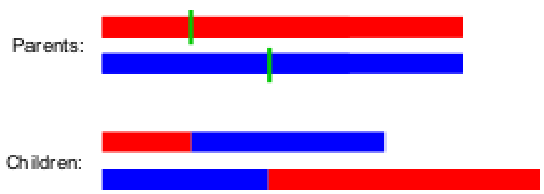
2. two-point crossover

Two-point crossover calls for two points to be selected on the parent organism strings. Everything between the two points is swapped between the parent organisms, rendering two child organisms:



3. Cut and splice

Another crossover variant, the "cut and splice" approach, results in a change in length of the children strings. The reason for this difference is that each parent string has a separate choice of crossover point.



3. Mutation: After the crossover is performed mutation takes place. Mutation is a genetic operator used to maintain genetic diversity from one generation of a population of chromosomes to the next. Mutation occurs during evolution according to user definable mutation probability, usually set to fairly low value, say 0.01 a good first choice. Mutation alters one or more gene values in a chromosome from its initial state. This result is entirely new gene values being added to the gene pool. With the new gene values , the GA may be able to arrive at better solution .

<u>Different mutation types are:</u>

1. Bit string mutation 4. Flip Bit

2. Boundary 5. Non-Uniform

3. Uniform 6. Gaussian

2.3 Genetic Algorithm for Image Segmentation

Flow chart analysis is shown in below fig. 1

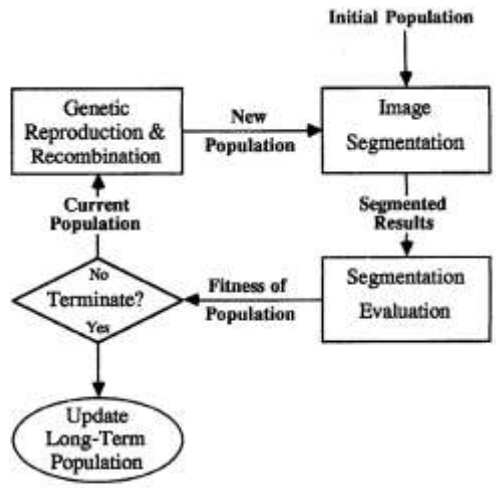


Fig.1 Flow chart

3. Biogeography- Based Optimization

Biogeography-Based Optimization (BBO) is a global optimization algorithm developed by **Dan Simon** in 2008 and is inspired by mathematical models of biogeography by Robert MacArthur and Edward Wilson. Biogeography is the study of distribution of species in nature over time and space; 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. In BBO, there are two main operators: migration (which includes both emigration and immigration) and mutation .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.

3.1 BBO Operators

a) **Migration: The** BBO migration strategy in which we decide whether to migrate from one region to other or not. The migration rates of each solution are used to probabilistically share features between solutions. BBO migration is used to change existing habitat. Migration in BBO is an adaptive process; it is used to modify existing islands. Migration stage arises when LSI occurs. When spices are less compatible with their habitat then they migrate.

b) **Mutation:** Mutation is a probabilistic operator the randomly modifies a solution feature. The purpose of mutation is to increase habitat among the population. For low value solutions, mutation gives them a chance of enhancing the quality of solutions, and for high fitness value solutions, mutation try to improve the value as compared to the previous value.

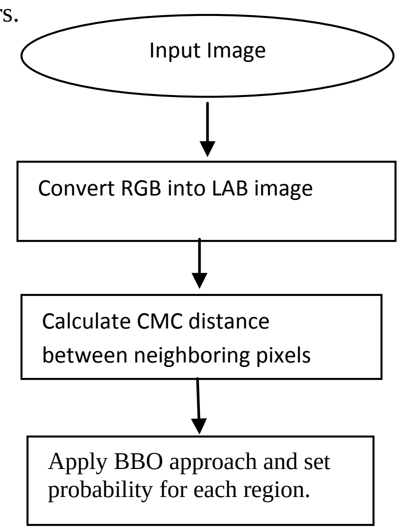
3.2 BBO APPROCH

For implementing BBO approach for image segmentation firstly we take RCB image, and then convert it into Lab image as shown below Fig.2. Then we segmented the objects in image and make different clusters. Those objects contain red objects are shown in Fig 3.

Fig. 2 Lab Image

Fig. 3 Red objects

Lab color model are widely used in this algorithm. The flow chart of this algorithm is shown in below Fig. 4. RGB image is taken as an input, which is an image of colorful fabric that consists of five different colors.



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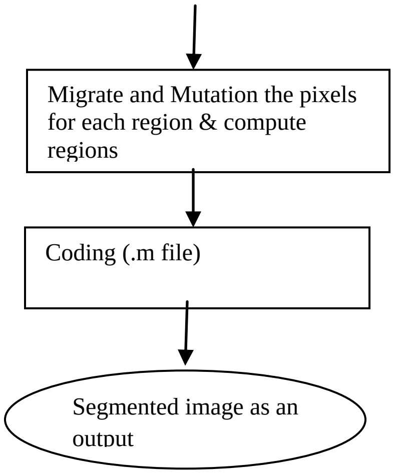

Fig 4: Flowchart of Proposed Work

4. Features of BBO

- First, Biogeography-Based Optimization is a type of evolutionary algorithm. As its name implies, Biogeography is the study of the migration, speciation, and extinction of species. 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 adapt those solutions.
- BBO has the most in common 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.
- In BBO the original population is not discarded after each generation. It is rather modified by migration.
- Another distinctive feature is that, for each generation, BBO uses the fitness of each solution to determine its immigration and emigration rate.
- BBO is easier to implement and there are fewer parameters to adjust.
- BBO has a more effective memory capability than GA.

5. Limitations of GA over BBO

- Operating on dynamic data sets is difficult.
- GAs is not directly suitable for solving constraint optimization problems
- In Genetic algorithm, the worse solutions are discarded and only the new ones are saved; i.e. in GA the population evolves around a subset of the best individuals.

- Genetic algorithms cannot guarantee finding a global optimum; they usually give a good approximation.
- A disadvantage of genetic algorithms is that they can take a long time to converge. Though this is the case, they are still much more efficient than performing an exhaustive search.
- Not easy to implement.
- Less effective memory capability.
- Genetic algorithms do not scale well with complexity. That is, where the number of elements which are exposed to mutation is large there is often an exponential increase in search space size. This makes it extremely difficult to use the technique on problems such as designing an engine, a house or plane. The second problem of complexity is the issue of how to protect parts that have evolved to represent good solutions from further destructive mutation, particularly when their fitness assessment requires them to combine well with other parts. The "better" solution is only in comparison to other solutions. As a result, the stop criterion is not clear in every problem.
- GA may have a tendency to converge towards local optima rather than the global optimum of the problem if the fitness function is not defined properly .This means that it does not "know how" to sacrifice short-term fitness to gain longer-term fitness. The likelihood of this occurring depends on the shape of the fitness landscape certain problems may provide an easy ascent towards a global optimum; others may make it easier for the function to find the local optima. This problem may be alleviated by using a different fitness function, increasing the rate of mutation, or by using selection techniques that maintain a diverse population of solutions.
- GAs cannot effectively solve problems in which the only fitness measure is a single right/wrong measure (like decision problems), as there is no way to converge on the solution. In these cases, a random search may find a solution as quickly as a GA. However, if the situation allows the success/failure trial to be repeated giving (possibly) different results, then the ratio of successes to failures provides a suitable fitness measure.
- Repeated fitness function evaluation for complex problems are often the most prohibitive and limiting segment of artificial evolutionary algorithms. Finding the optimal solution to complex high dimensional, multimodal problems often requires very expensive fitness function evaluations. In real world problems such as structural optimization problems, one single function evaluation may require several hours to several days of complete simulation. Typical optimization methods can not deal with such types of problem
- For specific optimization problems and problem instances, other optimization algorithms may find better solutions than genetic algorithms (given the same amount of computation time).

6. COMPARATIVE ANALYSIS

A Survey of Evolutionary Algorithms

ALGO-RITHM	REPRESEN-TATION	OPERATORS	AREAS OF APPLICATION	CONTROL PARAMETERS
GA	Binary, real no's, permutation of elements, list of rules, program ,elements, data structure trees,Matrix	Crossover Mutation Selection Inversion Gene silencing	Optimization problems in data mining and rule extraction, decision thresholds for distributed detection in wireless sensor networks, Computer aided design path planning of mobile robots, fixed charge transportation problem, flight control system design, and pattern recognition.	Population size(,max generation number),cross over probability, mutation probability ,length of chromosome, chromosome encoding
BBO	H=h1, h2……...as individuals of habitat.	Migration Mutation	The sensor selection problem for aircraft engine health estimation, Power system optimization, Groundwater detection and satellite image classification, Web-based BBO graphical user interface, Global numerical optimization, Color image optimization, Image enhancement, Image restoration.	No. of habitats (Population size), Maximum Migration rate, Mutation Rate, Species growth rate, Species evolution rate, Species immigration rate, Species decline rate, Species extinction rate, Species emigration rate

7. CONCLUSION & FUTURE SCOPE

The use of genetic algorithms & BBO algorithm in image segmentation shows promising results. Both these algorithms are a commonly used approach to optimizing the parameters of existing image segmentation algorithms The major decisions are choosing a method of segmentation to which these algorithms will be applied, finding a fitness function that is a good measure of the quality of image segmentation and finding a meaningful way to represent the chromosomes. Color images allow for more reliable Image Segmentation than for gray scale images. As concluded, Biogeography Based

Optimization is more reliable and fast search algorithm for Image Segmentation purposes. Biogeography Based Optimization generally results in better optimization results than the Genetic Algorithm for the problems that we investigate. Biogeography based Image Segmentation produce different cluster of different color at low migration rate with higher computational time. Biogeography Based Optimization is therefore a generalization of Genetic Algorithm. Future work includes extending this analysis to other BBO variations. This paper investigated the original BBO algorithm with linear migration curves, which is called partial immigration-based BBO.

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