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APPROXIMATE MEMETIC ALGORITHM FOR CONSISTENT CONVERGENCE

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Abstract: Genetic Algorithm (GA) is hybridized with Bacterial Foraging Optimization (BFO) to act as a local search (LS) to develop a new variant of memetic algorithm called Approximate Memetic Algorithm (AMA). The testing of AMA is carried out with four standard benchmark functions. When compared the MA-with-population-based LS and the MA-with-gradient-based LS, it is seen the meta-heuristic combination gives better results as compared to GA-deterministic searches in terms of consistency in convergence beside speed.

Keywords: Approximate Memetic Algorithm (AMA), Bacterial Foraging Optimization (BFO), Local Search (LS) and meta-heuristic.

1. INTRODUCTION

Memetic Algorithm is a population-based meta-heuristic search method. It is inspired by both Darwinian principle of natural evolution and Dawkins' notion of a meme as a unit of thought information or cultural evolution capable of individual learning [1][2]. In general, MA can be defined as a synergy of evolution and individual learning [1]. Memetic algorithms first locate a promising area in the solution space and then use local search technique to enhance the search within that region. The best offspring is then selected to replace the worst parent.

The GA or Evolutionary Computing (EC) is able to reach the global optimum with high probability and at lower cost than a multi-start deterministic search [3]. The evolutionary computing is good for finding promising regions those can be explored further. But it may be slow to converge within those regions and may not converge very accurately to the optimum. The deterministic methods like gradient search converge rapidly near optima. However, these gradient-based local searches get trapped in local optima. The ability of fast convergence near optima is used for local refinement in making MAs [3]. The memetic algorithm with analytical gradient achieved very good convergence in case of functions with unimodality. But these methods fail for multimodal and non-differentiable functions. Population based search algorithms have advantages of not getting trapped in local optima. Considering this property of population-based search methods, it is used for local search in the proposed algorithm. So by hybridizing two population-based methods of optimization meta-heuristic approach is used in this work, which shows better performance. The rest of the paper is organized as follows. Brief information on Evolutionary Algorithm is given in section 2. Section 3 and section 4 discussed about the Memetic Algorithm and the Bacterial Foraging Optimization respectively. In section 5 the proposed work i.e. Approximate Memetic Algorithm (AMA) is presented and in section 6 the conclusion is discussed.

2. EVOLUTIONARY ALGORITHM

The ways of the natural creatures solving their problems inspired researchers to mimic it to make the evolutionary algorithm. These algorithms simulate the natural selection process and blind mutation and crossover of genes. Based on this in 1960s, Holland invented genetic algorithm (GA) and Rechenberg and Schwefel invented evolutionary strategies [4][5]. The two methods differ mostly in the representation of individuals and use of operators such as crossover and mutation. Genetic Algorithms (GAs) are stochastic search algorithms modeled on the process of natural selection underlying biological evolution. They can be applied to many search, optimization, and machine learning problems [5]. The Genetic Algorithms and Evolutionary Algorithms combined are called Evolutionary Computing. So in general Evolutionary Computing is same as the natural processes and their mimic is stochastic. Every solution in the population is a string. These are encoded in binary, real, etc. formats [6][7]. An evaluation function gives a fitness measure of every string, indicating its fitness for the problem. Standard GA applies genetic operators such as selection, crossover, and mutation on an initially random population in order to compute a whole generation of new strings. The offspring then evaluated for fitness and become part of population in next generations.

3. MEMETIC ALGORITHM

The hybridization of evolutionary algorithms (EAs) with other techniques called Memetic Algorithm (MA) can greatly improve the search efficiency [1]. MAs are inspired by Dawkins' notion of a meme [2][8]. As such, the term MA has been used to describe a GA that heavily favors local search [3]. MAs are similar to GAs, however the elements that form a chromosome are called memes and not genes. MA scheme improves the new created solutions using a Local Search (LS) method. This is done with the exploitation in the best search regions identified in the global sampling done by the EA. MA generates the population randomly in the same way as that of GA. Subsequently, crossover and mutation operators are applied in a fashion similar to GAs to produce offspring. The best solution then subjected to the local search. Local search is applied in between the main search iterations for improving optimality further.

4. BACTERIAL FORAGING OPTIMIZATION

In the year 2002, K.M. Passino [9] proposed a new algorithm named Bacterial Foraging Optimization (BFO). The E. coli bacteria strategy of foraging (i.e. searching food) method of locating, handling, and ingesting food is followed from the bacteria's behavior [9]. In bacterial foraging optimization, the gradient information and the heuristic are combined in the search. Hence the possibility of avoiding local minima is higher [9].

5. APPROXIMATE MEMETIC ALGORITHM

Development of this algorithm is achieved by hybridizing the genetic algorithm with the bacterial foraging optimization. In AMA, BFO is used for local refinement. BFO is also the heuristic search, which is used instead of purely gradient-based search [3] to enhance its multimodal convergence. For that only the food search mechanism of BFO is used as local search. This combination of meta-heuristic search algorithm is having the feature of better exploration capability and exploitation of the search space around best candidate solution due to the former process. Again the meta-heuristic

combination gives it the strength to converge in the cases of unimodal as well as multimodal functions as shown in the Table 1. The GA is an optimization technique based on principle of natural selection. Adding one more local search in the process of convergence of the GA reduces the limitation of the GA of late convergence. So the GA is used for exploration and local search for exploitation. Hence this gives the better converging capacity to the algorithm for global convergence as well as better accuracy of the convergence beside speed. The approximation of crossover operation of GA is used to make the MA, hence it is named as Approximate Memetic Algorithm (AMA).

When compared with the gradient-based MAs the AMA shows better efficiency in converging in terms of speed, accuracy, and consistency. The AMA also has the capacity to converge efficiently in the cases of multimodal standard benchmark functions.

In the AMA the GA is used as main algorithm having the approximation in the operators such as crossover. Here the simple one point crossover of traits is applied except the trait at the crossover point [7]. At crossover point the traits are exchanged partially with the weight of the random number (λ) which is arithmetic crossover operator, where λ is in the range [0 , 1]. This is named as approximate operator. This algorithm does the optimization of functions with an approximate operator used in the genetic algorithm, which is named Approximate Genetic Algorithm (AGA). The AMA developed is also the hybrid of the AGA

Table 1 - Standard Benchmark Functions and Properties

Function	Range	Multimodality
$F_{Sphere} = \sum_{i=1}^{D} x_i^2$	$[-100,100]^D$	none
$F_{Rastrigin} = 10D + \sum_{i=1}^{D} (x_i^2 - 10\cos(2\pi\, x_i))$	$[-5.12,5.12]^D$	high
$F_{Ackley} = 20 + e - 20e^{(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2})} - e^{\frac{1}{D}\sum_{i=1}^{D}\cos 2\pi x_i}$	$[-32,32]^D$	moderate
$F_{Rosenbrock} = \sum_{i=1}^{D-1} (100(z_{i+1} - z_i^2)^2 + (1 - z_i)^2),$ $z_i = x_i + 1$	$[-2.048,2.048]^D$	weak

The characteristics of the above algorithms are tested on four test functions: Sphere, Rastrigin, Ackley and Rosenbrock. Table 1 shows a list of all test functions and their multimodal property.

5.1 Pseudo Code of AMA

1.Initialization: Generate a random initial population
2.Number of generation: G = 0, Glocal=0
while Stopping conditions are not satisfied do
3.Evaluate all individuals in the population
4.Select individuals for crossover
5.Mutate some of the descendant population
If Glocal=20 for best individual do
6.Obtain the population around the best individual in Gaussian window
7.Perform individual learning using a BFO-based local search
8.Glocal=0
9.Return best individual to population of main algorithm
end if
10.G++,Glocal++
end while

5.2 Parameters

All functions have 10 dimensional inputs. In the algorithms, a population of 100 individuals of real-valued representation is used. The operator used is as the one-point crossover or the simple crossover with crossover probability set to 0.8. The mutation probability is set to 0.05. The local searches are applied after a number of generations (Glocal) of main algorithm, with Glocal = 20. The algorithm uses generational replacement of individuals whereas 10 elites are preserved. 100,000 evaluations are considered for the algorithm. Once the fitness value fall below 10^{-8}, the algorithm is considered as reached the global optimum successfully. The population for local search is generated around the best individual within the Gaussian window with variance one-tenth the range of population in main algorithm.

5.3 Discussion

As per reference [3] MA-AG, MA-FD and MA-SPSA are Memetic Algorithms using gradient calculation with analytical gradient, finite differencing and simultaneous perturbation stochastic approximation respectively for local searches. In that the MA-SPSA usually takes more function evaluations to converge than MA-FD. MA-AG and MA-FD are faster for the unimodal functions but all the three do not perform well in cases of multimodality. Also the above methods are not consistent with their convergence properties. These limitations of gradient-based searches are overcome in the AMA, the meta-heuristic algorithm. Again, the consistency of the performance is checked with the 25 trails of the algorithm. The mean and standard deviation of number of fitness evaluations are used. For robustness, all the trails should give better results, convergence success and consistency. These features are seen for AMA as shown in the Table 2-5. Table 2 shows the comparison of AMA performance with other MAs for standard benchmark function – Sphere with 10 dimensions. Similarly in Tables 3-5 it is for Rastrigin, Ackley and Rosenbrock respectively.

Table 2 - Number of Evaluation and Success Rate (10 Dimensional Sphere)

Algorithm	Number of Evaluations and Success Rate							
	1st(best)	7th	13th(med)	19th	25th(worst)	Mean	Std	Success
MA-AG [3]	1795	2538	2734	3109	3499	2780.72	390.10	100%
MA-FD[3]	16973	18475	19392	20785	21805	19556	1443.84	100%
MA-SPSA[3]	10533	14103	31038	79129	100000	32034.04	27395.92	100%
GA[3]	100000	100000	100000	100000	100000	100000	0.00	0%
AGA	100000	100000	100000	100000	100000	100000	0.00	0%
AMA	8318	8384	8422	8476	8556	8431.9	62.9616	100%

Table 3 - Number of Evaluation and Success Rate (10 Dimensional Rastrigin)

Algorithm	Number of Evaluations and Success Rate							
	1st(best)	7th	13th(med)	19th	25th(worst)	Mean	Std	Success
MA-AG[3]	6471	11276	13048	15233	20765	13526.48	3472.18	100%
MA-FD[3]	14931	100000	100000	100000	100000	80676.8	35162.09	24%
MA-SPSA[3]	100000	100000	100000	100000	100000	100000	0.00	0%
GA [3]	100000	100000	100000	100000	100000	100000	0.00	0%
AGA	100000	100000	100000	100000	100000	100000	0.00	0%
AMA	6042	6094	6137	6176	6239	6139.3	55.3621	100%

Table 4 - Number of Evaluation and Success Rate (10 Dimensional Ackley)

Algorithm	Number of Evaluations and Success Rate							
	1st(best)	7th	13th(med)	19th	25th(worst)	Mean	Std	Success
MA-AG[3]	8894	12377	13194	14119	17386	13438.68	1782.47	100%
MA-FD[3]	81282	100000	100000	100000	100000	99251.28	3743.6	4%
MA-SPSA[3]	100000	100000	100000	100000	100000	100000	0.00	0%
GA [3]	100000	100000	100000	100000	100000	100000	0.00	0%
AGA	100000	100000	100000	100000	100000	100000	0.00	0%
AMA	6882	7139	7209	7311	7385	7210.0	114.69	100%

Table 5 - Number of Evaluation and Success Rate (10 Dimensional Rosenbrock)

Algorithm	Number of Evaluations and Success Rate							
	1st(best)	7th	13th(med)	19th	25th(worst)	Mean	Std	Success
MA-AG[3]	1159	1791	2597	2911	4679	2488.16	865.92	100%
MA-FD[3]	13052	17499	19652	21235	25069	19450.92	3100.81	100%
MA-SPSA[3]	100000	100000	100000	100000	100000	100000	0.00	0%
GA[3]	100000	100000	100000	100000	100000	100000	0.00	0%
AGA	100000	100000	100000	100000	100000	100000	0.00	0%
AMA	5864	5937	5960	5996	6070	5963.6	45.2604	100%

6. CONCLUSION

A new variant of memetic algorithm named as Approximate Memetic Algorithm (AMA) is developed and the performance is tested with 4 benchmark functions both unimodal and multimodal. This thought based hybrid algorithm performs better in term of accuracy of solution and speed of convergence. So the Memetic Algorithms having meta-heuristic combination using the Approximate Genetic Algorithm (AGA) and Bacterial Foraging Optimization (BFO) as a local search is better than the gradient-based Memetic Algorithms.

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