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A NEW SEARCH MODEL FOR EVOLUTIONARY ALGORITHMS

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Abstract. A new search model for evolutionary algorithms is proposed. This model is based on the simultaneously run of two different search operators. It is a good way to attend equilibrium between the exploration and the exploitation of the search space. By means of a basic evolutionary algorithm, it is proved that the proposed method improves the solution of the problem, and the resources needed to attend it are minimized.

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1. Introduction

Evolutionary algorithms prove them selves to be very efficient methods to solve difficult optimization problems. They are increasingly being applied to a diverse to a diverse spectrum of problem areas. In this paper, the search process within standard evolutionary algorithms is improved by means of a new way of applying search operators. The proposed model is based on the parallel run of two different operators, one that solves the problem of search space's exploration, and one that solves the request of exploiting the search space.

To prove the efficiency of the proposed model, we compare the total number of generations needed to attend the optimal points, and the percentage in which the real solution of the problem is correctly detected in both approaches - the standard evolutionary algorithm on one hand, and the modified evolutionary algorithm by using the proposed search model on the other hand. It is shown that the number of total operators applied during the hole search process is low increased, disadvantage compansated by the fact that the real solution of the problem is found in more cases, by comparing it with the standard approach.

2. Genetic algorithms

Genetic algorithms are stochastic optimization techniques that apply three basic genetic operators: selection, crossover and mutation. Applying these genetic operators to a population of chromosomes, or individuals that represents possible solutions of the problem, forms new generations of the population [3]. Each chromosome has an associated fitness value that represents its quality to reproduce. The search must be done in such a way that a balance between exploitation and exploration is achieved [1]. The selection process will favor the individuals having higher fitness value. The crossover mechanism represents the combination of genetic information of the individuals and it is passing it to their descendents. By means of mutation, in the population will be introduced new individuals that cannot be obtained by other mechanisms.

Solving a problem by applying a genetic algorithm supposes determining the following elements: the encoding (representation) of the chromosomes; the fitness function; the genetic operators; the parameter values (population size, probability of applying operators etc).

A new way of applying genetic operators is proposed. In this model, the equilibrium between exploitation and exploration is achieved by the simultaneously run of recombination followed by mutation on one hand, and mutation acting by its self on the other hand. The best between parents and offspring obtained by both operators is kept in the next generation. The next section presents a closer look to the new proposed model.

The standard genetic algorithm is thus modified as follows:

P1. Let $t := 0$.

P2. Initialize population $P(t)$.

P3. Individuals within population $P(t)$ *are evaluated by means of a fitness function* f.

P4. Until (termination condition) do

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P4.1 Some individuals of the current population $P(t)$ *are selected for recombination and mutation according to their fitness. Selected individuals represent an intermediate population* $P^1(t)$.

P4.2 The two parallel genetic operators are applied for each individual within population $P^1(t)$.

P4.3 The best between offspring and parents is kept in population $P(t+1)$.

P4.4 $t := t + 1$;

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3. Parallel Search Model

We may consider a new recombination - mutation search scheme. Proposed scheme may be viewed as a new composed search operator. Recombination followed by mutation can be considered as a unique search operator. We also consider another mutation operator which acts independently. In the proposed model, a difference between the two mutation operators is made. This because the role of the two mutation operators is asymmetric. Mutation in the composed recombination-mutation operator is a weak mutation. Mutation that acts parallel to it is a strong one. The proposed search model applies the two operators simultaneously and this scheme is called Parallel Search Model. Both genetic operators create offspring that compete for survival.

The role of the weak mutation is to improve the offspring obtained by recombination. It realizes a local search. It also avoids the interference between recombination and strong mutation. Indeed, if the offspring obtained after recombination is a good solution for the problem, we do not want to loose this descendent by applying a strong mutation [4]. This operator ensures the exploitation of the search space, followed by local search.

Strong mutation ensures the exploration of the search space. This mutation attends faster the optimal solutions. Also, without this operator, it is possible for the the search to become trapped into a local optimum.

The benefit of parallel search mechanism is the equilibrium between exploitation and exploration of the solutions space. Another advantage is the acceleration of the convergence of the search process.

This parallel scheme can be applied whether we have a binary or a real codification for the solutions of the problem, strong and weak mutation having different meanings depending on the codification we are using. For our experiments, real codification is used, weak mutation being a small rate mutation, and strong mutation being a large step mutation [5].

4. Evaluating the quality of the proposed model

The only disadvantage that the new proposed model presents is the fact that using a genetic algorithm with the parallel run of the two operators increases the number of applied operators, because for every individual within the intermediate population obtained after selection two operators will be applied and the best offspring is chosen. But, numerical experiments presented in the next section, show that the number of applied operators is low increased (on no account doubled). Comparing the number of generations needed to attend the solution of the problem in the standard approach with the number of generations in the new proposed approach, which is considerably decreased, proves this.

Also, the real solution of the problem (or a very good solution, very close to the real one) is obtained in more cases by using the proposed model. This is a very important advantage that compensates the disadvantage of the low increased number of applied operators.

5. Experimental results

For our experiments, we consider a number of four functions. Finding the global optimum becomes more difficult when we deal with multimodal functions, because of the possibility of being trapped into a local optimum [2]. This is the reason we have chosen multimodal functions to prove the efficiency of the proposed model.

$$f_1(x) = -\sum_{i=1}^{5} c_i[e^{-\frac{(x-a_i)^2}{\pi}} cos(\pi(x-a_i)^2)], x \in [0, 10],$$

$$f_2(x) = lnx(sin(e^x) + sin(3x)), x \in [0.1, 4],$$

$$f_3(x) = \frac{\sin^2 x - 0.5}{(1 + 10^{-3}x^2)^2}, x \in [-59, 59],$$

$$f_4(x) = 10 + (x^2 - 10cos(2x\pi)), x \in [1, 5].$$

Remark: Coefficients $c_i, i = 1, \ldots, 5$ in function f_1 (Langerman's function), are components of the vector $c = (0.8060.5171.50.9080.965)$, and coefficients $a_i, i = 1, \ldots, 5$ are components of the vector $a = (9.6819.48.0252.1968.074)$.

We consider the standard evolutionary algorithm (SEA) and the modified algorithm obtained by using the proposed parallel search model - parallel evolutionary algorithm (PEA). *Table 1* contains the results obtained after 100 runs of both algorithms for all considered functions, meaning the number of generations needed to attend the optimum of the functions. *Table 1* presents the average number of generations and the best number obtained after 100 runs.

Table 2 presents the percentage in which the real solution of the problem is detected by using the standard evolutionary algorithm and the new proposed

Table 1: Results obtained after 100 runs of SEA and PEA; the average and the best number of generations needed to find the optimal points.

Test function	**Average SEA**	**Average PEA**	**Best SEA**	**Best PEA**
f_1	**102**	**71**	**60**	**31**
f_2	**114**	**69**	**97**	**52**
f_3	**89**	**55**	**60**	**31**
f_4	**142**	**96**	**103**	**75**

algorithm. It can be noticed a real improvement brought by the proposed model, improvement that conpensates the low increased number of applied operators.

Table 2: The average percentage in which the real solution of the problem is found after 100 runs of SEA and PEA.

Test function	**Real solution found by SEA**	**Real solution found by PEA**
f_1	**67%**	**95%**
f_2	**73%**	**96%**
f_3	**70%**	**98%**
f_4	**82%**	**96%**

6. Conclusions and future work

A new search model for improving evolutionary algorithms is proposed. The model is based on the parallel run of two search operators, a better equilibrium between explorations and exploitation of the search space being thus obtained. Experimental results prove a significant improvement brought by the new model, in terms of number of generations needed to attend the solution of the problem. As future work, a most suitable quality measure for search operators will be proposed. This quality measure will take into account the number of applied operators that have improved the fitness of their parents compared to the total number of total applied operators on one hand, and the importance of finding a good solution of the problem, as close as possible to the real solution of the problem on the other hand.

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