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CULTURAL ALGORITHM PARAMETER CONTROL USING LÉVY FLIGHT

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Abstract: *This paper presents a comparative study between a traditional evolutionary algorithm with the values of the parameters set before the algorithm runs and that remain fixed during runtime, and a cultural algorithm using parameter control powered by Lévy flight to dynamically update the values of the parameters during runtime. The two algorithms are benchmarked on a subset of test problems, using an open-source platform for comparing continuous optimizers in a black box setting. The results obtained are examined in order to demonstrate the improved performance of the cultural algorithm using parameter control, its superiority becoming more evident as the dimensions of the test problems increase.*

Key words: *cultural algorithms, Lévy flight, optimization, benchmark functions.*

1. INTRODUCTION

In the field of engineering, optimization algorithms are essential, allowing engineers to discover efficient and optimal solutions, leading to improved design and performance for a variety of real-world problems [1]–[6].

One of the challenges of using optimization algorithms is making sure the algorithm parameters have good values. It is generally accepted that optimization algorithms with specific parameters configurations yield better results if applied on specific problem types [7].

When dealing with parameters of optimization algorithms, two distinct methods can be employed: parameter tuning and parameter control. Parameter tuning is the process of systematically exploring different combinations of parameter values before the algorithm is started and will remain fixed during the run [8], [9]. Parameter control on the other hand refers to the process of dynamically changing the parameter values during the run. The algorithm starts with initial parameter values that change according to the implemented heuristics [8], [10]. Parameter control might seem superior since it allows the algorithm to use multiple values for the parameters. In the following sections, both approaches are examined on a set of test problems.

2. ALGORITHMS

2.1 Evolutionary algorithm

Evolutionary algorithms (EA) emulate natural evolution, maintaining a population of solutions and iteratively applying genetic operators to create new candidate solutions, simulating the processes of reproduction, crossover, and mutation [11]. The most popular use-cases for EAs are solving optimization problems in various domains. The term EA usually refers to an entire family of algorithms: genetic algorithms, differential evolution, evolution strategy, evolutionary programming, and genetic programming [12].

2.2 Lévy flight

Lévy flight falls into the category of random-search algorithms, where the step lengths are drawn from a heavy-tailed probability distribution, also known as a Lévy distribution. Lévy flight behaves similarly to a random-walk algorithm with one key difference represented by the occasional large jumps, leading to a much more efficient exploration of the search space [13], [14].

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Lévy flight is typically used on the genes space [15], [16], however in this paper it is applied on the parameters space as a mechanism for implementing parameter control.

2.3 Cultural algorithm

Cultural algorithms (CA) are inspired by the concept of culture in human society and can be described as an EA enhanced with a belief space incorporating cultural knowledge. The belief space contains heuristics, insights and rules that are learned and shared between the individuals in the population [17]–[19]. The structure of a CA is presented in Fig. 1. The belief space is updated through the *Accept* function and typically only knowledge from the most competent individuals is considered. The information in the belief space can also be adjusted according to custom rules or heuristics using the *Update* function. The effect of the belief space on the population is possible through the *Influence* function, where individuals can access collective knowledge.

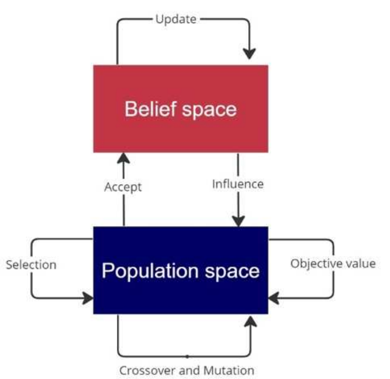

Fig. 1. Structure of CA

CAs have been successfully applied in various domains, including mechanical, civil, electrical and chemical engineering, and computer science [20].

In this article, a new cultural algorithm is proposed which uses a dedicated knowledge structure for parameter values, and updates them using Lévy flight, achieving an improved exploration of the search space of the parameters. The parameters are used in the recombination and mutation operators, having a direct effect on how close the offspring are to their parents, respectively how close mutants are to the original individuals. The mechanism is built on the idea that for any given position in the search space, some parameter values would yield better results than the ones obtained with fixed values during runtime.

In contrast, the EA used for comparison employs fixed values of these parameters favoring the exploration of the search space for the recombination and mutation operators.

3. BENCHMARK FRAMEWORK

The comparing continuous optimizers (COCO) [21], [22] platform was used to evaluate the performance of the two proposed algorithms. The main goal of COCO is to automate the laborious and repetitive process of benchmarking numerical algorithms as much as possible [23].

The structure of the COCO platform is illustrated in Fig. 2, where the code and data provided by the framework is represented in color blue and the code implemented by the user and the output generated by the platform is represented in color red.

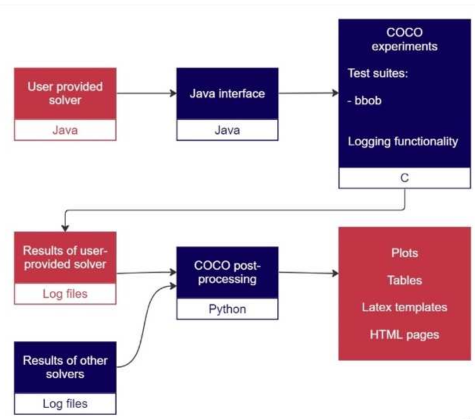

Fig. 2. Structure of COCO platform

The platform generates figures of the Empirical Cumulative Distribution Functions (ECDF) of the bootstrap distribution of the Expected Running Time (ERT) divided by the dimension. The outputs show the ECDFs of the running times of the simulated runs divided by the corresponding dimension for 51 different targets logarithmically uniformly distributed in the [1e–8, 1e2] interval. The crosses on the figures represent the median of the maximal length of the unsuccessful runs to solve the problems aggregated within the ECDF [24].

3.1 Sphere problem

The Sphere problem is one of the easiest continuous domain test problems, especially for non-specialized optimization algorithms. It is a unimodal function, highly symmetric and scale invariant [25]. The definition of the Sphere problem is given by:

$$f_1(x) = \sum x_i^2 \tag{1}$$

3.2 Ellipsoid problem

The Ellipsoid problem is a unimodal function, globally quadratic and ill-conditioned function with smooth local irregularities [25]. The Ellipsoid problem is defined as:

$$f_2(x) = \sum 10^{6\frac{i-1}{D-1}} x_i^2 \tag{2}$$

where *D* represents the number of dimensions (also in the other equations).

3.3 Rastrigin problem

The Rastrigin problem is a highly multimodal function that has proven to be difficult for EAs to solve due to the high number of local minima. The definition of the Rastrigin problem is given by:

$$f_3(x) = 10(D - \sum cos(2\pi x_i)) + \sum x_i^2 \tag{3}$$

3.4 Rastrigin-Büeche problem

The Rastrigin-Büeche problem is a highly multimodal function, constructed to be deceptive for symmetrically distributed search operators [25]. The definition of the Rastrigin-Büeche problem is given by:

$$f_4(x) = 10(D - \sum cos(2\pi x_i)) + \sum x_i^2 + 10^2 g(x) \tag{4}$$

where *g* function is defined as:

$$g(x): R^D \rightarrow R, x \rightarrow \sum_{i=1}^{D} max(0, |x_i| - 5)^2 \tag{5}$$

3.5 Linear slope problem

The Linear slope problem is a purely linear function which verifies if the search operator is able to break out of the initial convex hull of solutions into the domain boundary [25]. The definition of the Linear slope problem is given by:

$$f_5(x) = \sum 5|s_i| - s_i x_i \tag{6}$$

where *s* function is defined as:

$$s(i) = sign(x_i) 10^{\frac{i-1}{D-1}} \tag{7}$$

3.6 Rosenbrock problem

Another popular benchmark problem which is notoriously difficult for EAs to solve is Rosenbrock. The challenge comes from the fact that the global minimum is situated in a deep banana shaped valley, and typically the convergence of the search operators towards the optimum is very slow. Having a greater number of dimensions makes the convergence even slower. The definition of the Rosenbrock problem is given by:

$$f_8(x) = \sum(100\,(x_i^2 - x_{i+1})^2 + (x_i - 1)^2) \tag{8}$$

4. RESULTS

Both algorithms were tested on a subset of test functions for dimensions 2, 3, 5, 10, 20. The performance of the two algorithms is comparable for a low number of dimensions, however differences become noticeable for higher dimensions. The traditional evolutionary algorithm is depicted in blue color, annotated with the circle symbol, and labeled as *baseline*, whereas the cultural algorithm is depicted in magenta color, annotated with the diamond symbol, and labeled as *levy*.

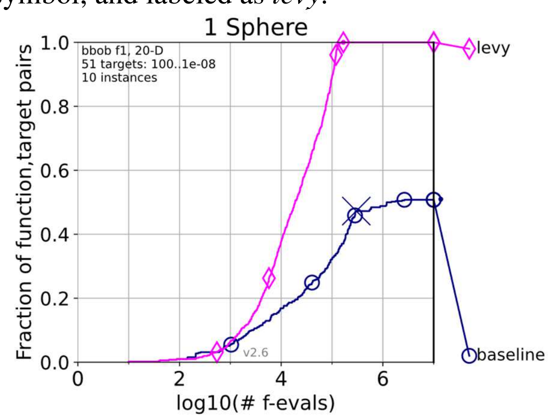

Fig. 3. Results for Sphere 20D problem

The results obtained for the Sphere problem with 20 genes are presented in Fig. 3 and indicate a superior performance of the CA over the traditional EA. The CA was able to hit all 51 targets, whereas for the evolutionary algorithm, runtimes to the right of the cross at approximately $10^{5.5}$ have at least one unsuccessful run.

The results obtained for the Ellipsoid problem with 20 genes are presented in Fig. 4 indicating a superior performance of the CA over the traditional EA. The CA was able to hit all 51 targets, whereas for the evolutionary algorithm, runtimes to the right of the cross at approximately $10^{5.5}$ have at least one unsuccessful run.

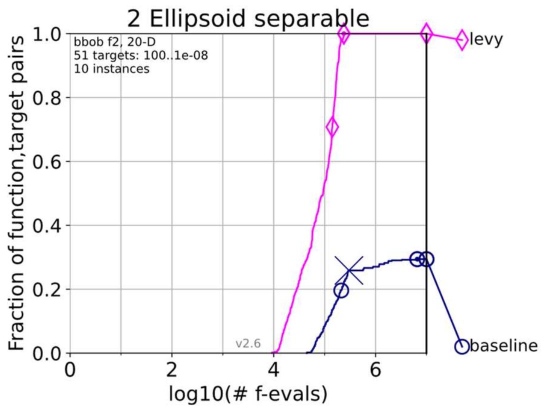

Fig. 4. Results for Ellipsoid separable 20D problem

The results obtained for the Rastrigin problem with 20 genes are presented in Fig. 5 and again indicate a superior performance of the CA over the traditional EA. For this particular problem however, runtimes to the right of the crosses at approximately $10^{5.5}$ have at least one unsuccessful run for both CA and EA algorithms.

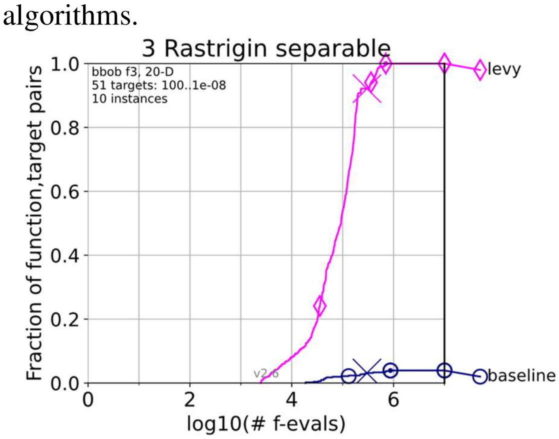

Fig. 5. Results for Rastrigin separable 20D problem

The results obtained for the Rastrigin-Büeche problem with 20 genes are presented in Fig. 6 and are similar to the ones obtained for the Rastrigin problem, showing that the CA performs better than the traditional EA, however, runtimes to the right of the crosses at approximately $10^{5.5}$ have at least one unsuccessful run for both algorithms.

The Linear slope problem with 20 genes proves to be an easy challenge for both algorithms, being able to hit all 51 targets. The ECDF plots in Fig. 7 show however that the CA has a slight advantage over the traditional EA.

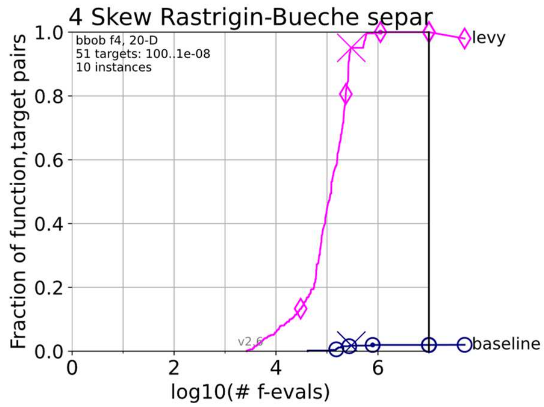

Fig. 6. Results for Rastrigin-Büeche 20D problem

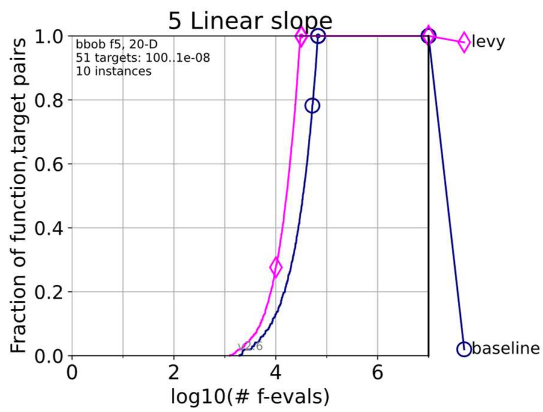

Fig. 7. Results for Linear slope 20D problem

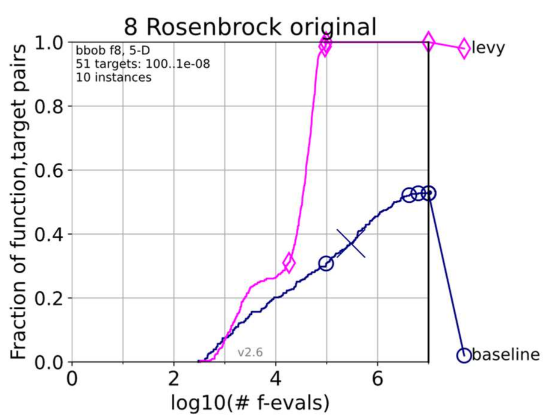

Fig. 8. Results for Rosenbrock 5D problem

For the Rosenbrock problem, differences between the two algorithms become visible starting with 5 dimensions. The ECDF plots in Fig. 8 show that the cultural algorithm is superior to the traditional evolutionary algorithm, being able to hit all 51 targets for the Rosenbrock problem with 5 genes. For the EA, runtimes to the right of the cross at approximately $10^{5.5}$ have at least one unsuccessful run.

5. CONCLUSIONS

The current paper examined two algorithms: a traditional evolutionary algorithm that uses fixed values of the parameters during the entire evolution favoring the exploration of the search space, and a cultural algorithm that uses Lévy flight to dynamically update the values of the parameters during the evolution.

The two algorithms were benchmarked using the COCO platform on a subset of test problems. The obtained results show that the cultural algorithm using parameter control clearly surpasses the traditional evolutionary algorithm. Some of the test problems, i.e., Rastrigin and Rastrigin-Büeche proved to be difficult also for the cultural algorithm, having some unsuccessful runs. However, the superiority of the CA was clear also for these functions. The results presented in this paper are promising and justify further research in the area of optimization algorithms using parameter control for tackling multimodal optimization problems.

5. ACKNOWLEDGMENTS

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CONTROLUL PARAMETRILOR UTILIZÂND ZBOR LÉVY ÎNTR-UN ALGORITM CULTURAL

Această lucrare prezintă un studiu comparativ între un algoritm evolutiv tradițional care utilizează valori ale parametrilor setate înainte să ruleze algoritmul și care rămân fixe pe toată durata de execuției algoritmului, și un algoritm cultural care modifică valorile parametrilor în timpul execuției algoritmului cu ajutorul unui mecanism bazat pe zbor Lévy. Cei doi algoritmi sunt comparați pe un subset de probleme de test cu ajutorul unei platforme open source dedicate comparării algoritmilor numerici de optimizare. Rezultatele obținute sunt analizate pentru a demonstra performanța îmbunătățită a algoritmului cultural care controlează dinamic valorile parametrilor, superioritatea acestuia devenind mai evidentă când problemele de test au un număr mai mare de dimensiuni.

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