Hybridizing Genetic Algorithm with Cross Entropy for Solving Continuous Functions

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ABSTRACT

In this paper, a metaheuristic that combines a Genetic Algorithm and a Cross Entropy Algorithm is presented. The aim of this work is to achieve a synergy between the capabilities of the algorithms using different population sizes in order to obtain the closest value to the optimal of the function. The proposal is applied to 12 benchmark functions with different characteristics, using different configurations.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search—*Heuristic Methods*

Keywords

Algorithms; Experimentation; Genetic Algorithm; Cross Entropy; Meta-heuristic; Real-world problem; Optimization Problem; Hybridization Technique

1. INTRODUCTION

In the last decades, different promising algorithms have been developed in order to give a solution to complex optimization problems. Some of the most used techniques, called metaheuristics, have been inspired in the behaviour of natural phenomena [4].

In this paper, a technique that combines a Genetic Algorithm (GA) with a Cross Entropy (CE) method is presented. These techniques by its own have been promising for resolving many optimization problems [1]. The aim is to find a synergy between the strenghts of both algorithms in order to reach to a suitable solution for 12 benchmark functions with different characteristics. The functions used are shown in Table 2. Formulas, characteristics and explanations about the functions are collected in the Black-Box Optimization Benchmarking (BBOB)*(http://coco.gforge.inria.fr)*.

The method, called GACE, works with two sub-populations (GA_{pop} and CE_{pop}). In each one, a GA and a CE is applied, respectively. After that, both sub-populations are joined and replace completely the actual population.

Type	Function	Name
Separable	F_1, F_2, F_3	Sphere, Ellipsoidal, Linear Slope
Low or moderate conditioning	F_4, F_5	Attractive Sector, Step Ellipsoidal
High conditioning and unimodal	F_6, F_7	Bent Cigar, Sharp Ridge
Multimodal with adequate global structure	F_8, F_9, F_{10}	Weierstrass, Schaffers F7, Schaffers F7, moderately ill-conditioned
Multimodal with weak global structure	F_{11}, F_{12}	Gallagher's Gaussian 101-me Peaks, Lunacek bi-Rastrigin

Table 2: Functions to be optimized by GACE.

2. EXPERIMENTAL SETUP

In order to find the best configuration, different population sizes for GA_{pop} and CE_{pop} are tested and compared. For each function, 15 instances have been considered. Each instance has a different optimum value. This is to avoid algorithms whose final solution is a specified value and, in that way, take better values than others. The value dim, which represents the dimension of the function, can take values of 5 and 20 ($dim = \{5, 20\}$) for each one of the functions presented before.

About the population size, $GA_{size} \in \{45, 35, 25, 15, 5\}$ is used while CE_{size} is determined by $50 - GA_{size}$. The chosen configurations are compared with pure GA ($CE_{size} = 0$) and pure CE ($GA_{size} = 0$) to test the benefits of using the proposed method in comparison with the isolated methods. The algorithm configuration is referred by their

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	Hill-Climbing	CMA-ES	PRCGA	CE	$GACE_{5-45}$	$GACE_{15-35}$	$GACE_{25-25}$	$GACE_{35-15}$	$GACE_{45-5}$	GA
$F_1(d=5)$	1.58e-05	1.77e-05	2.70e-05	**0.00e+00**	**0.00e+00**	**0.00e+00**	**0.00e+00**	**0.00e+00**	1.60e-07	7.69e-05
$F_2(d=5)$	2.09e+00	3.21e+02	1.81e-03	**0.00e+00**	**0.00e+00**	1.67e-05	**0.00e+00**	6.68e-06	2.88e-05	1.58e-02
$F_3(d=5)$	**-1.02e-14**	**-1.02e-14**	2.24e+00	-2.66e-15	**-1.02e-14**	**-1.02e-14**	**-1.02e-14**	**-1.02e-14**	**-1.02e-14**	**-1.02e-14**
$F_4(d=5)$	9.16e-02	2.81e-01	1.60e+00	3.55e+00	4.95e-01	3.07e-01	1.79e-01	5.16e-02	**3.54e-02**	1.15e-01
$F_5(d=5)$	9.74e-01	1.11e+00	2.26e-01	5.29e-01	2.74e-01	5.11e-01	3.63e-01	1.89e-01	4.34e-01	**4.61e-02**
$F_6(d=5)$	5.73e+01	3.62e+01	5.78e+00	6.08e+00	6.99e+00	**5.56e+00**	7.10e+00	8.36e+00	5.98e+00	1.80e+01
$F_7(d=5)$	3.12e+01	7.73e+00	4.59e+00	2.65e+00	**2.53e+00**	3.06e+00	3.14e+00	4.64e+00	1.03e+01	1.08e+01
$F_8(d=5)$	1.59e+00	6.74e+00	5.98e-01	3.10e-01	**1.60e-01**	2.54e-01	3.33e-01	2.09e-01	4.07e-01	4.81e-01
$F_9(d=5)$	1.01e+00	1.52e-01	8.71e-02	1.19e-02	**1.16e-03**	2.02e-03	1.36e-02	2.50e-02	2.76e-02	5.25e-02
$F_{10}(d=5)$	2.43e+00	1.33e+00	2.72e-01	7.10e-02	**5.92e-02**	7.28e-02	9.89e-02	1.97e-01	2.88e-01	4.66e-01
$F_{11}(d=5)$	2.80e+00	3.52e+00	**4.73e-01**	8.97e-01	9.47e-01	9.70e-01	9.36e-01	1.42e+00	1.95e+00	1.45e+00
$F_{12}(d=5)$	1.08e+01	1.98e+01	7.71e+00	**6.90e+00**	8.42e+00	8.75e+00	8.64e+00	9.32e+00	7.94e+00	8.35e+00
Rank (d=5)	8.00e+00	8.25e+00	5.83e+00	3.92e+00	**2.75e+00**	3.75e+00	3.75e+00	4.08e+00	5.08e+00	6.17e+00
$F_1(d=20)$	1.33e-03	5.64e-06	1.82e-04	**0.00e+00**	**0.00e+00**	1.83e-06	8.79e-05	3.89e-04	1.18e-01	3.88e-01
$F_2(d=20)$	6.54e+01	1.94e+04	3.16e+01	8.31e+00	6.63e-02	**1.24e-02**	6.61e-02	3.12e+00	2.98e+02	1.99e+03
$F_3(d=20)$	6.46e-14	**-3.61e-15**	1.19e+01	4.21e-06	1.46e-10	3.82e-10	2.94e-09	1.36e-07	2.11e-02	3.11e-02
$F_4(d=20)$	2.66e+01	1.89e+01	2.57e+01	4.37e+01	1.34e+01	1.19e+01	9.23e+00	**7.40e+00**	1.30e+01	2.61e+01
$F_5(d=20)$	3.38e+01	9.33e+00	1.72e+01	1.00e+01	1.09e+01	1.27e+01	1.68e+01	1.34e+01	**6.02e+00**	8.24e+00
$F_6(d=20)$	1.42e+03	2.83e+01	1.10e+02	2.91e+01	2.25e+01	**1.69e+01**	5.94e+01	3.54e+02	1.06e+05	2.42e+05
$F_7(d=20)$	2.46e+01	**8.17e+00**	2.19e+01	1.70e+01	2.08e+01	2.65e+01	3.97e+01	4.77e+01	7.78e+01	1.14e+02
$F_8(d=20)$	1.35e+01	1.31e+01	5.45e+00	2.11e+00	2.08e+00	2.03e+00	1.87e+00	**1.83e+00**	6.85e+00	8.44e+00
$F_9(d=20)$	1.12e+01	2.59e-01	7.40e-01	**6.24e-02**	6.86e-02	1.72e-01	2.85e-01	5.06e-01	6.63e-01	7.17e-01
$F_{10}(d=20)$	4.24e+01	1.25e+00	2.70e+00	6.14e-01	**6.09e-01**	9.66e-01	1.43e+00	1.64e+00	3.07e+00	3.63e+00
$F_{11}(d=20)$	1.86e+01	1.33e+01	1.12e+01	5.95e+00	7.73e+00	**4.76e+00**	1.03e+01	1.01e+01	9.96e+00	8.45e+00
$F_{12}(d=20)$	2.51e+02	1.74e+02	1.11e+02	**5.84e+01**	1.42e+02	1.48e+02	1.47e+02	1.51e+02	1.44e+02	1.39e+02
Rank (d=20)	8.25e+00	5.25e+00	6.67e+00	3.67e+00	**3.00e+00**	3.42e+00	4.92e+00	5.58e+00	6.67e+00	7.50e+00

Table 1: Comparative between average $f_{best} - f_{opt}$ of the techniques with dimension 5 and 20

population sizes, $\{GA_{size} - CE_{size}\}$. The maximum number of evaluations used as stopping criterion is established at 25000.

For the developed GA, BLX-α and Gaussian mutation are adopted as crossover and mutation operators, respectively. The probability of crossover has been set to 0.85 and mutation probability has been established in 0.1. In the case of CE, $Learning_{rate} = 0.7$ is used in order to update $\bar{x}$ and σ values.

Three of the participants in BBOB 2013 have been selected for comparison: Hill-climbing [2], CMA-ES [3] and PRCGA [5].

3. RESULTS

Table 1 shows the results obtained for dimension 5 and 20. The last row indicates the averaged position obtained by the technique.

For dimension 5, GACE obtains closest values to the optimum, in 9 of 12 functions. In F_3, GACE obtains the same results that Hill-Climbing and CMA-ES. In the rest of cases, GACE with $GA_{size} = \{5, 15\}$ obtains the best results in 5 of 9 cases and $GACE_{45-5}$ in 1 of 9 cases left. PRCGA, GA and CE obtain the best result in 1 of 12 cases. The method that has been chosen more times is $GACE_{5-45}$.

In the case of dimension 20, GACE obtains the best result in 9 of 12 cases too. In this dimension, $GACE_{5-45}$ continues obtaining the optimum in F_1 function. In the three previous cases in which GACE does not get the best value, in 2 of these 3 cases, GACE is the best one. However, in F_3 and F_7, CMA-ES occupies its place as the best method. For this dimension, $GACE_{5-45}$ obtains the best ranking.

4. CONCLUSIONS

In this paper, a hybrid method that combines a GA and a CE for continuous optimization benchmark functions has been presented. The aim of this hybridization is to obtain a synergy between the exploration and the exploitation ability of the methods in order to get values as close as possible to the optimum value of the function.

In future works, other crossovers and mutation operators can be used in order to obtain better results in GA part. Also, applying GACE to other problems and comparison with other methods in the literature will be done.

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