Benchmarking Covariance Matrix Self Adaption Evolution Strategy with Repelling Subpopulations for GECCO 2017 Competition on Multimodal Optimization[1]

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Abstract This report presents the benchmarking results of Covariance Matrix Self Adaption Evolution Strategy with Repelling Subpopulations (RS-CMSA) on the CEC2013 test suite. The benchmarking follows restrictions required by GECCO 2017 competition on multimodal optimization. In particular, no problem dependent parameter tuning is performed. A few minor modifications to the original method is proposed as well.

Keywords *Niching; Evolutionary Algorithms, Parallel Convergence*

1. Introduction

Covariance Matrix Self-Adaption Evolution Strategy with repelling subpopulations (RS-CMSA) [1] has recently been proposed for multimodal optimization. It runs N_s subpopulations in parallel such that each subpopulation maintains a distance to a number of taboo points, the superior subpopulations or previously identified basins, which are stored in an internal archive. The

[1] This method ranked the first in GECCO'2017 competition on niching methods for multimodal optimization

repelling powers of an archived point is adapted based on the number of subpopulations that converge to that basin. RS-CMSA employs hill-valley function [2] to check whether the best member of a terminated subpopulation refers to a new basin. If the new member shares the same basin with an archived solution, it replaces the archived solution only if it is fitter.

For an arbitrary subpopulation, the taboo regions conform to the mutation profile of the subpopulation and hence, the taboo regions perceived by different subpopulations are different in shape, size and numbers. When all subpopulations converge, a new set of subpopulations with an increased population size are initialized. The increasing factor of subpopulation size (*incPopF*) is set to two by default.

This report benchmarks RS-CMSA on the GECOO2017 test suite for multimodal optimization [3], which consists of 20 test problems whose dimensions vary from 1 to 20 [4]. Some minor modifications are proposed particularly for specialization with respect to performance measures of the competitions. The competition employs the following performance measures [3]:

- Peak Ratio (PR): The fraction of global minima found by the method.
- Static F_1 measure: The fraction of reported solutions that turned out to be independent global minima.
- Dynamic F_1 measure: It calculate the integral of F_1 measure over the convergence history.

2. Modified RS-CMSA

To maximize F_1 measures, we add a dummy archive which ideally stores only new basins. In contrast to the internal archive which may remove or add solutions, the dummy archive only adds new solutions which follows the requirements for the competition. Each time a solution is added to the internal archive, it is added to the dummy archive as well. If the new solution refers to an already identified basin, it is added to the dummy archive only if it is better than the already archived solution with a margin of 10^{-5} (maximum accuracy level in the competition). The corresponding evaluation number and time (second) are also recorded. The reported solutions for consideration are those stored in the dummy archive.

We also noticed that a smaller value for the default number of subpopulation N_s^0 with a smaller increase factor (*incPopF*) can be beneficial, Since the repelling power of the archived points is adapted at the end of each restart, it allows for a more reliable adaption as more restarts can be performed. For this competition, we used N_s^0=10 and *incPopF*=1.01. Lowering N_s^0 is recommended in general; however, such a low increase factor is only employed for this particular competition. For such a low value of *incPopF*, the final population size remains small even if a hundred restarts are performed. The initial population size is set to $3D^{0.5}$, in which D is the problem dimension. The rest of control parameters are set to their recommended default values [1].

3. Results and Discussion

Each test problem is solved 50 times independently. The solutions stored in the dummy archive are provided in the supplementary files for detailed evaluation. For each target tolerance (ε_f), Peak Ratio (PR) and the precision (for calculation of the F_1 measure) [3] are provided in Table 1 and Table 2, respectively.

A review of these tables reveals that:

- RS-CMSA could reach MPR=0.855 when all target tolerances and problems are considered (Table 1).
- Almost all reported solutions (99.95% of the times) are independent global minima.
- PR and the static F_1 measure are independent of the target tolerance.

Table 1. Peak Ratio (PR) of RS-CMSA for the 20 test problems of GECCO 2017 competition on multimodal optimization

PID	ε_f**=10**$^{-1}$	ε_f**=10**$^{-2}$	ε_f**=10**$^{-3}$	ε_f**=10**$^{-4}$	ε_f**=10**$^{-5}$	**Average**
1	1	1	1	1	1	1
2	1	1	1	1	1	1
3	1	1	1	1	1	1
4	1	1	1	1	1	1
5	1	1	1	1	1	1
6	0.999	0.999	0.999	0.999	0.999	0.999
7	0.997	0.997	0.997	0.997	0.997	0.997
8	0.871	0.871	0.871	0.871	0.871	0.871
9	0.730	0.730	0.730	0.730	0.730	0.730
10	1	1	1	1	1	1
11	0.997	0.997	0.997	0.997	0.997	0.997
12	0.948	0.948	0.948	0.948	0.948	0.948
13	0.997	0.997	0.997	0.997	0.997	0.997
14	0.810	0.810	0.810	0.810	0.810	0.810
15	0.748	0.748	0.748	0.748	0.748	0.748
16	0.667	0.667	0.667	0.667	0.667	0.667
17	0.703	0.703	0.703	0.703	0.703	0.703
18	0.667	0.667	0.667	0.667	0.667	0.667
19	0.503	0.503	0.503	0.503	0.503	0.503

20	0.483	0.483	0.483	0.483	0.483	0.483
Average	**0.856**	**0.856**	**0.856**	**0.856**	**0.856**	**0.856**

Table 2. Precision for static F_1 measure of RS-CMSA for the 20 test problems of GECCO 2017 competition on multimodal optimization

PID	ε_f **=10**$^{-1}$	ε_f **=10**$^{-2}$	ε_f **=10**$^{-3}$	ε_f **=10**$^{-4}$	ε_f **=10**$^{-5}$	**Average**
1	0.99	0.99	0.99	0.99	0.99	0.99
2	1	1	1	1	1	1
3	0.98	0.98	0.98	0.98	0.98	0.98
4	1	1	1	1	1	1
5	1	1	1	1	1	1
6	1	1	1	1	1	1
7	1	1	1	1	1	1
8	1	1	1	1	1	1
9	1	1	1	1	1	1
10	1	1	1	1	1	1
11	1	1	1	1	1	1
12	1	1	1	1	1	1
13	1	1	1	1	1	1
14	1	1	1	1	1	1
15	1	1	1	1	1	1
16	1	1	1	1	1	1
17	1	1	1	1	1	1
18	1	1	1	1	1	1
19	0.996	0.996	0.996	0.996	0.996	0.996
20	1	1	1	1	1	1
Average	0.998	0.998	0.998	0.998	0.998	0.998

4. Summary and Conclusions

In this report, we benchmarked Covariance Matrix Self Adaption Evolution Strategy with repelling subpopulations (RS-CMSA) on a recent test suite for multimodal optimization. Some minor revisions were performed. Particularly, a smaller value for the number of subpopulations and a slower rate of increasing population size turned out to be beneficial.

5. Acknowledgement

Computational work in support of this research was performed at Michigan State University's High Performance Computing Facility. Detailed history of identification of each problem in each run is provided in the format of [$\boldsymbol{x}$ = $f(\boldsymbol{x})$ @ FEs Time(s) Action] as supplementary materials. The source code of RS-CMSA in MATLAB can be found at COIN Lab website (https://www.coin-laboratory.com/codes)

References

[1] A. Ahrari, K. Deb and M. Preuss, "Multimodal Optimization by Covariance Matrix Self-Adaptation Evolution Strategy with Repelling Subpopulations," *Evolutionary Computation,* vol. in press, 2016.

[2] R. K. Ursem, "Multinational evolutionary algorithms," in *IEEE Congress on Evolutionary Computation (CEC'99)*, Washinton, 1999.

[3] "Competition on Niching Methods for Multimodal Optimization," [Online]. Available: http://www.epitropakis.co.uk/gecco2016/. [Accessed 13 June 2016].

[4] X. Li, A. Engelbrecht and M. G. Epitropakis, "Benchmark Functions for CEC'2013 Special Session and Competition on Niching Methods for Multimodal Function Optimization," volutionary Computation and Machine Learning Group, RMIT University, Australia, 2013.