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# Benchmarking sep-CMA-ES on the BBOB-2009 Function Testbed

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## ABSTRACT

A partly time and space linear CMA-ES is benchmarked on the BBOB-2009 noiseless function testbed. This algorithm with a multistart strategy with increasing population size solves 17 functions out of 24 in 20-D.

## Categories and Subject Descriptors

G.1.6 [Numerical Analysis]: Optimization—*global optimization, unconstrained optimization*; F.2.1 [Analysis of Algorithms and Problem Complexity]: Numerical Algorithms and Problems

## General Terms

Algorithms

## Keywords

Benchmarking, Black-box optimization, Evolutionary computation, Covariance matrix adaptation, Evolution strategy

## 1. INTRODUCTION

The sep-CMA-ES algorithm introduced in [7] is a variant of the covariance matrix adaptation evolution strategy (CMA-ES) [5] that is linear in time and space. This property combined with a faster learning rate makes sep-CMA-ES appropriate for separable function and larger dimensions. A mixed strategy of using sep-CMA-ES and CMA-ES is proposed here and benchmarked on a noiseless function testbed.

## 2. ALGORITHM PRESENTATION

In its design, the sep-CMA-ES differs from the CMA-ES by two aspects: first, the covariance matrix is constrained to be diagonal at each of its update, second, the learning rate is increased by a factor of  $\frac{n+3/2}{3}$ , where  $n$  is the dimension of the search space<sup>1</sup>. These modifications result

<sup>1</sup>Please note that the factor for the learning rate is smaller than the one in [7].

in an algorithm that trades model complexity with a time and space scaling that is better than the original CMA-ES. The  $(\mu/\mu_w, \lambda)$ -sep-CMA-ES has been shown to outperform  $(\mu/\mu_w, \lambda)$ -CMA-ES on separable functions.

We propose here what would be the best of two worlds: to use sep-CMA-ES for the first few iterations and then switch to CMA-ES. At the time of the switch, all parameters are retained except for the learning rate that is decreased back to its default value. This implies the diagonal covariance matrix acquired using sep-CMA-ES is directly used by CMA-ES. This mixed strategy is therefore expected to be faster than CMA-ES on separable functions. Ongoing work has also shown that for some test functions the first iterations using sep-CMA-ES would not disadvantage the latter use of CMA-ES in any way. In other terms, the cost of initially using sep-CMA-ES would not induce a penalty in the cost of solving the function with CMA-ES afterwards. The author admits some functions could induce such a penalty.

As for the multistart strategy, we use the increasing population size IPOPOP-CMA-ES [1]. Though this approach has shown its limits [6], independent restart may improve the probability of the algorithm reaching a given target function value.

## 3. EXPERIMENTAL PROCEDURE

The Matlab implementation of the CMA-ES (version 3.23 beta) is used<sup>2</sup>. We use the  $(\mu/\mu_w, \lambda)$ -IPOPOP-CMA-ES variant with an initial default population size  $\lambda = 4 + \lfloor 3 \ln(n) \rfloor$  increasing twice at each restart. Except the learning rate, all other algorithm parameters are set to their default values. The covariance matrix is constrained to be diagonal only for the first  $1 + 100n/\sqrt{\lambda}$  iterations of the *first start*. A maximum of 8 independent restarts is conducted. Restarts occur after  $100 + 300n\sqrt{n/\lambda}$  iterations or if any of the default stopping criterion is met. The initial stepsize has been set to 2 and the starting point has been chosen uniformly in  $[-4, 4]^n$ . The maximum number of function evaluations was set to  $10^4$  times the dimension. No parameter tuning was done, the CrE [3] is computed to zero.

## 4. RESULTS AND DISCUSSION

Results from experiments according to [3] on the benchmark functions given in [2, 4] are presented in Figures 1 and 2 and in Table 1. The algorithm solves 17 out of the 24 functions in 20-D. The algorithm performs well on uni-

<sup>2</sup>Latest version available here:<http://www.lri.fr/~hansen/cmaesintro.html>

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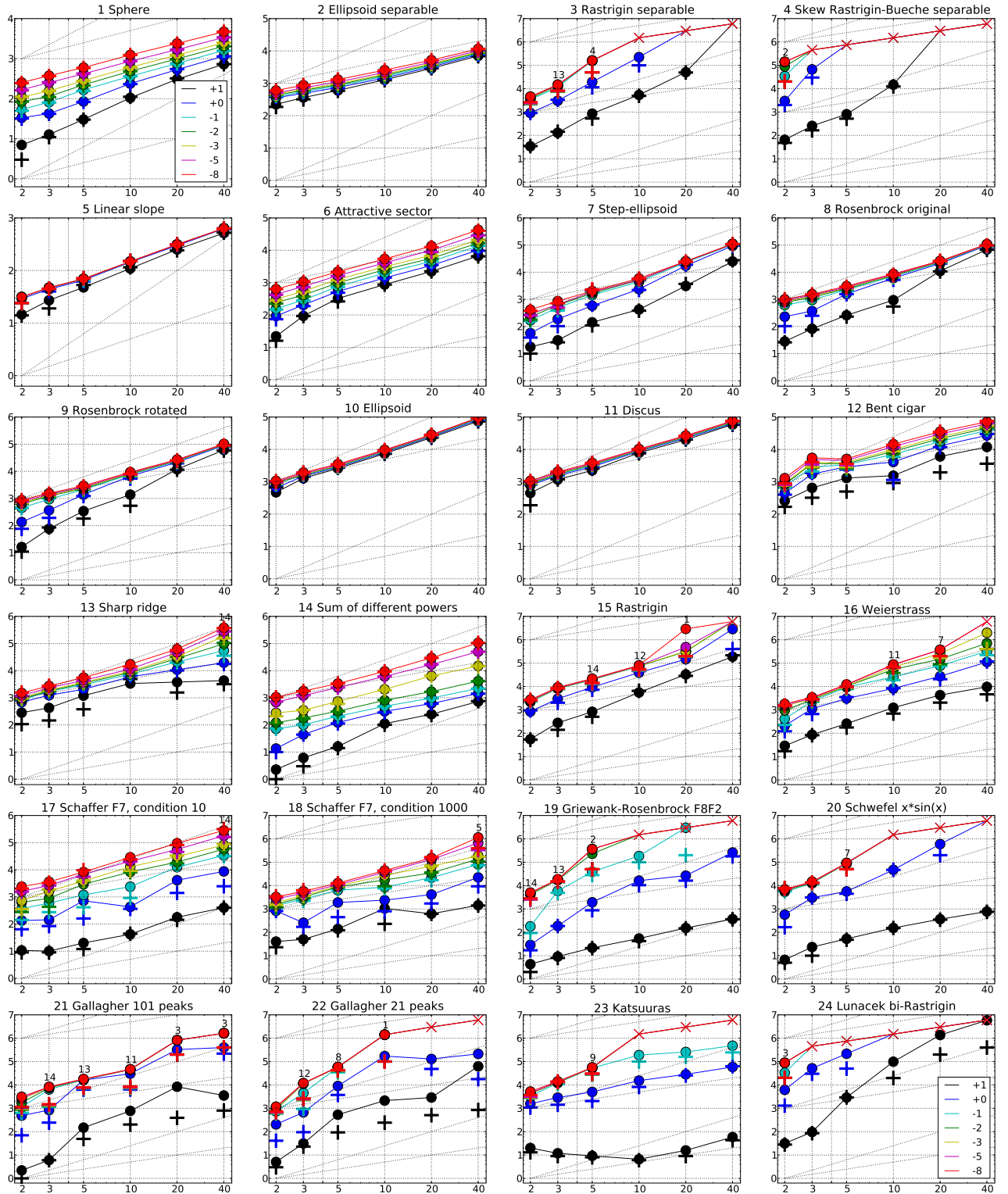
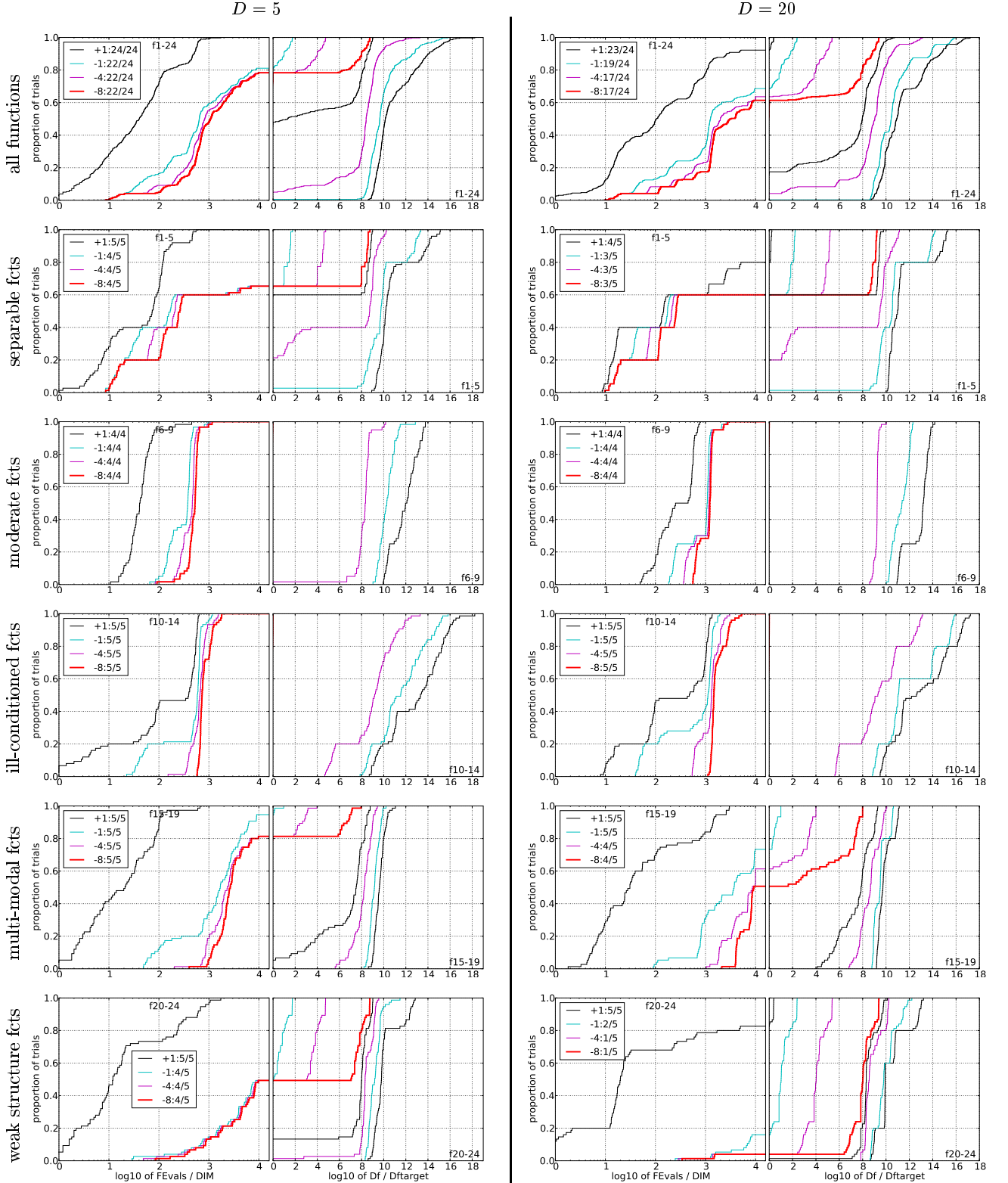


Figure 1: Expected Running Time (ERT, ●) to reach  $f_{\text{opt}} + \Delta f$  and median number of function evaluations of successful trials (+), shown for  $\Delta f = 10, 1, 10^{-1}, 10^{-2}, 10^{-3}, 10^{-5}, 10^{-8}$  (the exponent is given in the legend of  $f_1$  and  $f_{24}$ ) versus dimension in log-log presentation. The ERT( $\Delta f$ ) equals to  $\#FEs(\Delta f)$  divided by the number of successful trials, where a trial is successful if  $f_{\text{opt}} + \Delta f$  was surpassed during the trial. The  $\#FEs(\Delta f)$  are the total number of function evaluations while  $f_{\text{opt}} + \Delta f$  was not surpassed during the trial from all respective trials (successful and unsuccessful), and  $f_{\text{opt}}$  denotes the optimal function value. Crosses (×) indicate the total number of function evaluations  $\#FEs(-\infty)$ . Numbers above ERT-symbols indicate the number of successful trials. Annotated numbers on the ordinate are decimal logarithms. Additional grid lines show linear and quadratic scaling.

$f_1$ in 5-D, N=15, mFE=738					$f_1$ in 20-D, N=15, mFE=2594					$f_2$ in 5-D, N=15, mFE=1554					$f_2$ in 20-D, N=15, mFE=5750						
$\Delta f$	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	
10	15	3.0e1	2.3e1	3.7e1	3.0e1	15	3.1e2	2.9e2	3.2e2	3.1e2	10	6.0e2	5.5e2	6.5e2	6.0e2	15	2.9e3	2.8e3	3.0e3	2.9e3	
1	15	8.5e1	7.8e1	9.2e1	8.5e1	15	5.3e2	5.1e2	5.5e2	5.3e2	1	15	7.4e2	7.0e2	7.8e2	7.4e2	15	3.2e3	3.1e3	3.3e3	3.2e3
1e-1	15	1.7e2	1.5e2	1.8e2	1.7e2	15	7.6e2	7.4e2	7.8e2	7.6e2	1e-1	15	8.3e2	7.9e2	8.6e2	8.3e2	15	3.5e3	3.4e3	3.6e3	3.5e3
1e-3	15	2.8e2	2.7e2	3.0e2	2.8e2	15	1.2e3	1.2e3	1.3e3	1.2e3	1e-3	15	9.7e2	9.4e2	1.0e3	9.7e2	15	4.0e3	3.9e3	4.1e3	4.0e3
1e-5	15	4.2e2	4.0e2	4.3e2	4.2e2	15	1.7e3	1.6e3	1.7e3	1.7e3	1e-5	15	1.1e3	1.1e3	1.1e3	1.1e3	15	4.5e3	4.4e3	4.6e3	4.5e3
1e-8	15	6.0e2	5.8e2	6.2e2	6.0e2	15	2.4e3	2.4e3	2.4e3	2.4e3	1e-8	15	1.3e3	1.3e3	1.3e3	1.3e3	15	5.2e3	5.1e3	5.3e3	5.2e3
$f_3$ in 5-D, N=15, mFE=50422					$f_3$ in 20-D, N=15, mFE=200352					$f_4$ in 5-D, N=15, mFE=50430					$f_4$ in 20-D, N=15, mFE=200376						
$\Delta f$	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	
10	15	8.6e2	5.9e2	1.1e3	8.6e2	15	5.1e4	4.2e4	6.0e4	5.1e4	10	15	8.1e2	5.7e2	1.1e3	8.1e2	0	14e+0	13e+0	16e+0	1.1e5
1	13	1.9e4	1.3e4	2.7e4	1.5e4	0	60e-1	40e-1	70e-1	1.1e5	1	0	37e-1	30e-1	40e-1	1.8e4					
1e-1	4	1.6e5	9.6e4	3.4e5	3.7e4						1e-1										
1e-3	4	1.6e5	9.8e4	3.5e5	3.8e4						1e-3										
1e-5	4	1.6e5	9.9e4	3.5e5	3.8e4						1e-5										
1e-8	4	1.6e5	1.0e5	3.4e5	3.9e4						1e-8										
$f_5$ in 5-D, N=15, mFE=106					$f_5$ in 20-D, N=15, mFE=410					$f_6$ in 5-D, N=15, mFE=2650					$f_6$ in 20-D, N=15, mFE=24422						
$\Delta f$	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	
10	15	4.8e1	4.2e1	5.4e1	4.8e1	15	2.5e2	2.3e2	2.7e2	2.5e2	10	15	3.2e2	2.6e2	3.9e2	3.2e2	15	2.2e3	2.1e3	2.3e3	2.2e3
1	15	6.6e1	6.0e1	7.2e1	6.6e1	15	3.0e2	2.8e2	3.2e2	3.0e2	1	15	5.3e2	4.7e2	6.1e2	5.3e2	15	3.4e3	3.2e3	3.5e3	3.4e3
1e-1	15	6.8e1	6.2e1	7.4e1	6.8e1	15	3.1e2	2.9e2	3.3e2	3.1e2	1e-1	15	7.5e2	6.8e2	8.3e2	7.5e2	15	4.6e3	4.4e3	4.7e3	4.6e3
1e-3	15	6.9e1	6.4e1	7.5e1	6.9e1	15	3.1e2	2.9e2	3.3e2	3.1e2	1e-3	15	1.3e3	1.2e3	1.3e3	1.3e3	15	7.0e3	6.8e3	7.2e3	7.0e3
1e-5	15	6.9e1	6.4e1	7.5e1	6.9e1	15	3.1e2	2.9e2	3.3e2	3.1e2	1e-5	15	1.7e3	1.6e3	1.7e3	1.7e3	15	1.0e4	9.3e3	1.1e4	1.0e4
1e-8	15	6.9e1	6.4e1	7.5e1	6.9e1	15	3.1e2	2.9e2	3.3e2	3.1e2	1e-8	15	2.2e3	2.1e3	2.2e3	2.2e3	15	1.4e4	1.3e4	1.5e4	1.4e4
$f_7$ in 5-D, N=15, mFE=3288					$f_7$ in 20-D, N=15, mFE=46966					$f_8$ in 5-D, N=15, mFE=5788					$f_8$ in 20-D, N=15, mFE=28922						
$\Delta f$	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	
10	15	1.4e2	1.2e2	1.7e2	1.4e2	15	3.1e3	2.6e3	3.6e3	3.1e3	10	15	2.6e2	2.1e2	3.1e2	2.6e2	15	1.1e4	1.1e4	1.1e4	1.1e4
1	15	5.8e2	5.0e2	6.6e2	5.8e2	15	1.7e4	1.5e4	2.0e4	1.7e4	1	15	1.6e3	1.3e3	1.9e3	1.6e3	15	2.1e4	2.1e4	2.1e4	2.1e4
1e-1	15	1.4e3	1.2e3	1.7e3	1.4e3	15	2.3e4	2.0e4	2.6e4	2.3e4	1e-1	15	2.3e3	2.1e3	2.5e3	2.3e3	15	2.3e4	2.2e4	2.3e4	2.3e4
1e-3	15	1.9e3	1.6e3	2.1e3	1.9e3	15	2.5e4	2.2e4	2.8e4	2.5e4	1e-3	15	2.7e3	2.5e3	2.9e3	2.7e3	15	2.4e4	2.4e4	2.5e4	2.4e4
1e-5	15	1.9e3	1.6e3	2.1e3	1.9e3	15	2.5e4	2.2e4	2.8e4	2.5e4	1e-5	15	2.8e3	2.6e3	3.1e3	2.8e3	15	2.5e4	2.5e4	2.6e4	2.5e4
1e-8	15	2.0e3	1.8e3	2.3e3	2.0e3	15	2.5e4	2.2e4	2.9e4	2.5e4	1e-8	15	3.1e3	2.9e3	3.3e3	3.1e3	15	2.6e4	2.6e4	2.7e4	2.6e4
$f_9$ in 5-D, N=15, mFE=4914					$f_9$ in 20-D, N=15, mFE=55924					$f_{10}$ in 5-D, N=15, mFE=4042					$f_{10}$ in 20-D, N=15, mFE=30386						
$\Delta f$	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	
10	15	3.4e2	1.9e2	4.9e2	3.4e2	15	1.2e4	1.1e4	1.2e4	1.2e4	10	15	2.6e3	2.5e3	2.7e3	2.6e3	15	2.3e4	2.2e4	2.4e4	2.3e4
1	15	1.4e3	1.2e3	1.6e3	1.4e3	15	2.2e4	1.9e4	2.4e4	2.2e4	1	15	2.8e3	2.7e3	2.9e3	2.8e3	15	2.5e4	2.4e4	2.6e4	2.5e4
1e-1	15	2.1e3	2.0e3	2.3e3	2.1e3	15	2.4e4	2.1e4	2.6e4	2.4e4	1e-1	15	2.9e3	2.8e3	3.0e3	2.9e3	15	2.6e4	2.6e4	2.7e4	2.6e4
1e-3	15	2.5e3	2.3e3	2.7e3	2.5e3	15	2.5e4	2.3e4	2.7e4	2.5e4	1e-3	15	3.1e3	3.0e3	3.2e3	3.1e3	15	2.7e4	2.7e4	2.8e4	2.7e4
1e-5	15	2.7e3	2.5e3	2.8e3	2.7e3	15	2.6e4	2.4e4	2.8e4	2.6e4	1e-5	15	3.3e3	3.2e3	3.3e3	3.3e3	15	2.8e4	2.7e4	2.8e4	2.8e4
1e-8	15	2.9e3	2.8e3	3.1e3	2.9e3	15	2.7e4	2.5e4	2.9e4	2.7e4	1e-8	15	3.5e3	3.4e3	3.6e3	3.5e3	15	2.9e4	2.8e4	2.9e4	2.9e4
$f_{11}$ in 5-D, N=15, mFE=4226					$f_{11}$ in 20-D, N=15, mFE=31418					$f_{12}$ in 5-D, N=15, mFE=9042					$f_{12}$ in 20-D, N=15, mFE=58382						
$\Delta f$	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	
10	15	2.2e3	1.9e3	2.5e3	2.2e3	15	2.0e4	1.9e4	2.0e4	2.0e4	10	15	1.3e3	9.4e2	1.7e3	1.3e3	15	6.1e3	4.0e3	8.2e3	6.1e3
1	15	2.9e3	2.8e3	3.0e3	2.9e3	15	2.2e4	2.2e4	2.3e4	2.2e4	1	15	2.9e3	2.6e3	3.2e3	2.9e3	15	1.3e4	9.9e3	1.6e4	1.3e4
1e-1	15	3.2e3	3.1e3	3.3e3	3.2e3	15	2.3e4	2.3e4	2.4e4	2.3e4	1e-1	15	3.4e3	2.9e3	3.8e3	3.4e3	15	1.8e4	1.4e4	2.1e4	1.8e4
1e-3	15	3.4e3	3.4e3	3.5e3	3.4e3	15	2.5e4	2.4e4	2.5e4	2.5e4	1e-3	15	3.9e3	3.4e3	4.6e3	3.9e3	15	2.5e4	2.4e4	2.8e4	2.5e4
1e-5	15	3.6e3	3.5e3	3.7e3	3.6e3	15	2.6e4	2.5e4	2.6e4	2.6e4	1e-5	15	4.5e3	3.8e3	5.2e3	4.5e3	15	3.0e4	2.7e4	3.3e4	3.0e4
1e-8	15	3.8e3	3.8e3	3.9e3	3.8e3	15	2.7e4	2.6e4	2.7e4	2.7e4	1e-8	15	5.1e3	4.3e3	5.9e3	5.1e3	15	3.5e4	3.2e4	3.8e4	3.5e4
$f_{13}$ in 5-D, N=15, mFE=6308					$f_{13}$ in 20-D, N=15, mFE=105488					$f_{14}$ in 5-D, N=15, mFE=3634					$f_{14}$ in 20-D, N=15, mFE=31850						
$\Delta f$	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	
10	15	1.2e3	8.5e2	1.6e3	1.2e3	15	3.8e3	2.6e3	5.0e3	3.8e3	10	15	1.6e1	1.2e1	2.0e1	1.6e1	15	2.5e2	2.3e2	2.7e2	2.5e2
1	15	2.1e3	1.7e3	2.4e3	2.1e3	15	1.1e4	8.4e3	1.3e4	1.1e4	1	15	1.2e2	1.1e2	1.4e2	1.2e2	15	6.1e2	5.8e2	6.5e2	6.1e2
1e-1	15	3.0e3	2.8e3	3.2e3	3.0e3	15	2.1e4	1.7e4	2.5e4	2.1e4	1e-1	15	2.1e2	1.9e2	2.3e2	2.1e2	15	9.8e2	9.4e2	1.0e3	9.8e2
1e-3	15	3.7e3	3.6e3	3.8e3	3.7e3	15	3.3e4	2.9e4	3.6e4	3.3e4	1e-3	15	7.4e2	6.3e2	8.5e2	7.4e2	15	6.4e3	6.1e3	6.7e3	6.4e3
1e-5	15	4.4e3	4.3e3	4.5e3	4.4e3	15	4.7e4	4.4e4	5.0e4	4.7e4	1e-5	15	2.4e3	2.3e3	2.5e3	2.4e3	15	1.7e4	1.6e4	1.7e4	1.7e4
1e-8	15	5.5e3	5.4e3	5.7e3	5.5e3	15	6.2e4	5.7e4	6.8e4	6.2e4	1e-8	15	3.3e3	3.3e3	3.4e3	3.3e3	15	3.0e4	2.9e4	3.0e4	3.0e4
$f_{15}$ in 5-D, N=15, mFE=50430					$f_{15}$ in 20-D, N=15, mFE=200340					$f_{16}$ in 5-D, N=15, mFE=32578					$f_{16}$ in 20-D, N=15, mFE=200340						
$\Delta f$	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	#	ERT	10%	90%	RT <sub>succ</sub>	
10	15	8.3e2	5.1e2	1.2e3	8.3e2	15	3.3e4	2.8e4	3.8e4	3.3e4	10	15	2.6e2	2.0e2	3.1e2	2.6e2	15	4.3e3	2.3e3	6.3e3	4.3e3
1	15</																				



**Figure 2: Empirical cumulative distribution functions (ECDFs), plotting the fraction of trials versus running time (left subplots) or versus  $\Delta f$  (right subplots). The thick red line represents the best achieved results. Left subplots: ECDF of the running time (number of function evaluations), divided by search space dimension  $D$ , to fall below  $f_{\text{opt}} + \Delta f$  with  $\Delta f = 10^k$ , where  $k$  is the first value in the legend. Right subplots: ECDF of the best achieved  $\Delta f$  divided by  $10^k$  (upper left lines in continuation of the left subplot), and best achieved  $\Delta f$  divided by  $10^{-8}$  for running times of  $D, 10D, 100D \dots$  function evaluations (from right to left cycling black-cyan-magenta). Top row: all results from all functions; second row: separable functions; third row: misc. moderate functions; fourth row: ill-conditioned functions; fifth row: multi-modal functions with adequate structure; last row: multi-modal functions with weak structure. The legends indicate the number of functions that were solved in at least one trial. FEvals denotes number of function evaluations,  $D$  and DIM denote search space dimension, and  $\Delta f$  and Df denote the difference to the optimal function value.**

modal separable functions as expected. Its performances on multimodal functions, even separable ones such as  $f_3$  and  $f_4$ , are limited though. Whereas for multimodal functions increasing the maximum number of function evaluations is likely to improve the performances of the algorithm, this should not be the case for  $f_{24}$ . For the timing experiment, the proposed algorithm was run on  $f_8$  and restarted until at least 30 seconds have passed (according to Figure 2 in [3]). The experiments were conducted with an Intel Core 2 6700 processor (2.66GHz) with Matlab R2008a on Linux 2.6.24.7. The results were 15, 13, 11, 9.7, 9.9, and  $13 \times 10^{-5}$  seconds per function evaluations in dimension 2, 3, 5, 10, 20, and 40 respectively.

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