

*Benchmarking IPOP-CMA-ES-TPA and  
IPOP-CMA-ES-MSR on the BBOB Noiseless  
Testbed*

**Asma Atamna**

TAO Team

Inria - LRI - University of Paris-Sud

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# Outline

- 1 Motivation
- 2 Testbed Overview
- 3 Algorithms
  - The  $(\mu/\mu, \lambda)$ -ES
  - CMA-ES-TPA
  - CMA-ES-MSR
  - CMA-ES-CSA
- 4 Results
  - Experimental Setting
  - ERT vs. Dimension
  - ECDFs
- 5 Discussion

# Motivation

- Benchmark two relatively new step-size adaptation mechanisms on the BBOB noiseless testbed
  - Covariance Matrix Adaptation Evolution Strategy with Two-Point step-size Adaptation ([CMA-ES-TPA](#))
  - Covariance Matrix Adaptation Evolution Strategy with Median Success Rule ([CMA-ES-MSR](#))
- Restarts
  - [IPOP](#): Increase POPulation size by a factor of 2
- Compare [CMA-ES-TPA](#) and [CMA-ES-MSR](#) to state-of-the-art [CMA-ES-CSA](#) (Covariance Matrix Adaptation Evolution Strategy with Cumulative Step-size Adaptation)

# Testbed Overview

24 functions, 5 categories

- **Separable:** sphere, separable ellipsoid, separable Rastrigin, Bueche-Rastrigin, linear slope
- **Moderate:** attractive sector, step-ellipsoid, Rosenbrock, rotated Rosenbrock
- **Ill-conditioned:** ellipsoid, discus, bent cigar, sharp ridge, sum of different powers
- **Multi-modal:** Rastrigin, Weierstrass, Schaffer F7 with condition 10, Schaffer F7 with condition 1000, Griewank-Rosenbrock F8F2
- **Weakly structured multi-modal:** Schwefel, Gallagher 101 peaks, Gallagher 21 peaks, Katsuuras, Lunacek bi-Rastrigin

# The $(\mu/\mu, \lambda)$ -ES

$\lambda$ : population size

$\mu$ : number of parents

$'$ : non-elitist selection

At time step  $t$

- Sample  $\lambda$  offspring,  $\mathbf{X}_t^1, \dots, \mathbf{X}_t^\lambda$  according to

$$\mathbf{X}_t^i = \mathbf{X}_t + \sigma_t \mathcal{N}_t^i(0, \mathbf{C}_t)$$

$i = 1, \dots, \lambda$ ,  $\mathcal{N}_t^i(0, \mathbf{C}_t)$  is the multivariate normal distribution with mean 0 and covariance matrix  $\mathbf{C}_t$ ,  $\sigma_t$  is the step-size

- Select the  $\mu$  best offspring fitness-wise and recombine them according to

$$\mathbf{X}_{t+1} = \sum_{i=1}^{\mu} w_i \mathbf{X}_t^{i:\lambda}$$

$\mathbf{X}_t^{i:\lambda}$  is the  $i$ th best offspring,  $w_i$  are positive weights

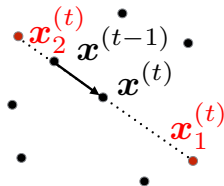
- Update  $\sigma_t$ ,  $\mathbf{C}_t$

# CMA-ES-TPA

- Sample the first two offspring,  $\mathbf{X}_t^1$  and  $\mathbf{X}_t^2$ , along the shift vector from  $\mathbf{X}_{t-1}$  to  $\mathbf{X}_t$ , as a mirrored pair, symmetric to  $\mathbf{X}_t$ , according to

$$\mathbf{X}_t^{1,2} = \mathbf{X}_t \pm \sigma_t \|\mathcal{N}_t(0, \mathbf{I})\| \frac{\mathbf{X}_t - \mathbf{X}_{t-1}}{\|\mathbf{X}_t - \mathbf{X}_{t-1}\|}$$

$\mathbf{I}$ : identity matrix



# CMA-ES-TPA

- If  $\mathbf{X}_t^1$  is better than  $\mathbf{X}_t^2$ , increase  $\sigma_t$ . Otherwise, decrease  $\sigma_t$

$$s_t = (1 - c_\sigma)s_{t-1} + c_\sigma \frac{\text{rank}(\mathbf{X}_t^2) - \text{rank}(\mathbf{X}_t^1)}{\lambda - 1}$$

$$\sigma_{t+1} = \sigma_t \exp\left(\frac{s_t}{d_\sigma}\right)$$

$s_0 = 0$ ,  $c_\sigma = 0.3$ ,  $d_\sigma = \sqrt{D}$ ,  $D$  is the dimension of the search space

# CMA-ES-MSR

- Generalization of the 1/5th success rule to the case of  $(\mu/\mu, \lambda)$ -ES
- **Success:** the median offspring of the current population,  $\mathbf{X}_t^{m(\lambda)}$ , is better than the  $j$ th best individual of the previous population,  $\mathbf{X}_{t-1}^{j:\lambda}$
- $j$ : chosen such that the median success probability is 1/2 on the sphere with optimal step-size
- If  $\mathbf{X}_t^{m(\lambda)}$  is better than  $\mathbf{X}_{t-1}^{j:\lambda}$ , increase  $\sigma_t$ . Otherwise, decrease  $\sigma_t$

$$s_t = (1 - c_\sigma)s_{t-1} + c_\sigma \frac{2}{\lambda} \left( K_{\text{succ}} - \frac{\lambda}{2} \right)$$

$$\sigma_{t+1} = \sigma_t \exp\left(\frac{s_t}{d_\sigma}\right)$$

$K_{\text{succ}}$  is the number of successful offspring,  $s_0 = 0$ ,  $c_\sigma = 0.3$ ,  
 $d_\sigma = 2 - 2/D$



# CMA-ES-CSA

- Record the path (consecutive steps) taken by the algorithm

$$\mathbf{p}_{t+1} = (1 - c_\sigma)\mathbf{p}_t + \sqrt{c_\sigma(2 - c_\sigma) / \sum_{k=1}^{\mu} w_k^2} \sum_{k=1}^{\mu} w_k \mathbf{z}_t^{k:\lambda}$$

$\mathbf{z}_t^{k:\lambda}$ : step corresponding to the  $k$ th best offspring,

$$\mathbf{x}_t^{k:\lambda} = \mathbf{X}_t + \sigma_t \mathbf{z}_t^{k:\lambda}$$

- If  $\mathbf{p}_t$  is “too long”, increase  $\sigma_t$ . Otherwise, decrease  $\sigma_t$

$$\sigma_{t+1} = \sigma_t \exp^{c_\sigma/d} \left( \frac{\|\mathbf{p}_{t+1}\|}{\mathbb{E}\|\mathcal{N}(0, \mathbf{I})\|} - 1 \right)$$

$$c_\sigma = \frac{1 / \sum_{k=1}^{\mu} w_k^2 + 2}{1 / \sum_{k=1}^{\mu} w_k^2 + D + 3}$$

# Experimental Setting

- Maximum budget:  $10^5 \times D$
- Tested dimensions: 2, 3, 5, 10, 20, 40
- Maximum number of restarts: 9
- $\mathbf{X}_0 \sim \mathcal{U}[-4, 4]^D$
- $\sigma_0 = 2.5$
- Source code: [cma 1.1.06](#)
- Default parameters
  - $\lambda = 4 + \lfloor 3 \ln D \rfloor$
  - $\mu = \lambda/2$

# ERT vs. Dimension

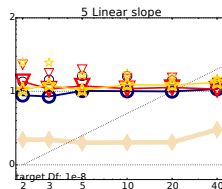
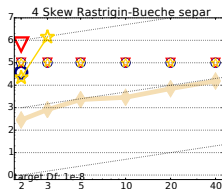
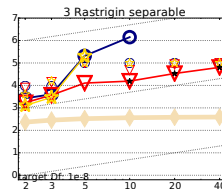
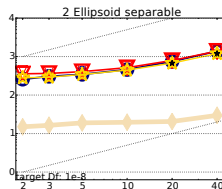
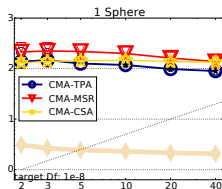
- Expected Running Time

$$\text{ERT}(f_{\text{target}}) = \frac{\#\text{FEs}(f_{\text{best}} \geq f_{\text{target}})}{\#\text{succ}}$$

- $f_{\text{target}} = f_{\text{opt}} + \Delta f$
- $\Delta f = 10^{-8}$

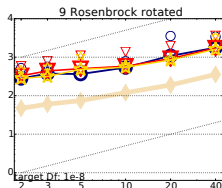
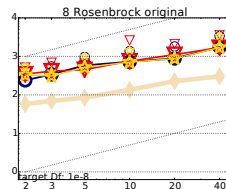
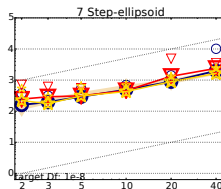
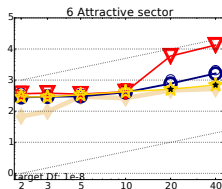
# ERT vs. Dimension

## Separable functions



# ERT vs. Dimension

## Moderate functions



# ERT vs. Dimension

Single runs of CMA-MSR, CMA-TPA, and CMA-CSA on the attractive sector in 20D

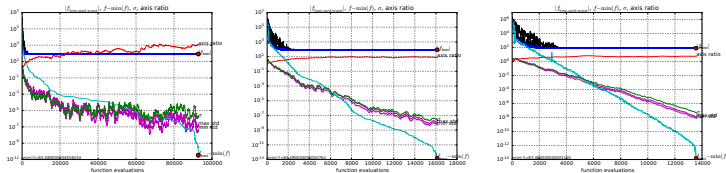
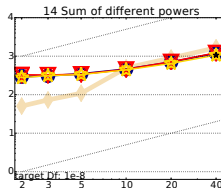
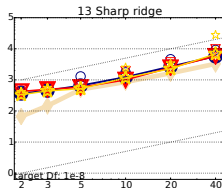
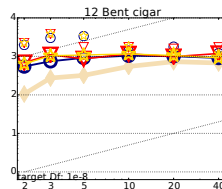
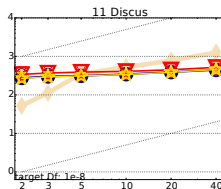
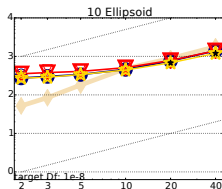


Figure: Left: CMA-ES-MSR, middle: CMA-ES-TPA, right: CMA-ES-CSA

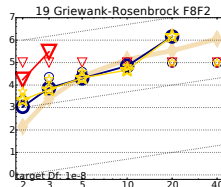
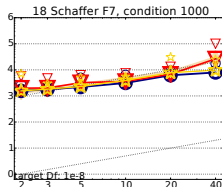
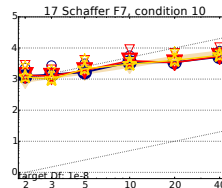
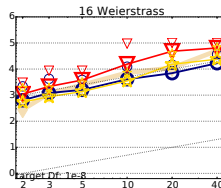
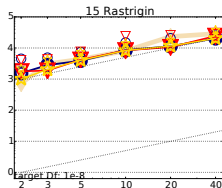
# ERT vs. Dimension

## Ill-conditioned functions



# ERT vs. Dimension

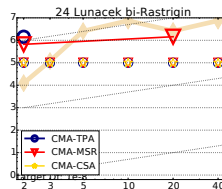
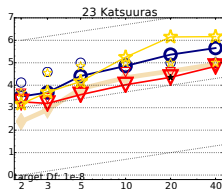
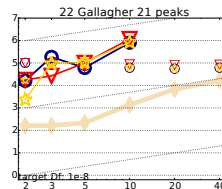
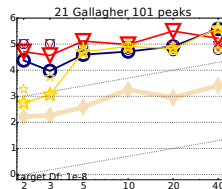
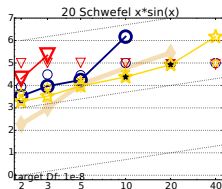
## Multi-modal functions





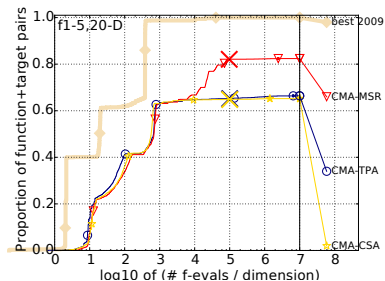
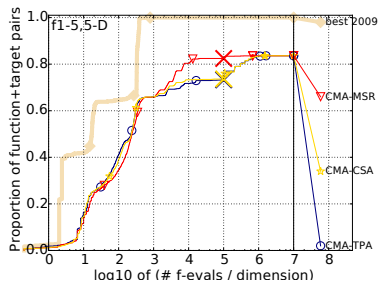
# ERT vs. Dimension

## Weakly structured multi-modal functions



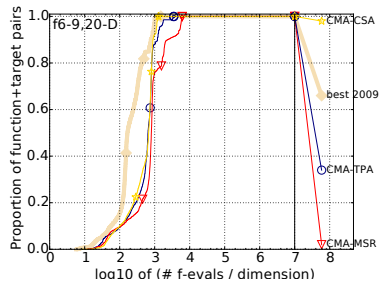
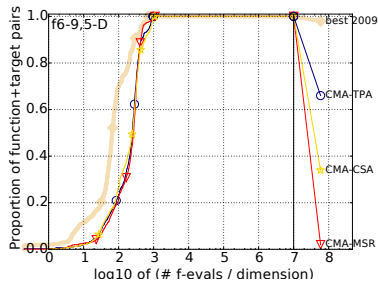
# ECDFs

## Separable functions



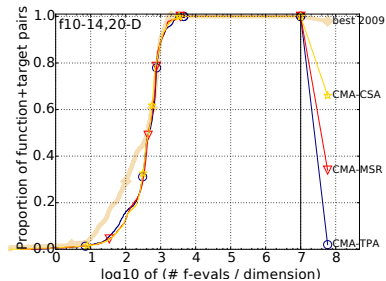
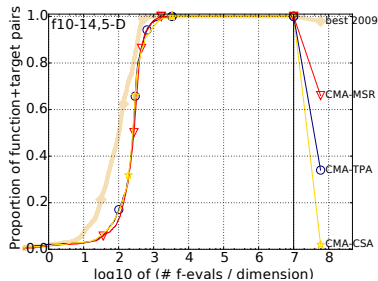
# ECDFs

## Moderate functions



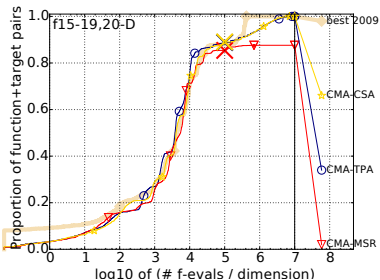
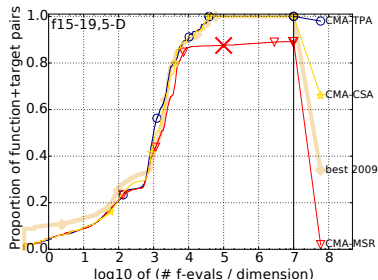
# ECDFs

## III-conditioned functions



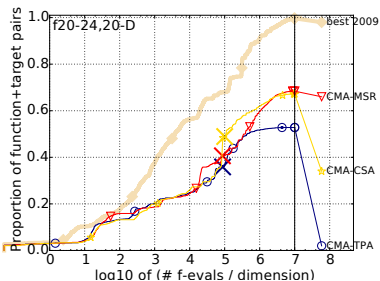
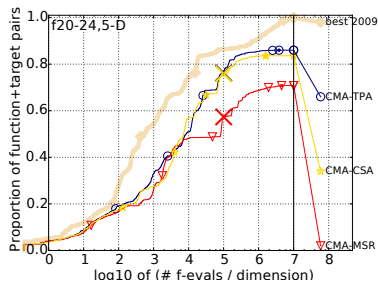
# ECDFs

## Multi-modal functions



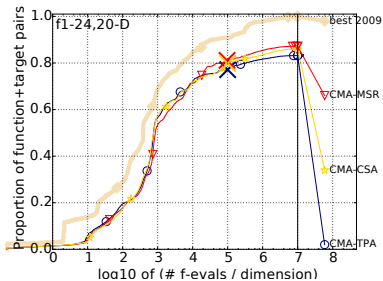
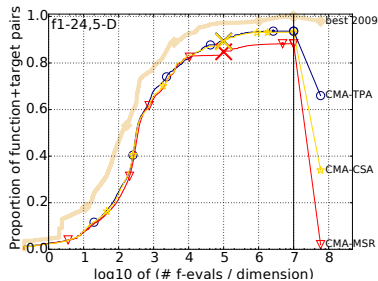
# ECDFs

## Weakly structured multi-modal functions



# ECDFs

## All functions



# Discussion

- As expected by design, the three algorithms have comparable performance on most of the functions
- **However**, significant differences were observed: attractive sector, separable Rastrigin
- The influence of the step-size is more important on multi-modal and weakly structured multi-modal functions
- CMA-ES-CSA and CMA-ES-TPA have similar behavior
- Different performance on separable and rotated Rastrigin: different functions



Thank You