# TRIBES

A parameter-free particle swarm optimization algorithm

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# Presentation outline

- **Particle swarm optimization**
- **Why a parameter-free algorithm ?**
- **TRIBES,** the first parameter-free PSO algorithm
- **CEC'05 testing procedure**
- **Numerical results**
- **Conclusions and perspectives**

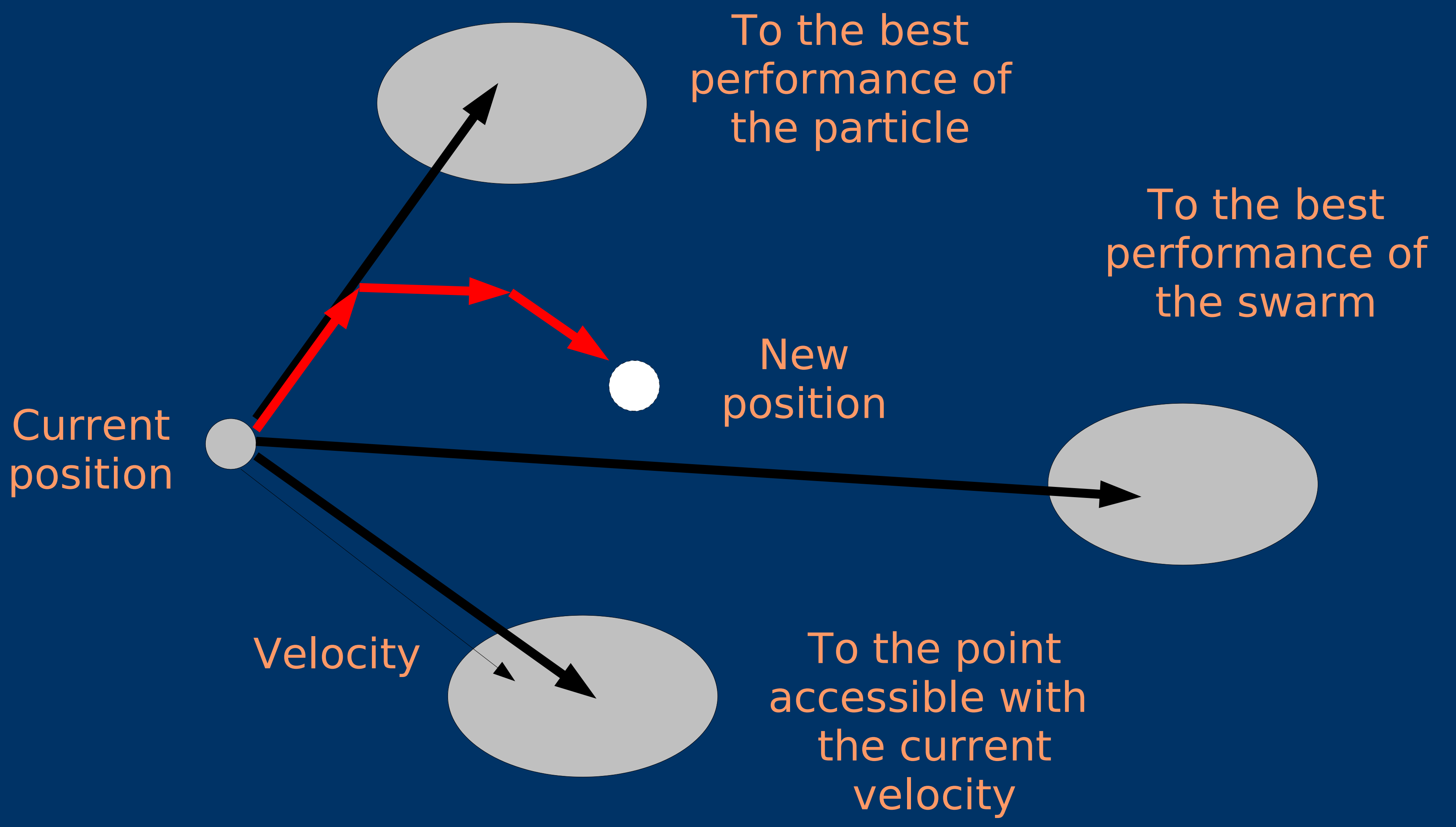
# **Particle Swarm Optimization** (1/4)

# **Particle Swarm Optimization** (2/4)

- **Stochastic method**
- **Biological inspiration** (fish schooling and bird flocking)
- **Principle** :
  - Generation of a swarm of particles in the search space
  - A fitness is associated to each particle
  - Particles move according to their own experience and that of the swarm
  - Convergence made possible by the cooperation between particles

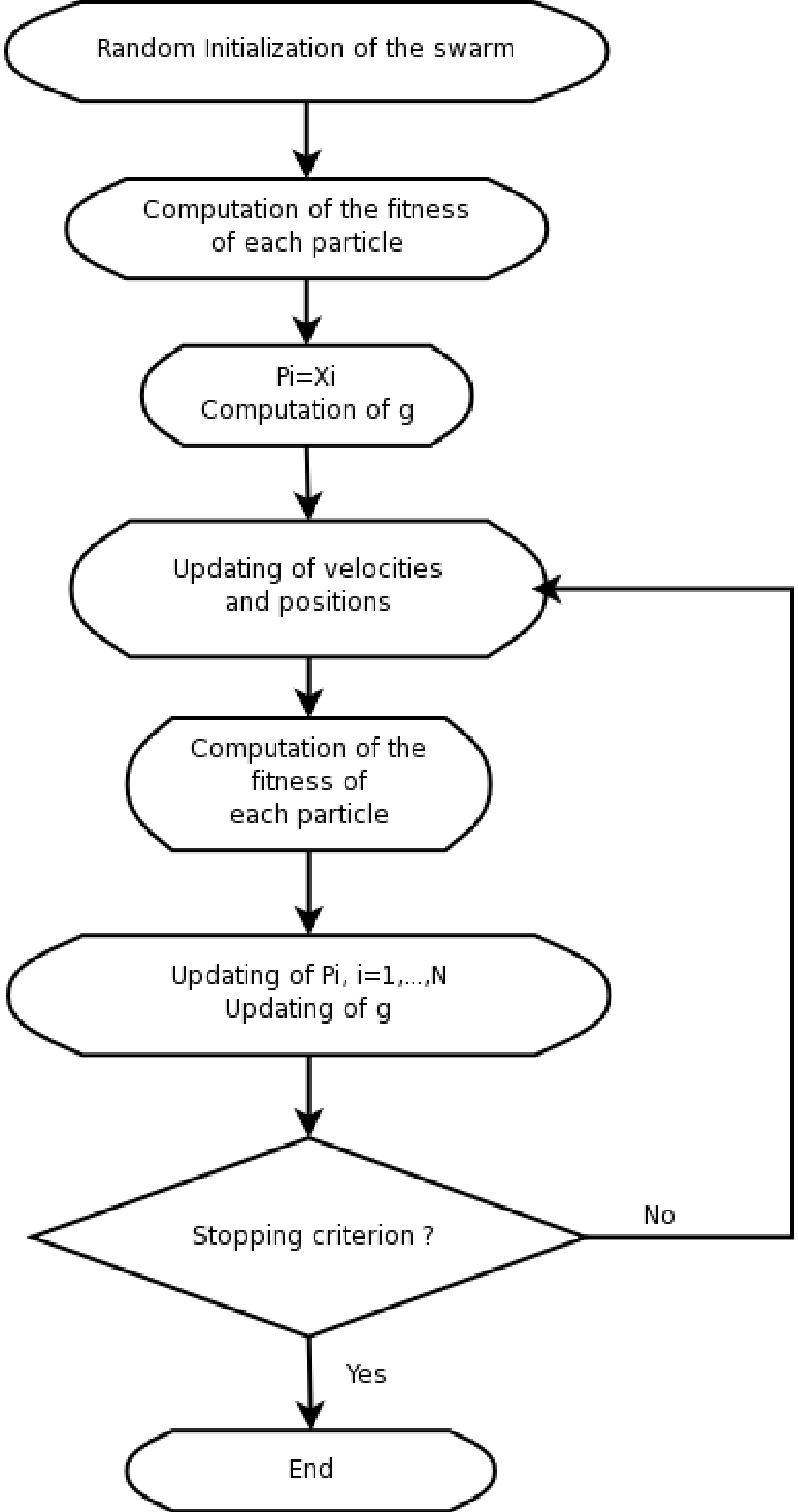
# Particle Swarm Optimization (3/4)

## Strategy of displacement



# Particle Swarm Optimization (4/4)
## Algorithm

- **Particles randomly initialized in the search space**
- **2 stopping criteria :**
  - Accuracy
  - Number of evaluations of the objective function



# Why a parameter-free algorithm ?

- Common problem among all metaheuristics
- Algorithms very dependent of parameters values
- Time consuming to find the optimal value of a parameter
- The tendency is to reduce the number of "free" parameters

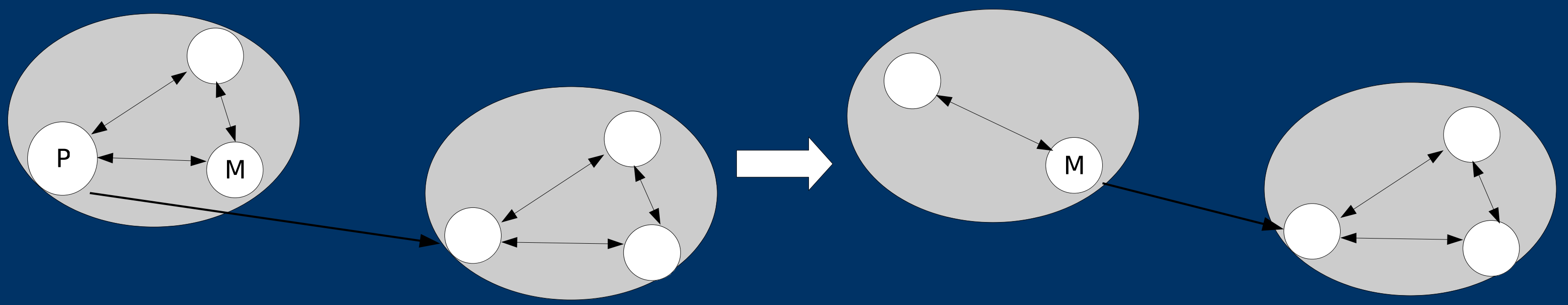
# **TRIBES** (1/4)

- **A parameter-free particle swarm optimization algorithm**
- **Principles :**
  - Swarm divided in "tribes"
  - At the beginning, the swarm is composed of only one particle
  - According to tribes' behaviors, particles are added or removed
  - According to the performances of the particles, their strategies of displacement are adapted

→ **Adaptation of the swarm according to the performances of the particles**

# **Tribes** (2/4)
## Structural adaptations

- **Definition of a status for each tribe** : *good*, *neutral* or bad
- **Definition of a status for each particle** : good or neutral
- ***Removal of a particle*** *: worst* particle of a *good* tribe




- **Generation of a particle** : improvement of performances of a *bad* tribe

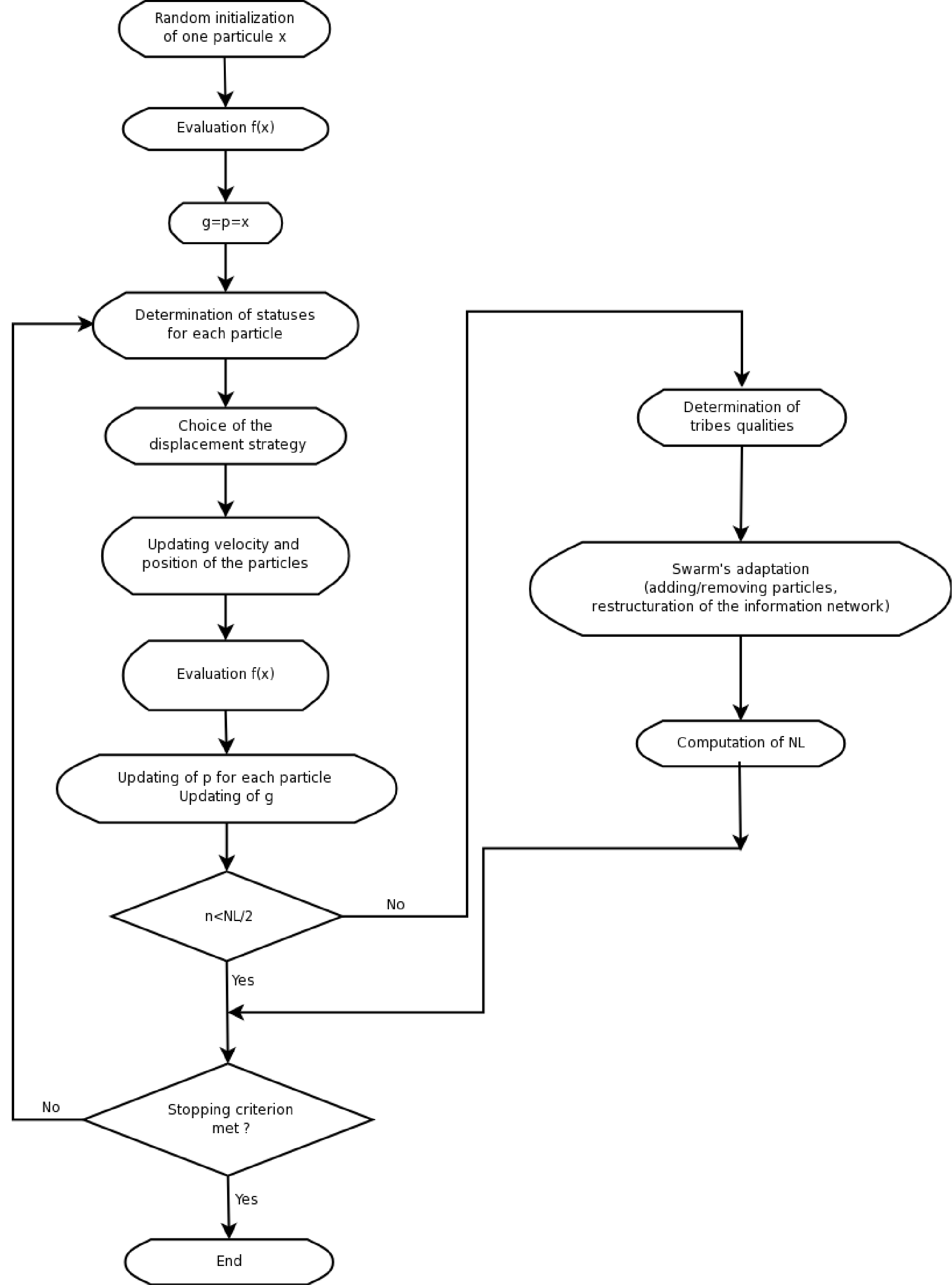
# **Tribes** (3/4)
## Behavioral adaptations

- **3 possibilities of variations between 2 iterations** :
  - Improvement of the performance (+)
  - Statu quo (=)
  - Deterioration of the performance (-)
- **Memorization of the 2 last variations**
- **Choice of the strategy of displacement according to the 2 last variations**

| *Gathered statuses* | *Strategy of displacement* |
|---|---|
| (= +) (+ +) | local by independent gaussians |
| (+ =) (- +) | disturbed pivot |
| (- -) (= -) (+ -) (- =) (= =) | pivot |

# Tribes (4/4)
## Algorithm

- **structural adaptations must not occur at each iteration**
- **$N_L$** : information links number at the moment of the last adaptation
- **n** : number of iterations since the last swarm's adaptation



# CEC'05 testing procedure (1/5)

- Defined during th IEEE Congress on Evolutionary Computation 2005
- 2 tests :
  - Error values for a fixed number of evaluations of the objective function
  - Number of evaluations of the objective function for a fixed accuracy level
- A benchmark of 25 functions
- Objective : standardizing tests performed on metaheuristics for continuous optimization in view of facilitating comparisons between competing algorithms

# CEC'05 testing procedure (2/5) Tests

- 1[rst] test : study of the error
  - D dimension of the problem
  - 25 runs
  - Single stopping criterion MaxEval=10000.D
  - Recording of $|f(x)-f(x_{opt})|$ for each run at different numbers of evaluations of the objective function
  - Building of Convergence Graphs

- 2[nd] test : study of the number of function evaluations
  - Fixed accuracy level for each function of the benchmark
  - Computation of *Success Rate* and *Performance Rate*

# CEC'05 testing procedure (3/5)
# *Success* and *Performance* rates

- ***Success rate***

$$\frac{number\ \ of\ \ successful\ \ runs}{total\ \ number\ \ of\ \ runs}$$

- ***Performance rate***

$$\frac{MaxEval_{mean}.total\ \ number\ \ of\ \ runs}{number\ \ of\ \ successful\ \ runs}$$

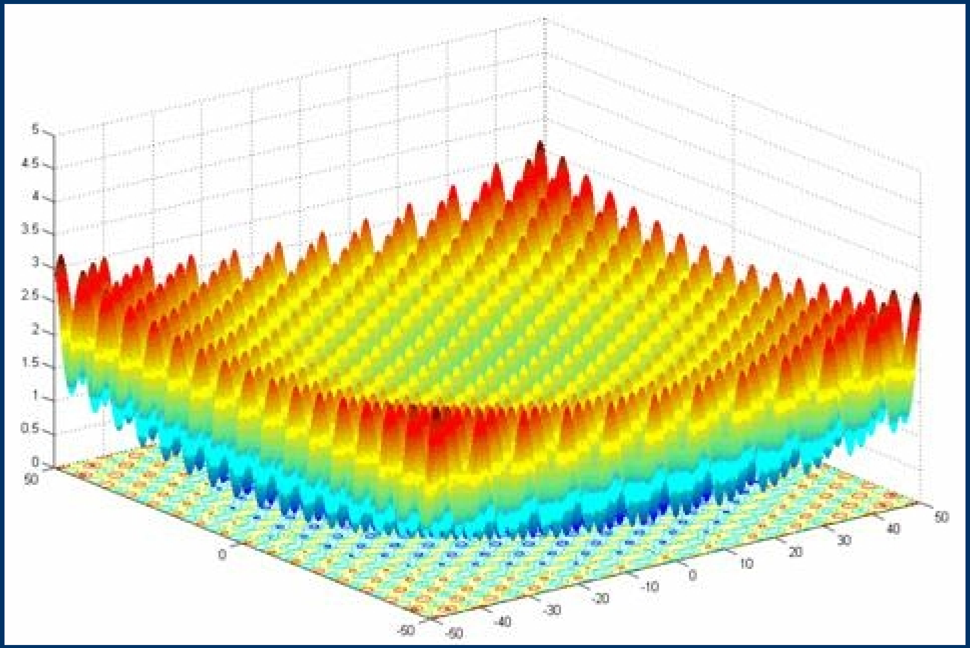
# CEC'05 testing procedure (4/5) Benchmark

- 25 unimodal or multimodal functions

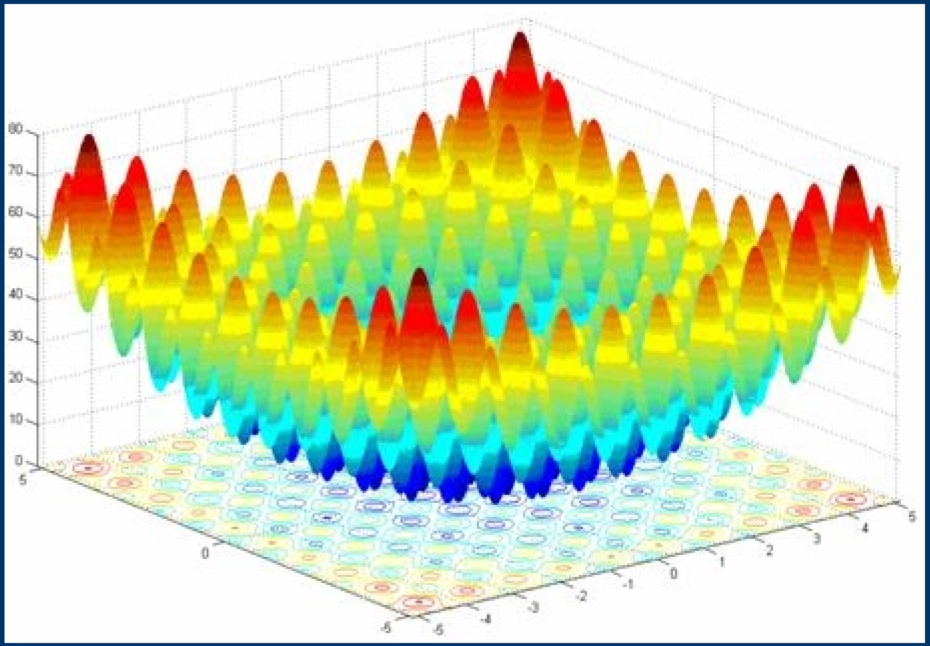
- Some characteristics :
  - Shifted
  - Rotated
  - Optimum on bounds

- Interest : Avoid particular cases which can be exploited by some algorithms

# CEC'05 testing procedure (5/5) Examples



Griewank Function (F7)



Rastrigin Function (F9)

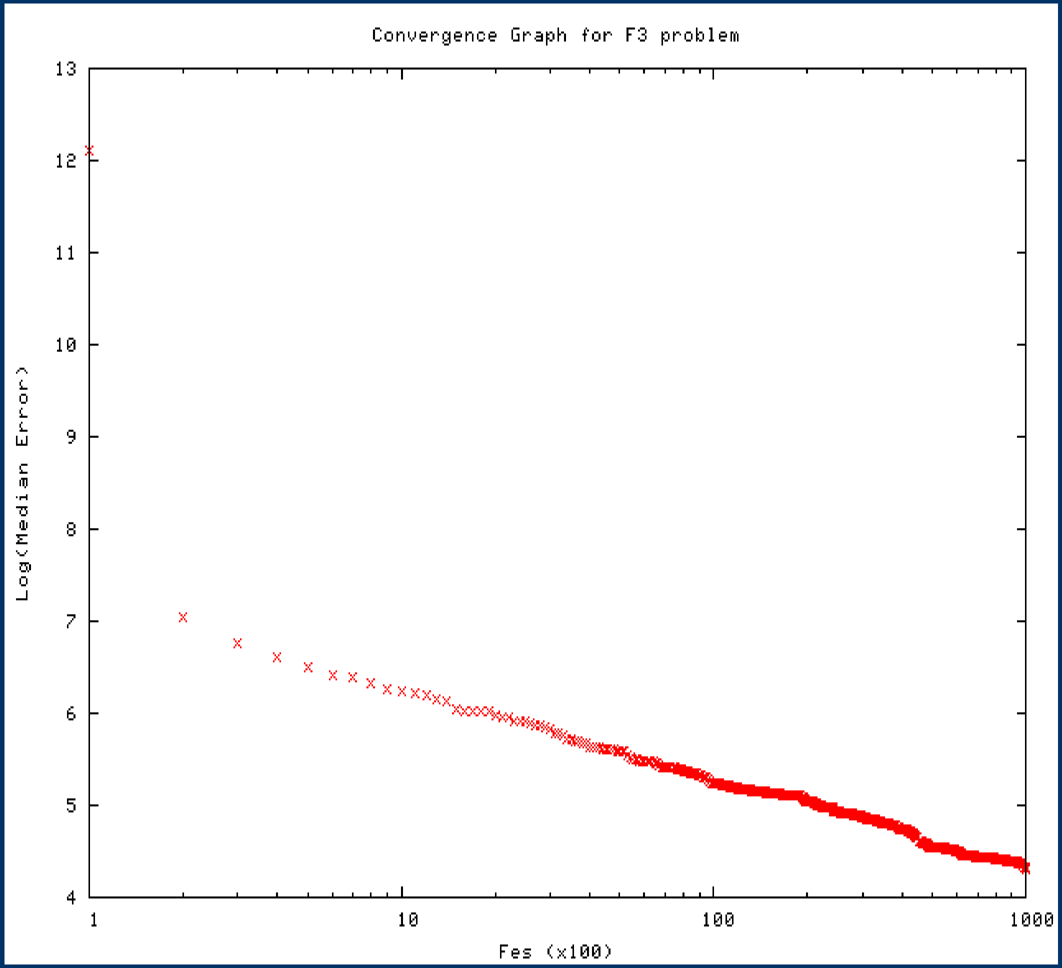
# Numerical results (1/5)
# 1rst test, Unimodal problems

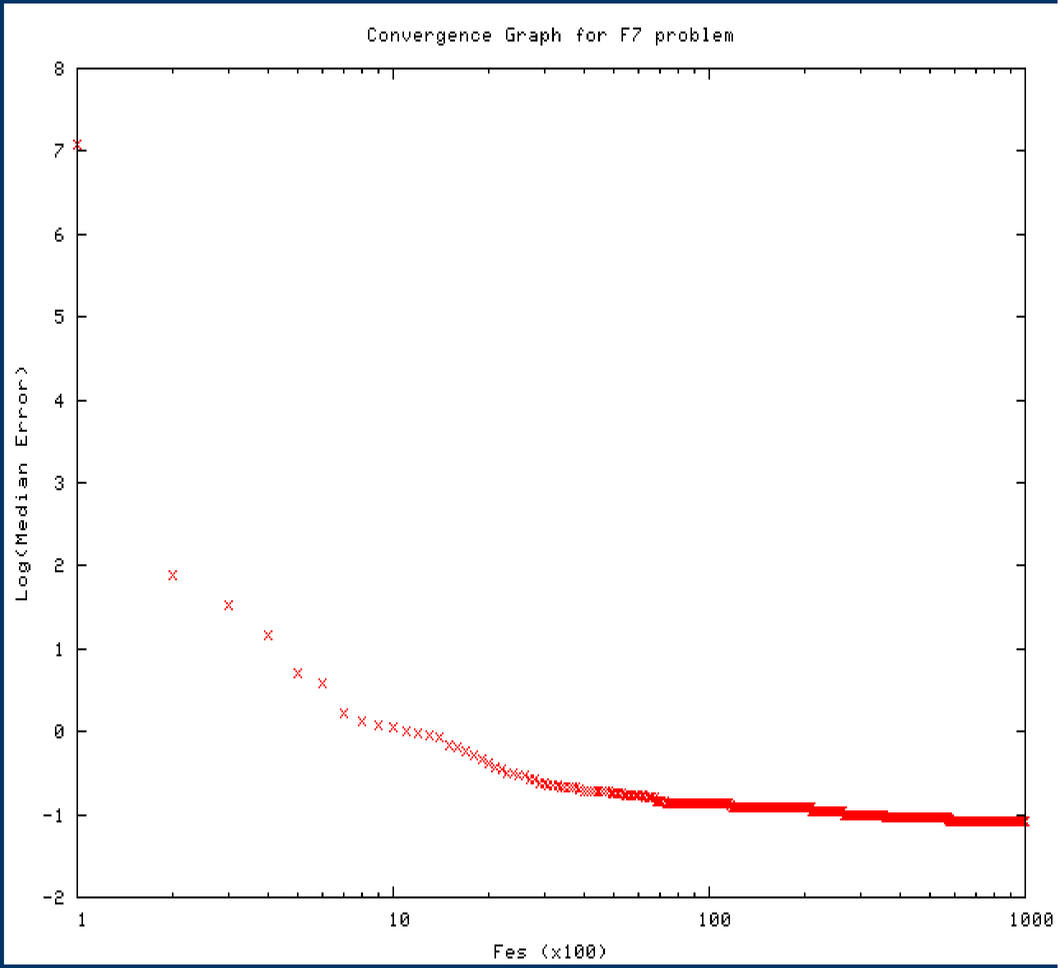
| | | F1 | F2 | F3 | F4 | F5 |
|---|---|---|---|---|---|---|
| D | 10 | | | | | |
| Fes=100000 | | | | | | |
| | 1st | 0 | 0 | 4597.106467 | 5.644608E-09 | 0 |
| | 7th | 0 | 0 | 13055.935128 | 8.671009E-09 | 1.136868E-13 |
| | 13th | 0 | 0 | 21110.612218 | 9.399173E-09 | 4.985168E-11 |
| | 19th | 0 | 0 | 29909.419575 | 9.703854E-09 | 3.866887E-09 |
| | 25th | 0 | 5.68E-14 | 80596.986396 | 9.961525E-09 | 4.225578E-04 |
| | Mean | 0 | 2.27E-015 | 26848.899836 | 8.536590E-09 | 1.755978E-05 |
| | Std dev | 0 | 1.11E-14 | 18773.347486 | 2.048813E-09 | 8.272286E-05 |

# Numerical results (2/5)
# 1rst test, Multimodal problems

| | | F6 | F7 | F8 | F9 | F10 | F11 |
|---|---|---|---|---|---|---|---|
| D | 10 | | | | | | |
| Fes=100000 | | | | | | | |
| | 1st | 0.004314 | 0.015287 | 0 | 2.984877 | 5.969754 | 2.792143 |
| | 7th | 0.541085 | 0.051984 | 2.84E-14 | 5.969754 | 9.098987 | 3.456094 |
| | 13th | 0.747254 | 0.073769 | 1.042691 | 7.959667 | 10.94454 | 4.158164 |
| | 19th | 1.103226 | 0.091044 | 19.93683 | 9.949586 | 12.934458 | 4.871277 |
| | 25th | 2.169582 | 0.201614 | 20.37673 | 16.914269 | 27.858783 | 6.097017 |
| | Mean | 0.85882 | 0.077474 | 7.222521 | 8.556642 | 12.118002 | 4.233992 |
| | Std dev | 0.570887 | 0.03942 | 9.199135 | 3.66922 | 4.660575 | 0.958315 |

# Numerical results (3/5)
# Convergence Graphs



# Numerical results (4/5)
# $2^{nd}$ test, Unimodal problems

| | Number of solved functions | Success rate | F1 | F2 | F3 | F4 | F5 |
|---|---|---|---|---|---|---|---|
| | | | 1000 | 2400 | 6500 | 2900 | 5900 |
| G-CMA-ES | 5 | 100% | 1.6 (25) | 1 (25) | 1 (25) | 1 (25) | 1 (25) |
| EDA | 5 | 98% | 10 (25) | 4.6 (25) | 2.5 (23) | 4.1 (25) | 4.2 (25) |
| DE | 5 | 96% | 29 (25) | 19.2 (25) | 18.5 (20) | 17.9 (25) | 6.9 (25) |
| L-CMA-ES | 5 | 86% | 1.7 (25) | 1.1 (25) | 1 (25) | 65.5 (7) | 1 (25) |
| BLX-GL50 | 4 | 80% | 19 (25) | 17.1 (25) | - | 14.5 (25) | 4.7 (25) |
| SPC-PNX | 4 | 80% | 6.7 (25) | 12.9 (25) | - | 10.7 (25) | 6.8 (25) |
| CoEVO | 4 | 80% | 23 (25) | 11.3 (25) | 6.8 (25) | 16.2 (25) | - |
| DMS-L-PSO | 4 | 76% | 12 (25) | 5 (25) | 1.8 (25) | - | 18.6 (20) |
| L-SaDE | 4 | 72% | 10 (25) | 4.2 (25) | 8 (16) | 15.9 (24) | - |
| BLX-MA | 3 | 59% | 12 (25) | 15.4 (25) | - | 25.9 (24) | - |
| K-PCX | 3 | 57% | 1 (25) | 1 (25) | - | 19.7 (21) | - |
| | | | | | | | |
| **TRIBES** | **4** | **80%** | **1.3 (25)** | **2.75 (25)** | **-** | **3.91 (25)** | **6,7 (25)** |

# Numerical results (5/5)
# $2^{nd}$ test, Multimodal problems

| | | | F6 | F7 | F8 | F9 | F10 | F11 |
|---|---|---|---|---|---|---|---|---|
| | Number of solved functions | Success rate | 7100 | 4700 | 59585 | 17000 | 55000 | 190000 |
| G-CMA-ES | 5 | 65% | 1.5 (25) | 1 (25) | - | 4.5 (19) | 1.2 (23) | 1.4 (6) |
| K-PCX | 3 | 45% | 9.6 (22) | - | - | 2.9 (24) | 1 (22) | - |
| L-SaDE | 3 | 37% | 6.6 (24) | 36.2 (6) | - | 1 (25) | - | - |
| DMS-L-PSO | 3 | 36% | 1.3 (25) | 126 (4) | - | 2.1 (25) | - | - |
| DE | 4 | 33% | 7.3 (25) | 255 (2) | - | 10.6 (11) | - | 1 (12) |
| L-CMA-ES | 1 | 33% | 7.7 (25) | 1.2 (25) | - | - | - | - |
| BLX-GL50 | 3 | 25% | 6.69 (25) | 12.3 (9) | - | 10 (3) | - | - |
| SPC-PNX | 3 | 16% | 1 (22) | 383 (1) | - | - | - | 5.8 (1) |
| BLX-MA | 1 | 12% | - | - | - | 5.7 (18) | - | - |
| EDA | 2 | 3% | - | 404 (1) | - | - | - | 2.9 (3) |
| CoEVO | 0 | 0 | - | - | - | - | - | - |
| | | | | | | | | |
| **TRIBES** | **4** | **41%** | **3.8 (25)** | **0.16 (25)** | **1 (10)** | **63 (2)** | **-** | **-** |

# *Conclusions and perspectives*

- **Competitive algorithm**
- **Parameter-free**

  → **No waste of time without loss of performance**

- **Possible improvements :**
  - Better choice of adaptation rules
  - More accurate strategies of displacement
  - Hybridization with an Estimation of Distribution Algorithm

  → **Better adaptation of the choices made to the specificity of the problem**

# Thanks for your attention

| Algorithm | Name | Reference |
|---|---|---|
| Hybrid Real-Coded Genetic Algorithm with Female and Male Differentiation | BLX-GL50 | [García-Martínez and Lozano, 2005] |
| Real-Coded Memetic Algorithm | BLX-MA | [Molina et al., 2005] |
| Real Parameter Optimization Using Mutation Step Co-evolution | CoEVO | [Posik (2005)] |
| Real-Parameter Optimization with Differential Evolution | DE | [Rönkkönen and Kukkonen, 2005] |
| Dynamic Multi-Swarm Particle Swarm Optimizer with Local Search | DMS-L-PSO | [Liang and Suganthan, 2005] |
| Simple Continuous EDA | EDA | [Yuan and Gallagher, 2005] |
| Restart CMA Evolution Strategy with Increasing Population Size | G-CMA-ES | [Auger et al., 2005a] |
| Population-Based, Steady-State Procedure for Real-Parameter Optimization | K-PCX | [Sinha et al., 2005] |
| Advanced Local Search Evolutionary Algorithm | L-CMA-ES | [Auger et al., 2005b] |
| Self-adaptive Differential Evolution Algorithm | L-SaDE | [Qin and Suganthan, 2005] |
| Steady-State Real-Parameter Genetic Algorithm | SPC-PNX | [Ballester et al., 2005] |

# Pivot strategy

$$X = c_1 . alea(H_p) + c_2 . alea(H_g)$$

$$c_1 = \frac{f(p)}{f(p) + f(g)}$$

$$c_2 = \frac{f(g)}{f(p) + f(g)}$$

**alea($H_p$) a point uniformly chosen in the hyper-sphere of center *p* and radius ||p-g||**

**alea($H_g$) a point uniformly chosen in the hyper-sphere of center *g* and radius ||p-g||**

# Disturbed pivot strategy

$$X = c_1 . alea(H_p) + c_2 . alea(H_g)$$

$$b = N(0, \frac{f(p) - f(g)}{f(p) + f(g)})$$

$$X = (1 + b) . X$$

# Local independent gaussians

$$X_j = g_j + alea_{normal}\left(g_j - X_j, \left\| g_j - X_j \right\|\right)$$