MÁSTER OFICIAL DE LA UNIVERSIDAD DE GRANADA

"SOFT COMPUTING Y SISTEMAS INTELIGENTES"

SF1. COMPUTACIÓN EVOLUTIVA Y ALGORITMOS BIOINSPIRADOS

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Tema 10. Algoritmos Basados en Evolución Diferencial (Diferential Evolution – DE)

A Snapshot on the use of Evolutionary Algorithms for Parameter Optimization: Milestones and Current Trends

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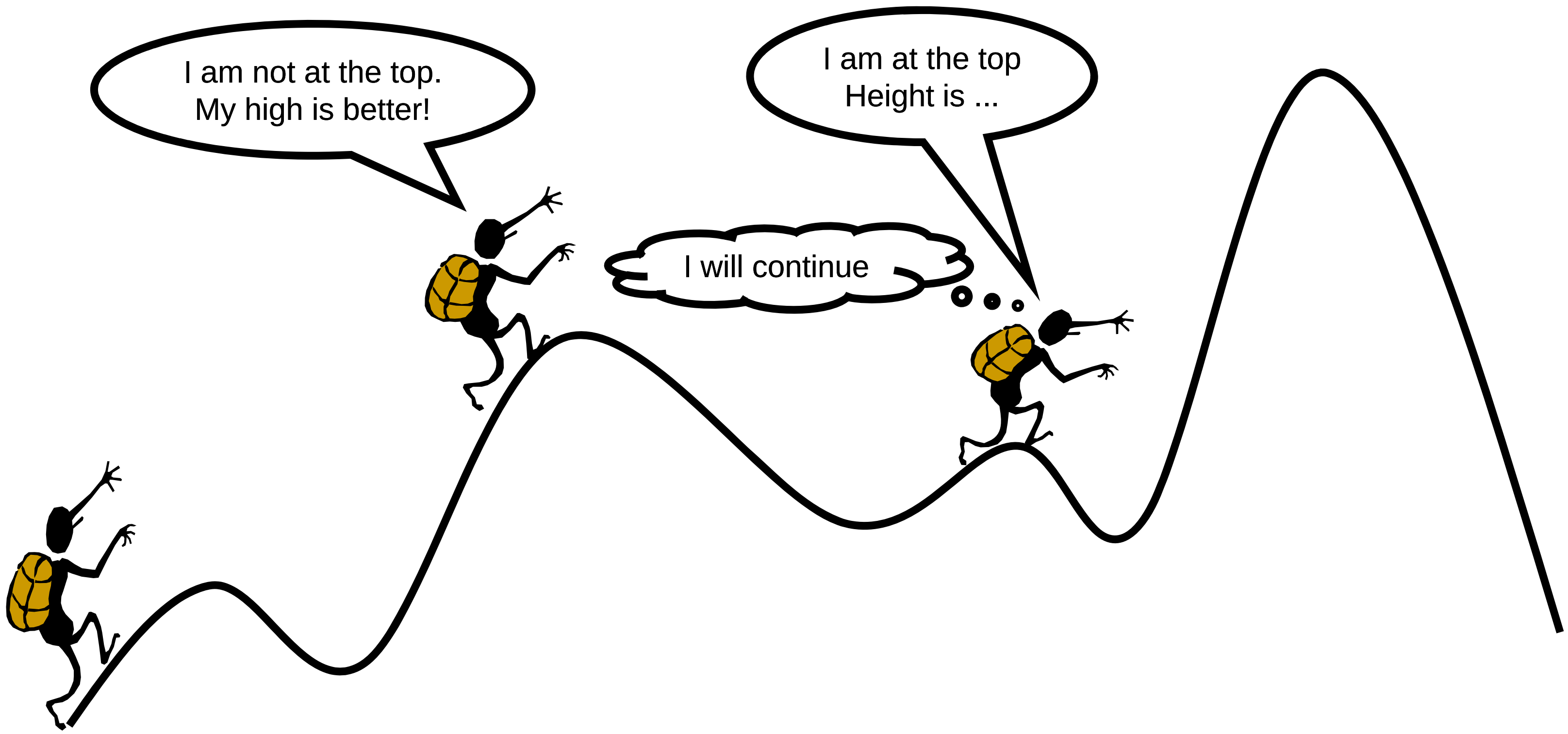
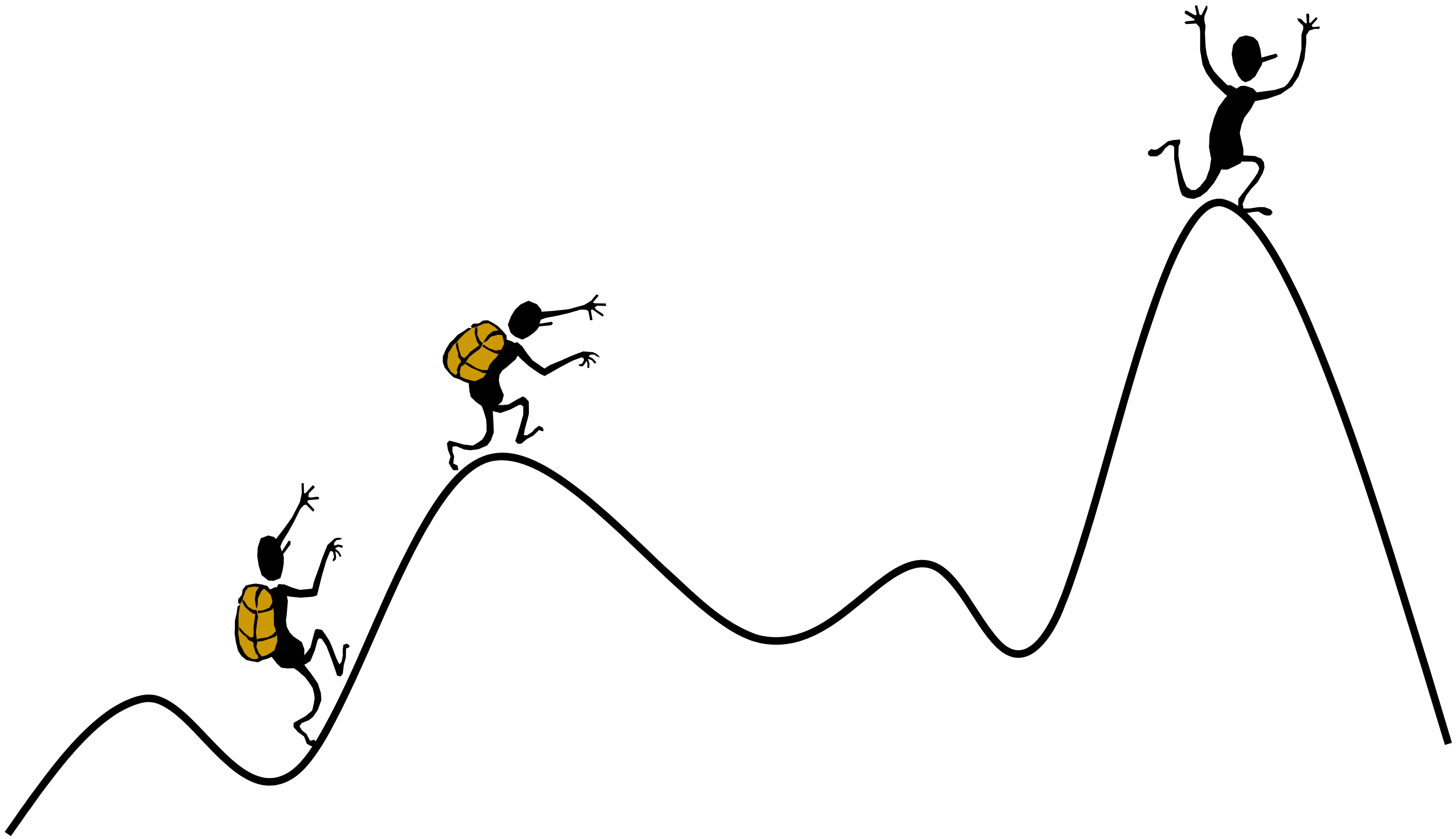
Evolutionary Algorithms…

- **Are function optimizers**
- **Inspired by natural evolution**
- **Population of individuals**
- **Are robust, hence preferred for real world problems**
- **Have little theory to explain how and why they work**
- **They come with various flavours**

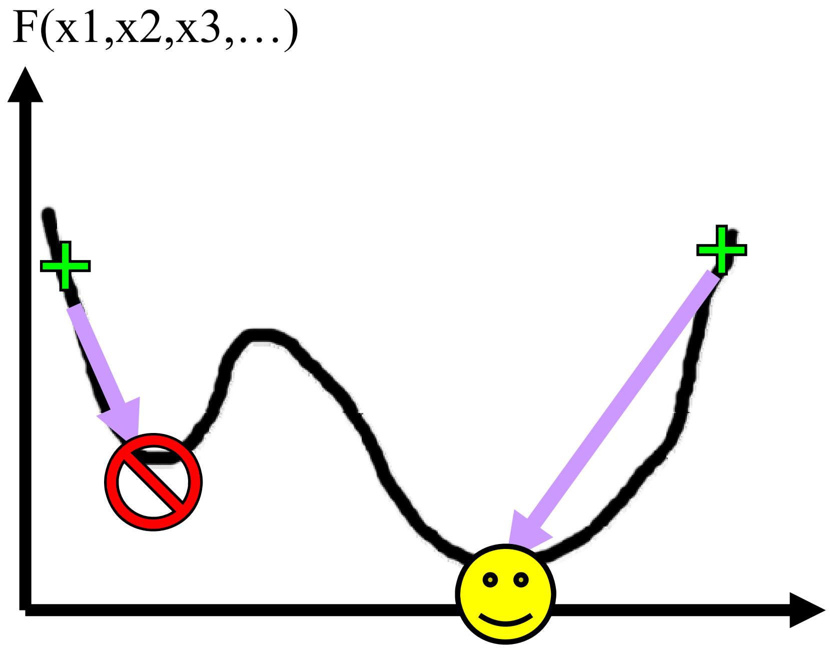
Evolutionary Parameter Optimization: Introduction



Evolutionary Parameter Optimization: Introduction



Evolutionary Parameter Optimization: Introduction



Evolutionary Algorithms don’t have this problem!!!

Evolutionary Parameter Optimization: Introduction

- The idea of using simulated evolution to solve engineering and design problems have been around since the 1950's (Fogel, 2000).
  - Bremermann, 1962
  - Box, 1957
  - Friedberg, 1958

- However, it wasn't until the early 1960's that we began to see three influential forms of EC emerge (Back et al, 1997):
  - Evolutionary Programming (Lawrence Fogel, 1962),
  - Genetic Algorithms (Holland, 1962)
  - Evolution Strategies (Rechenberg, 1965 & Schwefel, 1968),

Evolutionary Parameter Optimization: Introduction

- The designers of each of the EC techniques saw that their particular problems could be solved via simulated evolution.
  - Fogel was concerned with solving programs evolution.
  - **Rechenberg & Schwefel were concerned with solving parameter optimization problems.**
  - Holland was concerned with developing robust adaptive systems.

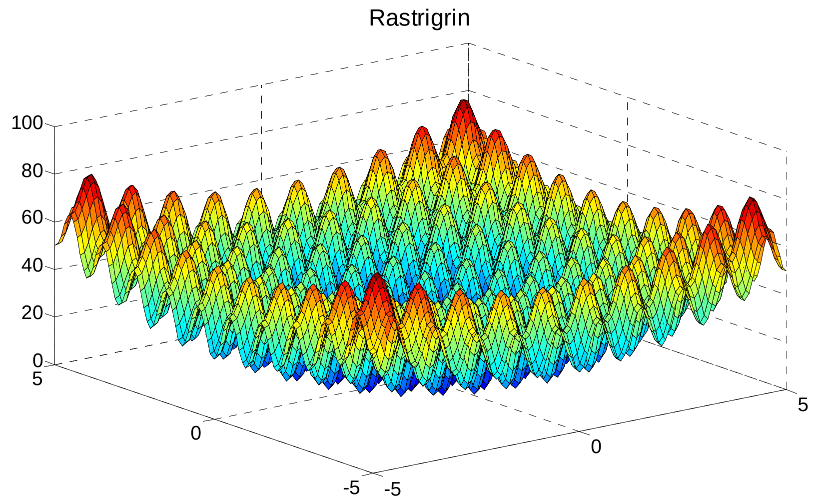
Evolutionary Parameter Optimization: Introduction

We focus our attention on the problem of finding the global optimum of a function that is characterized by:

multiple minima
non-differentiable
non-linear

$$f(X_i) = D \cdot 10 + \sum_{j=1}^{D} \left[x^2_{ij} - 10 \cdot \cos\left(2\pi x_{ij}\right) \right]$$

it has many local minima and highly multimodal.

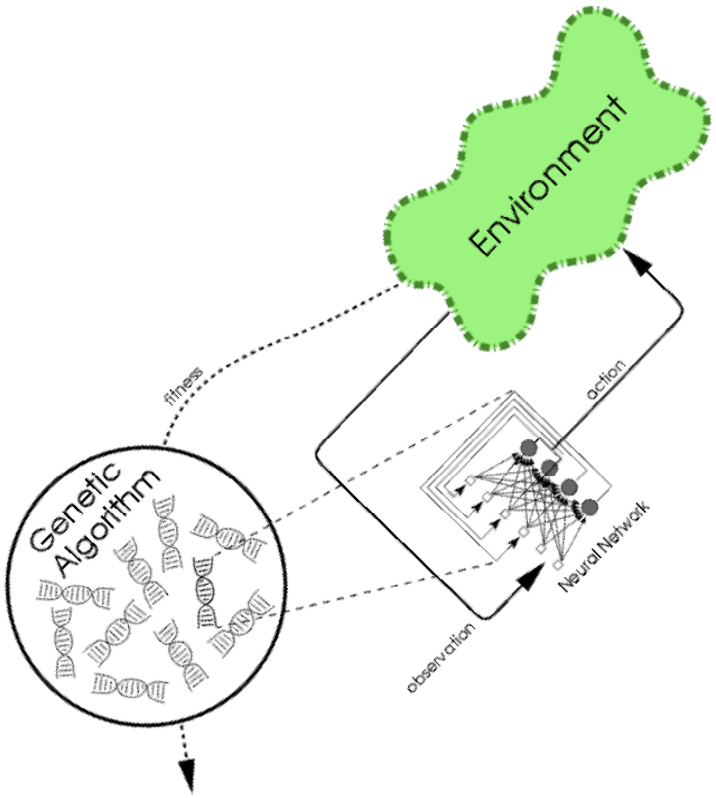


Evolutionary Parameter Optimization: Introduction

Problem Motivation

- **There are a lot of applications where a scientist/engineer has to optimize a non-linear, non-differentiable function that has multiple minima.**

- **An example of such an application is found in the field of neural networks where one has to optimize the topology and weights of a neural network to solve a mapping problem**
- **Neural networks have been extensively used in the literature to solve classification problems, regression problems, prediction problems**

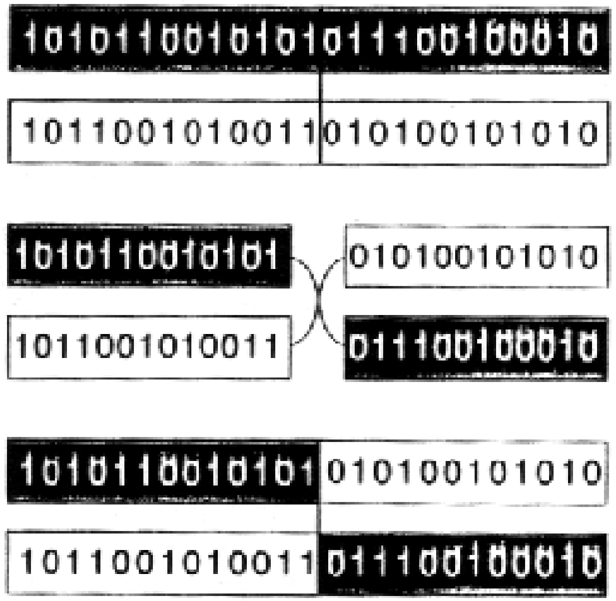


Most Popular Real-Parameter Evolutionary Algorithms

- Real-coded (parameter) genetic algorithm (RCGAs)
- Evolution strategies (ES)
- Particle swarm optimization (PSO)
- Differential evolution (DE)
- Real coding memetic algorithms (RCMA)

Contents

Binary Coding



CROSSOVER is the fundamental mechanism of genetic rearrangement for both real organisms and genetic algorithms.

Chromosomes line up and then swap the portions of their genetic code beyond the crossover point.

Binary GAs in Continuous Search Space
Difficulties with binary-coded EAs

- Binary GAs make the search space discrete
- Hamming cliffs: (10000)'s neighbor (01111)
  - Gray coding isn't the solution
- Arbitrary precision impossible due to fixed-length coding
- Search restricted with variable boundaries
- Not all Holland's schemata are important
  - (1****) more important than (****1)

- **Solution: Redesign crossover which gives more importance to meaningful schemata in real space**

Real Coding Genetic Algorithms

- **Decision variables are coded directly, instead of using binary strings**
- **Recombination and mutation need structural changes**

Recombination

$$\Rightarrow ?$$

Mutation

$$(x_1 x_2 \ldots\ldots\ldots\ldots\ldots x_n) \Rightarrow ?$$

- **Selection operator remains the same**
- **Simple exchanges are not adequate**

Discrete

Pioneers and outstanding work

Problems with real crossover: Neighbourhood and Crossover

Crossover idea: combining parents genotypes to get children genotypes "somewhere in between" them

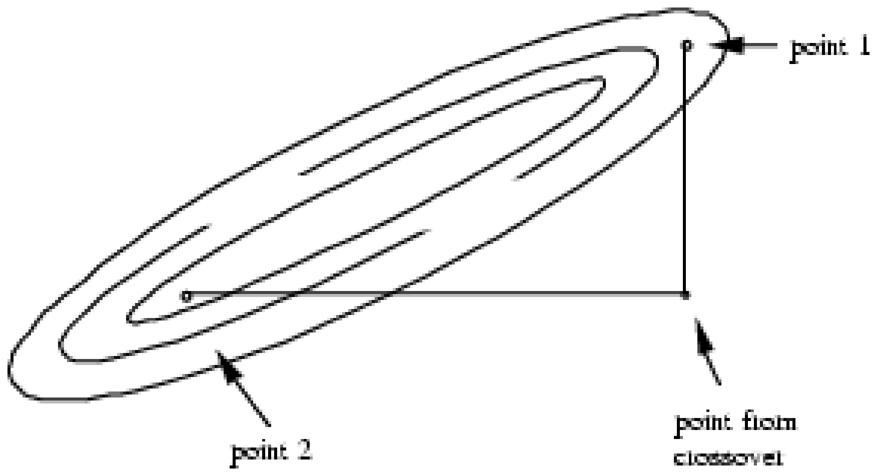


Figure 2

Interpretation & Generalization

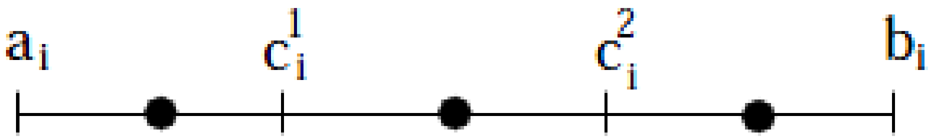
Traditional **mutation** & **crossover** have a natural interpretation in the neighbourhood structure in terms of **closeness** and **betweenness**

Pioneers and outstanding work

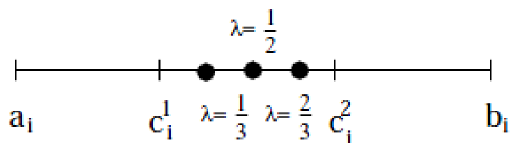
First Real Coding proposal: Linear/Arithmetical crossover

Wright, A. (1991). **Genetic Algorithms for Real Parameter Optimization**. FOGA 1, 205-218.

- ***Linear Crossover***
  - ***From 2 parent points, 3 new points are generated:***
    - ***(1/2)p1 + (1/2)p2, (3/2)p1 - (1/2)p2, (-1/2)p1+(3/2)p2***
      - ***(1/2)p1 + (1/2)p2 is the midpoint of p1 and p2***
      - ***The others are on the line determined by p1 and p2***
  - ***The best 2 of the 3 points are sent to the next generation***
  - ***Disadvantage - Highly disrupted schemata. It is not compatible with the schema theorem described in the next slide.***



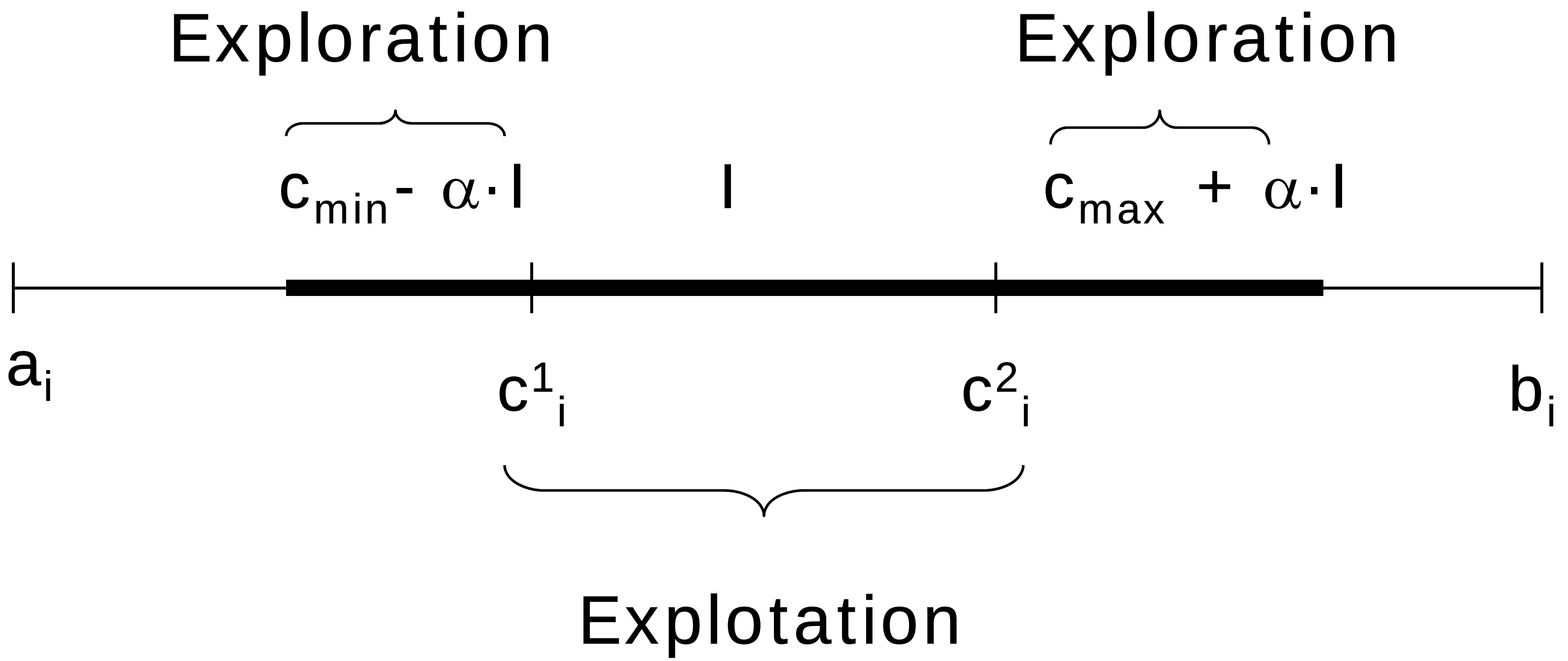
Extended models: Arithmetical crossover (Michalewicz, 1992), Max-Min Arithmetic operator (Herrera, Lozano, Verdegay, 1995)



Pioneers and outstanding work

Variable-wise recombination: Blend Crossover (BLX-α)

Eshelman L.J., Schaffer J.D. (1993). **Real-Coded Genetic Algorithms and Interval-Schemata**. FOGA 2, 187-202.

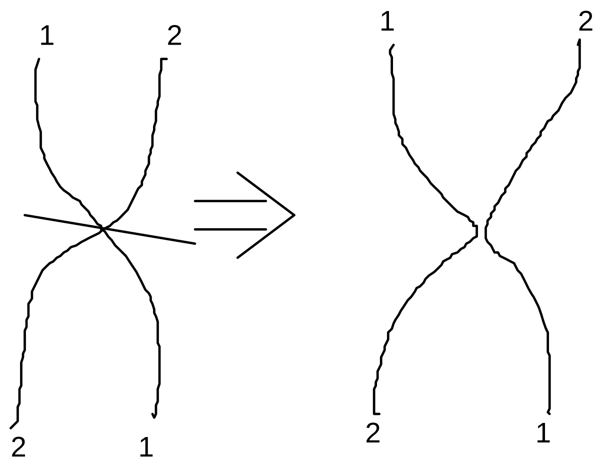


- Uniform probability distribution within a bound controlled by α
- Diversity in children proportional to that in parents
- The search is too wide if parents are distant

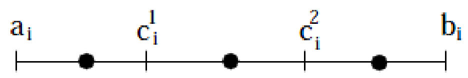
Pioneers and outstanding work

Real-coded Genetic Algorithms: First studies

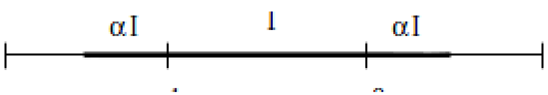
• Goldberg D.E. (1991).
Real-Coded Genetic Algorithms, Virtual Alphabets, and Blocking.
Complex Systems 5, 139-167.



• Wright, A. (1991). **Genetic Algorithms for Real Parameter Optimization**. FOGA 1, 205-218.



• Eshelman L.J., Schaffer J.D. (1993). **Real-Coded Genetic Algorithms and Interval-Schemata**. FOGA 2, 187-202.



Pioneers and outstanding work

Variable-wise recombination of Parents

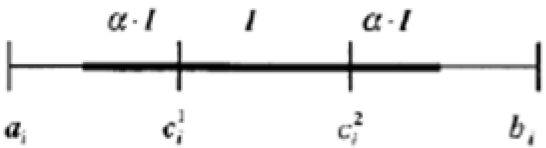
(RCGA first generation)

- Use a probability distribution to create offspring
- Different implementations since 1991:
  - Blend crossover (BLX-α), 1993
  - Simulated binary crossover (SBX-β), 1995
  - Fuzzy recombination (FR-d), 1995
  - Fuzzy connectives based operator (FCB), 1994
- **Main feature: Difference between parents used to create children**
  - Provides self-adaptive property

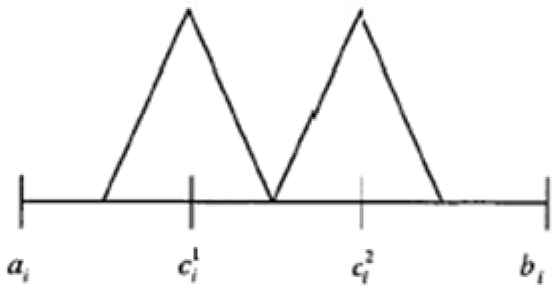
Experimental analysis: F. Herrera, M. Lozano, J.L. Verdegay (1998). **Tackling real-coded genetic algorithms: operators and tools for the behavioural analysis**. Artificial Intelligence Reviews 12(4): 265-319

Pioneers and outstanding work

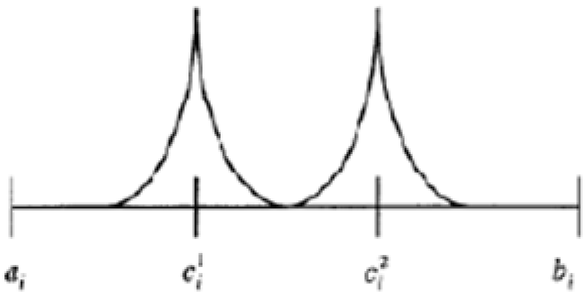
BLX-α (Eshelman et al., 1993)



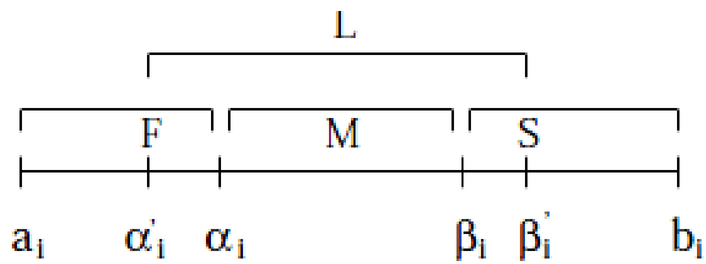
Fuzzy recombination (Voigt et al., 1995)



SBX (Deb et al., 1995)



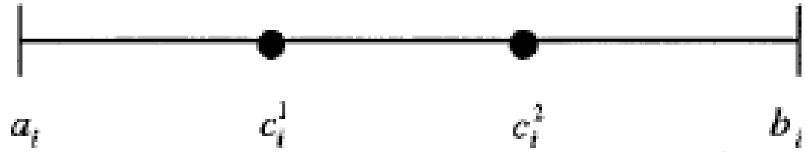
Fuzzy Connectives based Operator (Herrera et al. 1994)



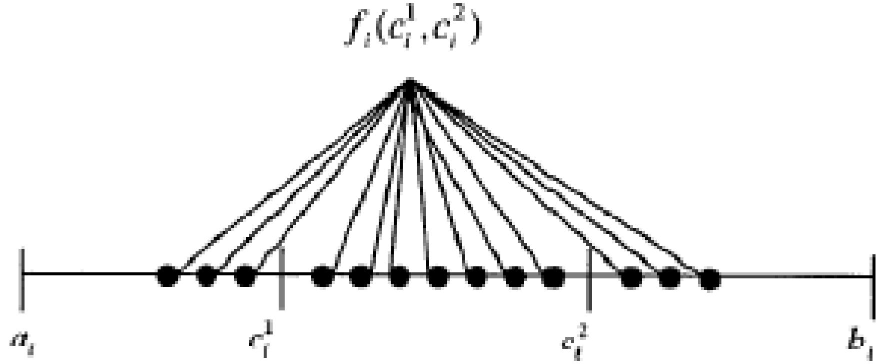
Pioneers and outstanding work

Taxonomy of Crossover operators

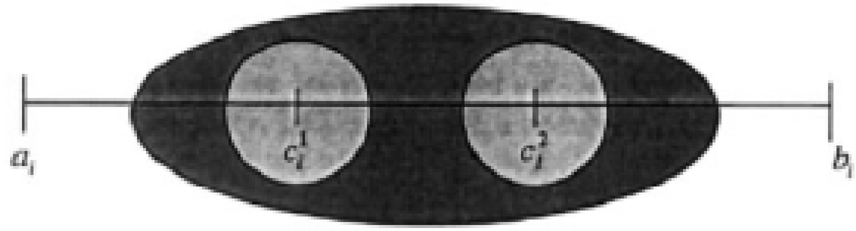
Discrete crossover



Aggregation based Crossover



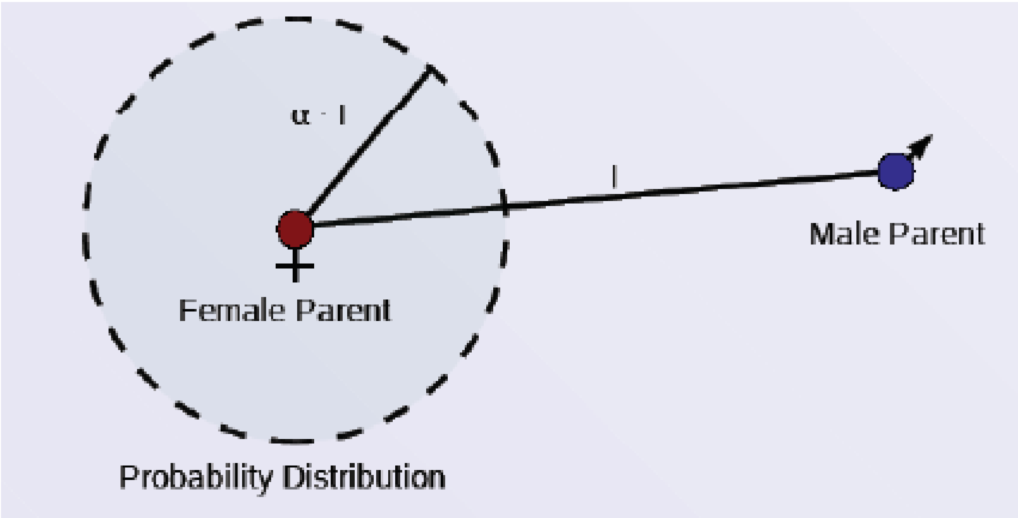
Neighborhood based Crossover



Herrera, F., Lozano, M., Sánchez, A.M. (2003). **A taxonomy for the crossover operator for real-coded genetic algorithms. An experimental study.** *International Journal of Intelligent Systems 18(3): 309-338.*

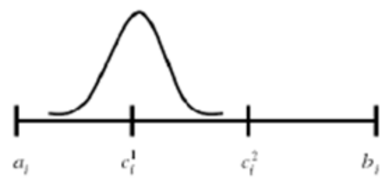
Pioneers and outstanding work

Parent Center based Crossover operators



- FR (Voigt et al, 1995)
- SBX (Deb et al,1995)
- XLM (Takahashi et al 2001)
- PCX (Deb et al, 2002)
- vSBX (Ballester et al, 2003)
- PNX (Ballester et al, 2004)
- PBX-α (Lozano et al, 2004)

PNX (Ballester et al., 2004)



Similar behaviour than auto-adapted operators

Pioneers and outstanding work

Vector-Wise Recombination Operators

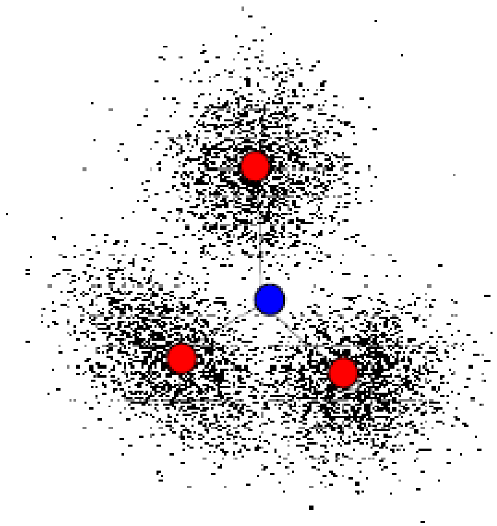
- Variable-wise recombination cannot capture nonlinear interactions
- **Alternative:** Recombine parents as vectors (RCGA second generation)
  - Parent-centric recombination (PCX)
  - Unimodal normally-distributed crossover (UNDX)
  - Simplex crossover (SPX)
- Difference between parents is used to create offspring solutions (some models in this special issue).

F. Herrera, M. Lozano (Eds.) (2005). Special Issue on Real Coded Genetic Algorithms: Foundations, Models and Operators. Soft Computing 9:4.

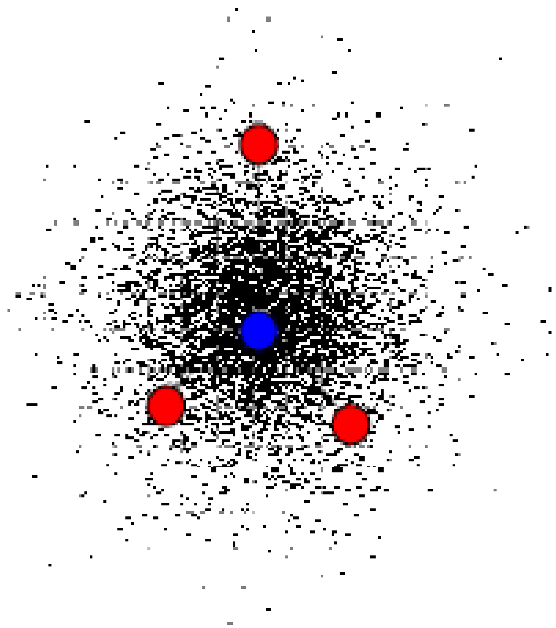
Pioneers and outstanding work

Recombine parents as vectors
PCX, UNDX & SPX Operators

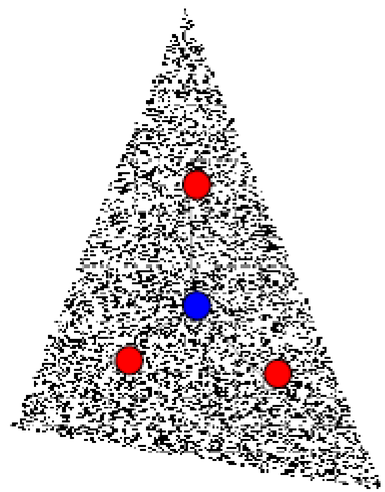
PCX



UNDX



SPX



Deb, K., Anand, A., Joshi, D. (2002). **A computationally efficient evolutionary algorithm for real-parameter evolution.** *Evolutionary Computation Journal 10(4): 371-395.*

Pioneers and outstanding work

Vector-Wise Recombination Operators

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- Difference between parents is used to create offspring solutions (some models in this special issue).

- **New algorithms (second EAs generation): DE, PSO, CMA-ES**

Pioneers and outstanding work

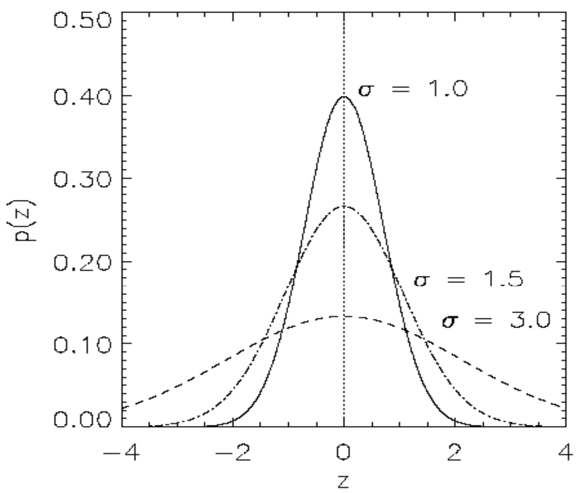
Evolution Strategies

Rechenberg & Schwefel (1964) were concerned with solving parameter optimization problems. Autoadaptation of parameters.

$$\text{Mut: } I \longrightarrow I$$

$$\text{Mut}(x) = x' = (x_1 + z_1, \ldots, x_n + z_n)$$

$$z_i \sim N_i(0, \sigma'^2)$$



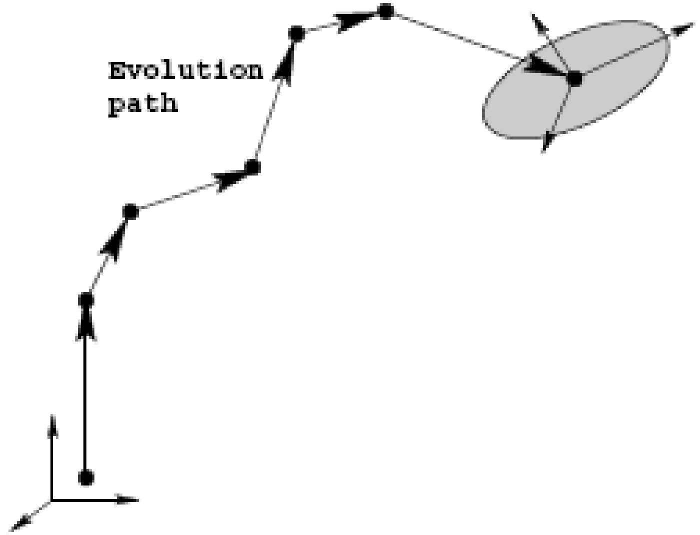
State of the art of the first generation: *Schwefel, H.P. Evolution and Optimum Seeking. Sixth-Generation Computer Technology Series. Wiley, New York, 1995.*

Pioneers and outstanding work

State of the art of the ES second generation: CMA-ES

Evolution Strategy with Covariance Matrix Adaptation (Hansen & Ostermeier, 1996)

- Selection-mutation ES is run for *n* iterations
- Successful steps are recorded
- They are analyzed to find uncorrelated basis directions and strengths
- Required $O(n^3)$ computations to solve an eigenvalue problem
- Rotation invariant



Nikolaus Hansen
*www.lri.fr/~**hansen**/*

- **Hansen, N. and A. Ostermeier (2001). Completely Derandomized Self-Adaptation in Evolution Strategies. *Evolutionary Computation*, 9(2), pp. 159-195;**
- **Hansen, N., S.D. Müller and P. Koumoutsakos (2003). Reducing the Time Complexity of the Derandomized Evolution Strategy with Covariance Matrix Adaptation (CMA-ES). *Evolutionary Computation*, 11(1), pp. 1-18;**

Particle Swarm Optimization

The PSO (Kennedy and Eberhart (1995)) starts from an initial population of solutions (particles) for the optimization problem.

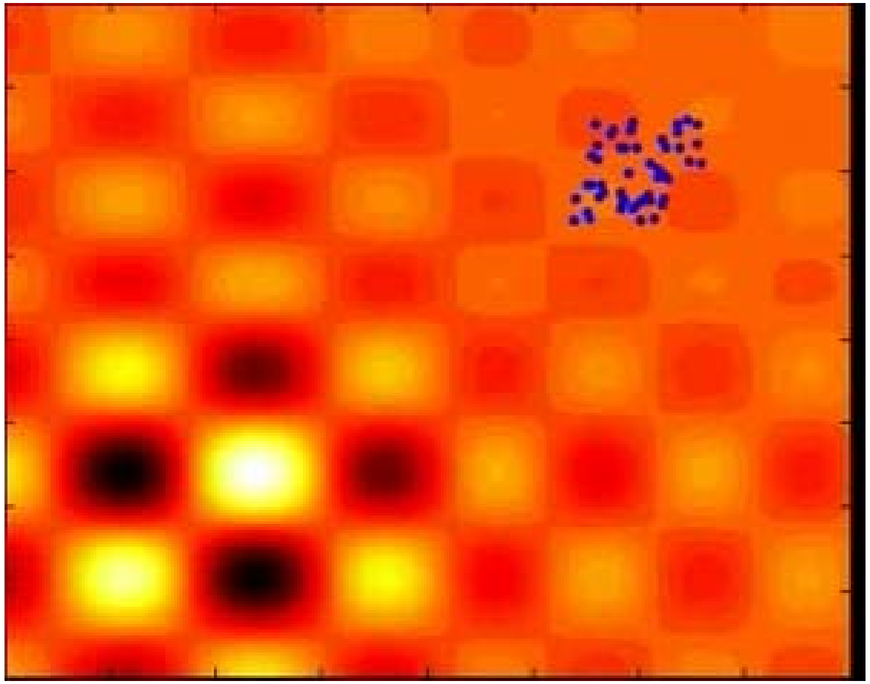
It finds new solutions by co-jointly exploring the space and exploiting the information provided by already found, good solutions.

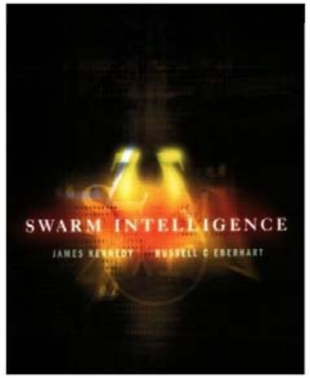
J. Kennedy and R.C. Eberhart. Particle Swarm Optimization.
Proceeding of IEEE International Conference on Neural Networks, IV, pages 1942–1948, 1995.

Pioneers and outstanding work

Particle Swarm Optimization

Particles fly through the search space
(biological inspiration)



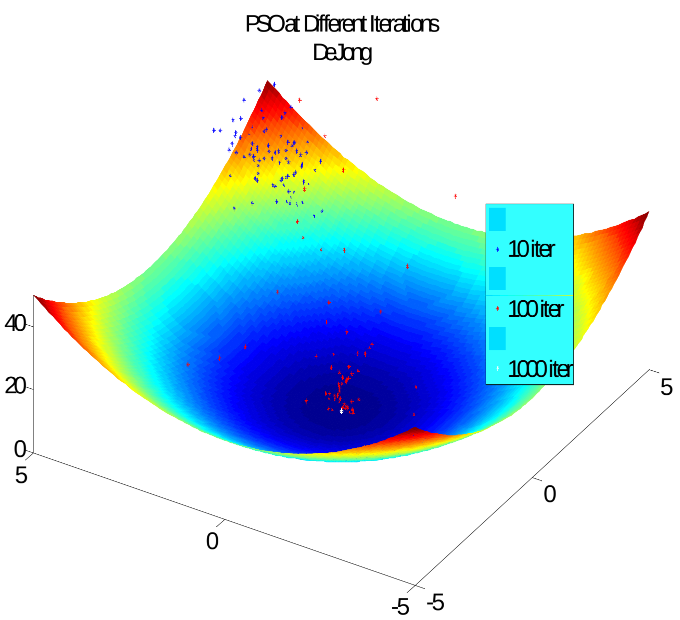


Kennedy, J., Eberhart, R.C. (2001). **Swarm Intelligence**. Morgan Kauffmann.

Particle Swarm Optimization

- Kennedy and Eberhart, 1995
- Particles fly through the search space
- Velocity dynamically adjusted
- $x_i = x_i + v_i$
- $v_i = v_i + c_1 rnd()(p_{i,best} - x_i) + c_2 rnd()(p_g - x_i)$
- p_i: best position of i-th particle
- p_g: position of best particle so far
  - 1^{st} term: momentum part (history)
  - 2^{nd} term: cognitive part (private thinking)
  - 3^{rd} term: social part (collaboration)
  - $\boxed{c_1, c_2 \text{ in } [0,2]}$

Vector-Wise Recombination

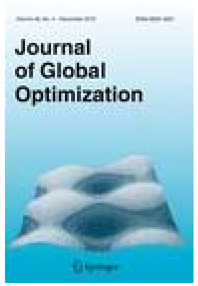


Evolutionary Parameter Optimization: Introduction

Differential Evolution

The DE approach (Storn and Price (1997)) starts from an initial population of solutions that are mutated and crossed over to eventually obtain better solutions for the optimization problem at hand.

R. Storn and K. V. Price, "Differential evolution-A simple and Efficient Heuristic for Global Optimization over Continuous Spaces," *Journal of Global Optimization*, 11:341-359,1997.



Pioneers and outstanding work

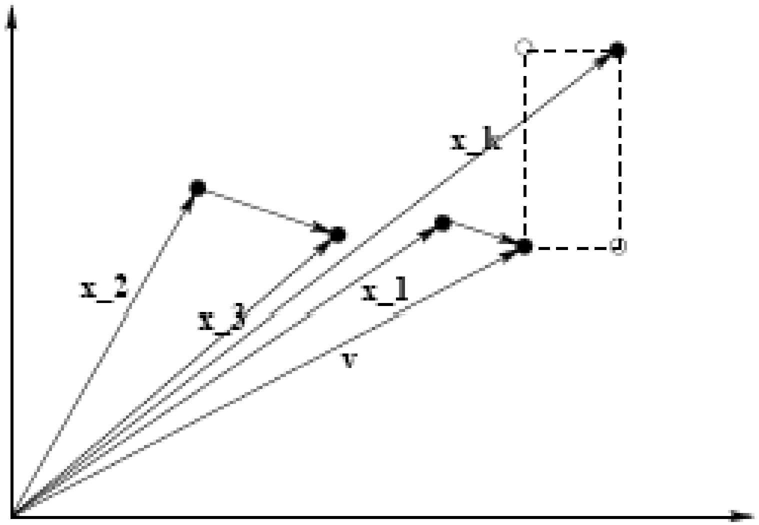
Differential Evolution

1. Start with a pool of random solutions
2. Create a child v
3. x_k and v are recombined with *p*
4. Keep better of y and $x^{(k)}$

- Difference of parents in creating a child is important
- A number of modifications exist

– $\mathbf{v} = \mathbf{x}^{(1)} + \lambda(\mathbf{x}^{(2)} - \mathbf{x}^{(3)})$

– $y_i = \begin{cases} v_i, & \text{with a prob. } p \\ \mathbf{x}_i^{(k)}, & \text{else} \end{cases}$



Vector-Wise Recombination

Contents

Milestone: CEC'2005 Real Parameter Optimization Session and Benchmark

Special Session on Real-Parameter Optimization.
2005 IEEE CEC, Edinburgh, UK, Sept 2-5. 2005.
Organizers: K. Deb and P.N. Suganthan.

Unimodal Functions
Success Performance Indices

Multimodal Functions
Solved in at least one run

Multimodal Functions
Never solved

The study was made with dimensions **D = 10**, **D = 30**, **D=50**.
The maximum number of fitness evaluations is **10,000·D**.
Each run stops when the maximal number of evaluations is achieved.

P. N. Suganthan, N. Hansen, J. J. Liang, K. Deb, Y.-P. Chen, A. Auger and S. Tiwari, "Problem Definitions and Evaluation Criteria for the CEC 2005 Special Session on Real-Parameter Optimization", *Technical Report,* Nanyang Technological University, Singapore, May 2005 AND KanGAL Report #2005005, IIT Kanpur, India.

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Unimodal Functions

Success Performance Indices

6 functions

1 Sphere
2 Schwefel 1.2
3 Ellipsoid Condition 10^6
4 Schwefel 1.2 with Noise
5 Schwefel 2.6 on Bounds
6 Rosenbrock

Multimodal Functions

Solved in at least one run

6 functions

7 Griewank out Bounds
9 Rastrigin Separable
10 Rastrigin Rotated
11 Weierstrass
12 Schwefel 2.13
15 Hybrid Separabl

Multimodal Functions

Never solved

13 functions

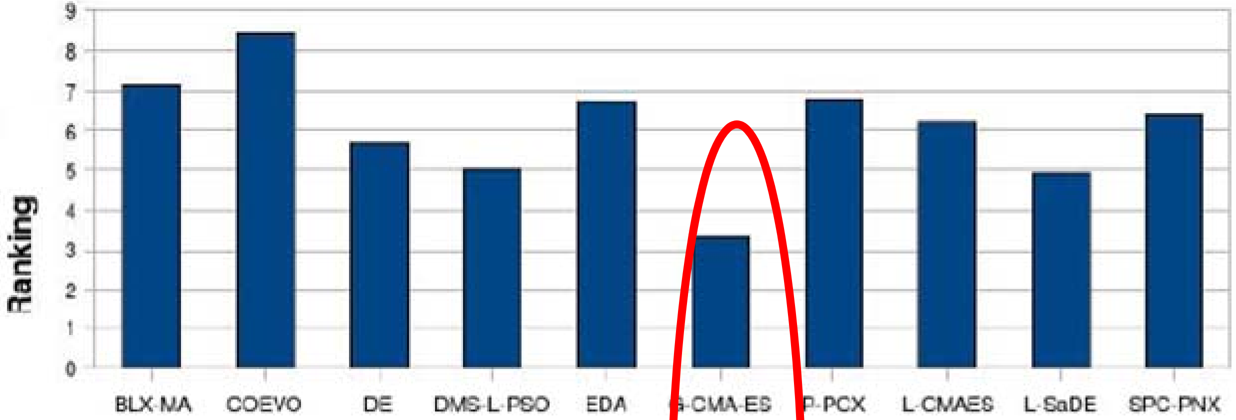
8 Ackley Condition 10^2
13 Expanded 6&7
14 Expanded Schaffer F6
16 Hybrid Rotated
17 Hybrid with Noise
18 Hybrid F18
19 Hybrid Narrow
20 Hybrid on Bounds
21 Hybrid F21
22 Hybrid High Condition
23 Hybrid Non-Continuous
24 Hybrid F24
25 Hybrid ou

Milestone: CEC'2005 Real Parameter Optimization Session and Benchmark

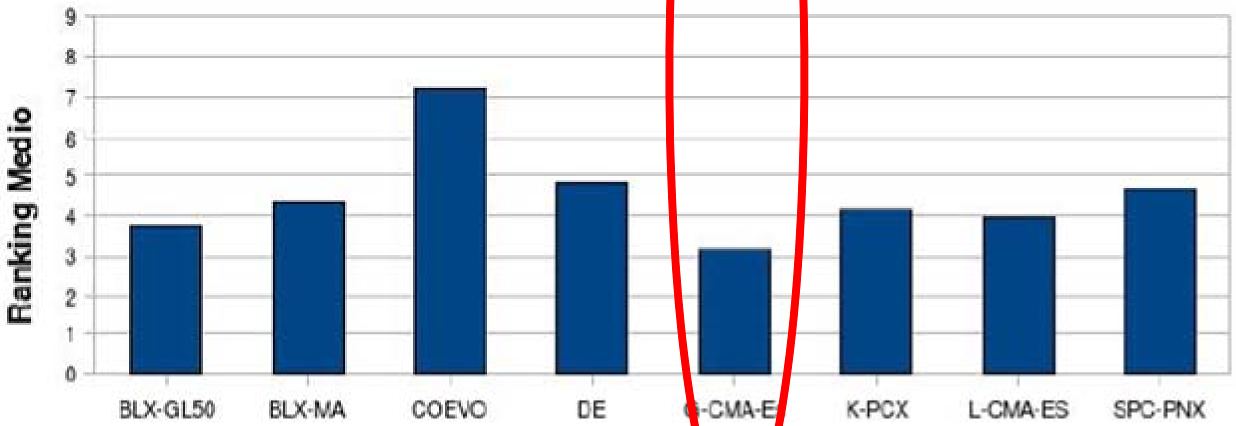
- Algorithms involved in the comparison: **(11 algorithms)**
  - **BLX-GL50 (Garcia-Martinez & Lozano, 2005):** Hybrid Real-Coded Genetic Algorithms with Female and Male Differentiation
  - **BLX-MA (Molina *et al.*, 2005):** Adaptive Local Search Parameters for Real-Coded Memetic Algorithms
  - **CoEVO (Posik, 2005):** Mutation Step Co-evolution
  - **DE (Ronkkonen *et al.*,2005):**Differential Evolution
  - **DMS-L-PSO:** Dynamic Multi-Swarm Particle Swarm Optimizer with Local Search
  - **EDA (Yuan & Gallagher, 2005):** Estimation of Distribution Algorithm
  - **G-CMA-ES (Auger & Hansen, 2005):** A restart Covariance Matrix Adaptation Evolution Strategy with increasing population size
  - **K-PCX (Sinha *et al.*, 2005):** A Population-based, Steady-State real-parameter optimization algorithm with parent-centric recombination operator, a polynomial mutation operator and a niched -selection operation.
  - **L-CMA-ES (Auger & Hansen, 2005):** A restart local search Covariance Matrix Adaptation Evolution Strategy
  - **L-SaDE (Qin & Suganthan, 2005):** Self-adaptive Differential Evolution algorithm with Local Search
  - **SPC-PNX (Ballester *et al.*,2005):** A steady-state real-parameter GA with PNX crossover operator

Milestone: CEC’2005 Real Parameter Optimization Session and Benchmark

D = 10



D = 30



S. García, D. Molina, M. Lozano, F. Herrera, **A Study on the Use of Non-Parametric Tests for Analyzing the Evolutionary Algorithms' Behaviour: A Case Study on the CEC'2005 Special Session on Real Parameter Optimization**. *Journal of Heuristics, 15 (2009) 617-644.* doi: 10.1007/s10732-008-9080-4.

Milestone: CEC'2005 Real Parameter Optimization Session and Benchmark

G-CMA-ES vs.	R^+	R^-	p-value
BLX-GL50	289.5	35.5	0.001
BLX-MA	295.5	29.5	0.001
CoEVO	301.0	24.0	0.000
DE	262.5	62.5	0.009
DMS-L-PSO	199.0	126.0	0.357
EDA	284.5	40.5	0.001
K-PCX	269.0	56.0	0.004
L-CMA-ES	273.0	52.0	0.003
L-SaDE	209.0	116.0	0.259
SPC-PNX	305.5	19.5	0.000

G-CMAES versus the remaining algorithms. D = 10
P-value obtained through normal approximation

S. García, D. Molina, M. Lozano, F. Herrera, **A Study on the Use of Non-Parametric Tests for Analyzing the Evolutionary Algorithms' Behaviour: A Case Study on the CEC'2005 Special Session on Real Parameter Optimization**. *Journal of Heuristics, 15 (2009) 617-644.* *doi: 10.1007/s10732-008-9080-4*.

Milestone: CEC'2005 Real Parameter Optimization Session and Benchmark

Two recent algorithms with good ranking and similar statistical behaviour:

AMALGAM – SO: Vrugt, J.A.; Robinson, B.A.; Hyman, J.M.; , "Self-Adaptive Multimethod Search for Global Optimization in Real-Parameter Spaces," Evolutionary Computation, IEEE Transactions on , vol.13, no.2, pp.243-259, April 2009
http://math.lanl.gov/~vrugt/software/

AMALGAM - SO**:** A Multi ALgorithm Genetically Adaptive Method for Single Objective Optimization. This method simultaneously merges the strengths of the Covariance Matrix Adaptation (CMA) evolution strategy, Genetic Algorithm (GA) and Particle Swarm Optimizer (PSO) for population evolution and implements a self-adaptive learning strategy to automatically tune the number of offspring these three individual algorithms are allowed to contribute during each generation.

Milestone: CEC'2005 Real Parameter Optimization Session and Benchmark

Two recent algorithms with good ranking and similar statistical behaviour:

MA-CMA-Chains: D. Molina, M. Lozano, C. García-Martínez, F. Herrera, Memetic Algorithms for Continuous Optimization Based on Local Search Chains. *Evolutionary Computation*, 18(1), 2010, 27–63.

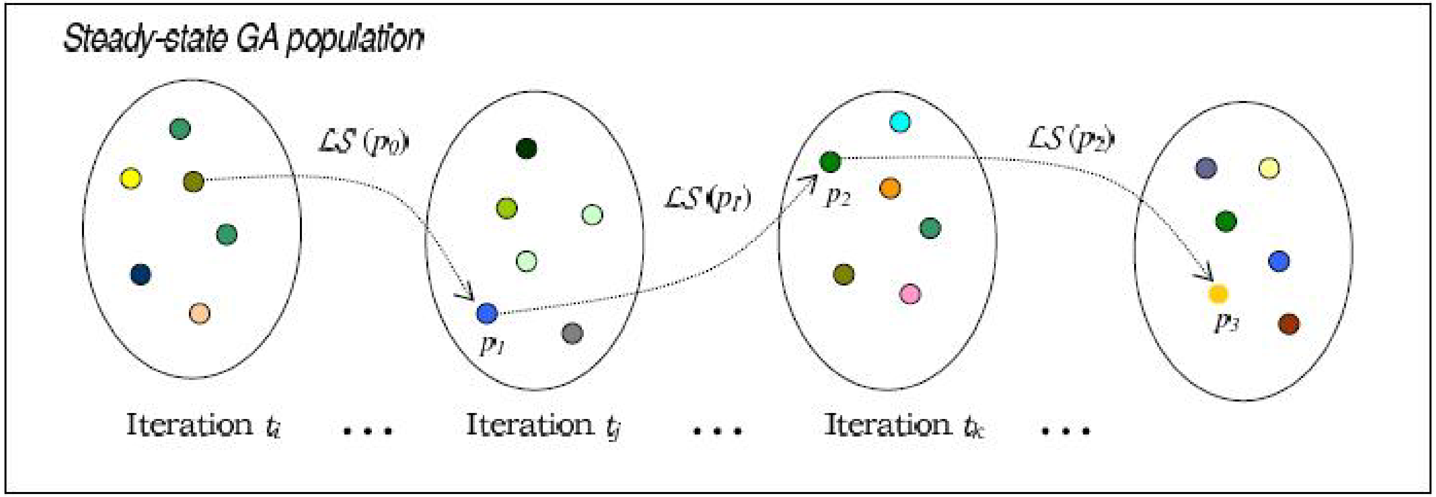


Figure 3: Example of LS chain. p_{i+1} is the final parameter value reached by the LS algorithm when it started with a value of p_i. p_0 is the default value for the strategy parameter

MA-CMA-Chains: Local search adaptation

Milestone: CEC'2005 Real Parameter Optimization Session and Benchmark

MA-CMA-Chains: Local search adaptation

D. Molina, M. Lozano, C. García-Martínez, F. Herrera, Memetic Algorithms for Continuous Optimization Based on Local Search Chains. *Evolutionary Computation,* 18(1), 2010, 27–63

Every time the LS algorithm is applied to refine a particular chromosome, a fixed LS intensity should be considered for it, which will be called *LS intensity stretch* (I_str). In this way, a LS chain formed throughout n_app LS applications and started from solution s_0 will return the same solution as the application of the continuous LS algorithm to s_0 employing n_app · I_str fitness function evaluations.

After the LS operation, the parameters that define the current state of the LS processing are stored along with the reached final individual (in the steady-state GA population). When this individual is latter selected to be improved, the initial values for the parameters of the LS algorithm will be directly available. For example, if we employ the Solis and Wets' algorithm as LS algorithm, the stored strategy parameter may be the current value of the ρ parameter. For the more elaborate CMA-ES, the state of the LS operation may be defined by the covariance matrix (C), the mean of the distribution (~m), the size (σ), and some additional variables used to guide the adaptation of these parameters.

Milestone: CEC'2005 Real Parameter Optimization Session and Benchmark

MA-CMA-Chains: Local search adaptation

D. Molina, M. Lozano, C. García-Martínez, F. Herrera, Memetic Algorithms for Continuous Optimization Based on Local Search Chains. *Evolutionary Computation,* 18(1), 2010, 27–63

1. Generate the initial population.
2. Perform the steady-state GA throughout n_{frec} evaluations.
3. Build the set S_{LS} with those individuals that potentially may be refined by LS.
4. Pick the best individual in S_{LS} (Let's c_{LS} to be this individual).
5. if c_{LS} belongs to an existing LS chain then
6. Initialise the LS operator with the LS state stored together with c_{LS}.
7. else
8. Initialise the LS operator with the default LS state.
9. Apply the LS algorithm to c_{LS} with an LS intensity of I_{str} (Let's c^r_{LS} to be the resulting individual).
10. Replace c_{LS} by c^r_{LS} in the steady-state GA population.
11. Store the final LS state along with c^r_{LS}.
12. If (*not termination-condition*) go to step 2.

Figure 4: Pseudocode algorithm for the proposed MACO model

Milestone: CEC'2005 Real Parameter Optimization Session and Benchmark

MA-CMA-Chains: Local search adaptation

D. Molina, M. Lozano, C. García-Martínez, F. Herrera, **Memetic Algorithms for Continuous Optimization Based on Local Search Chains.** ***Evolutionary Computation,*** **18(1), 2010**

MA-LSCh-CMA

Steady-state GA.

BLX-α.
Negative Assortative Mating.
BGA Mutation Operator.
Standard replacement strategy

CMA-ES as Continuous LS algorithm.

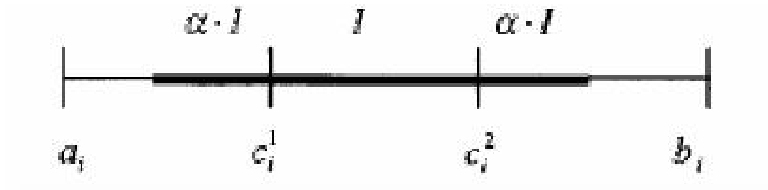


Figure 5: BLX-α

Hansen, N. and Ostermeier,A. (2001). Completely derandomized self-adaptation in evolution strategies. *Evolutionary Computation 9(2): 159–195.*

Parameter setting. For the experiments,MA-LSCh-CMA applies BLX-α with α = 0.5. The population size is 60 individuals and the probability of updating a chromosome by mutation is 0.125. The n_ass parameter associated with the negative assortative mating is set to 3. The value of the L G ratio, r_L/G, was set to 0.5, which represents an equilibrated choice. Finally, a value of 1e-8 was assigned to the δmin LS threshold.

Milestone: CEC'2005 Real Parameter Optimization Session and Benchmark

MA-CMA-Chains: Local search adaptation

D. Molina, M. Lozano, C. García-Martínez, F. Herrera, **Memetic Algorithms for Continuous Optimization Based on Local Search Chains.** ***Evolutionary Computation,*** **18(1), 2010, 27–63**

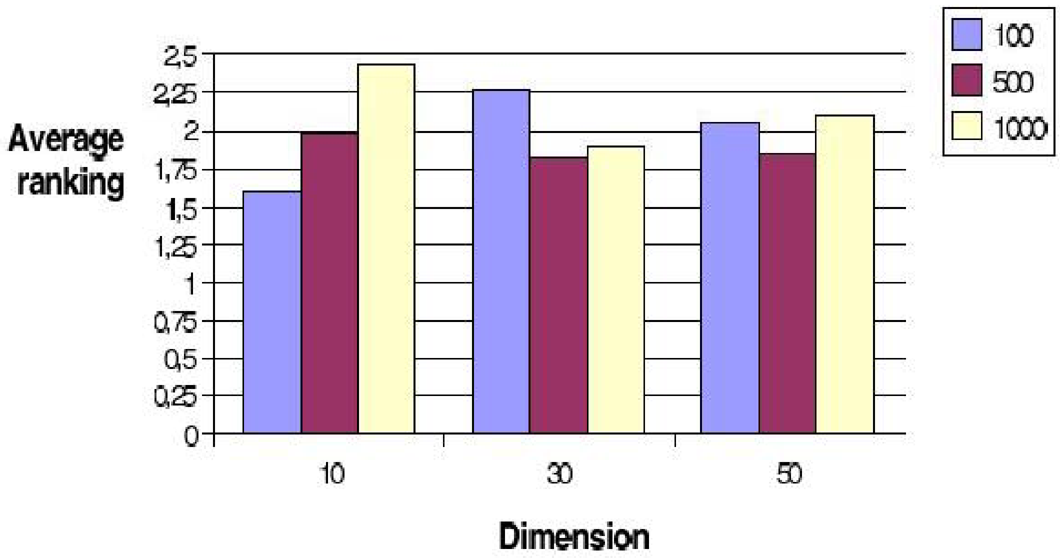


Figure 6: Rankings obtained by MA-LSCh-CMA instances with different I_{str} values

I_str = 500 is the best choice

Milestone: CEC'2005 Real Parameter Optimization Session and Benchmark

MA-CMA-Chains: Local search adaptation

D. Molina, M. Lozano, C. García-Martínez, F. Herrera, Memetic Algorithms for Continuous Optimization Based on Local Search Chains. *Evolutionary Computation,* 18(1), 2010, 27–63

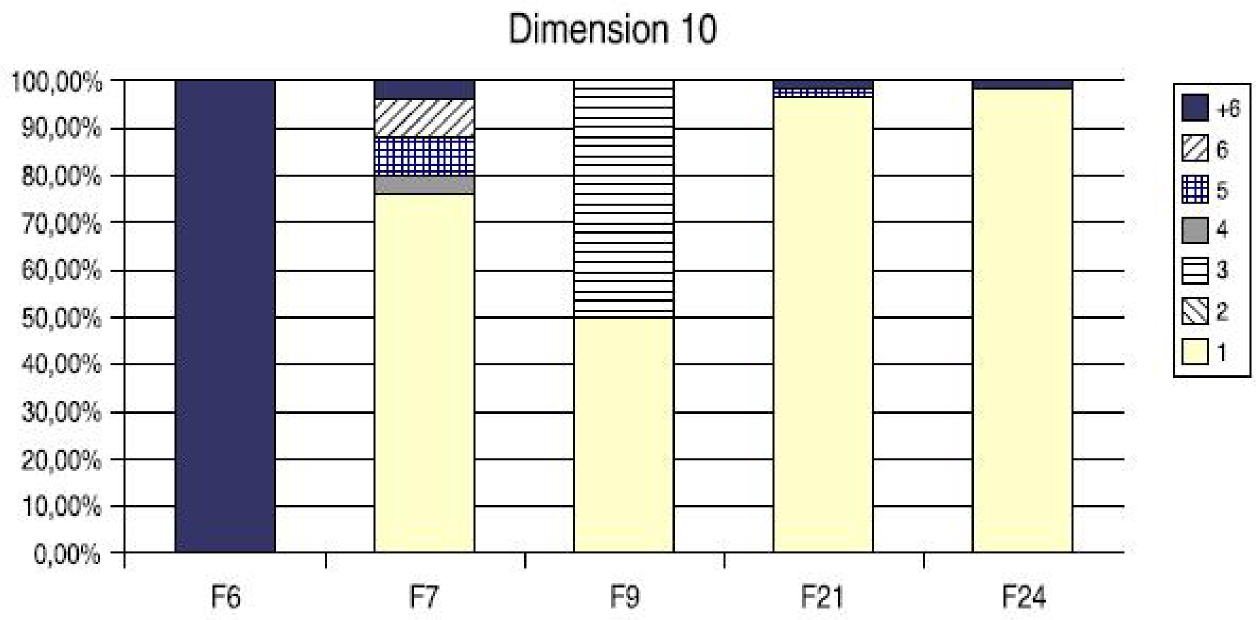


Figure 7: Percentages of LS chains with different lengths ($D = 10$)

Milestone: CEC'2005 Real Parameter Optimization Session and Benchmark

MA-CMA-Chains: Local search adaptation

D. Molina, M. Lozano, C. García-Martínez, F. Herrera, Memetic Algorithms for Continuous Optimization Based on Local Search Chains. *Evolutionary Computation,* 18(1), 2010, 27–63

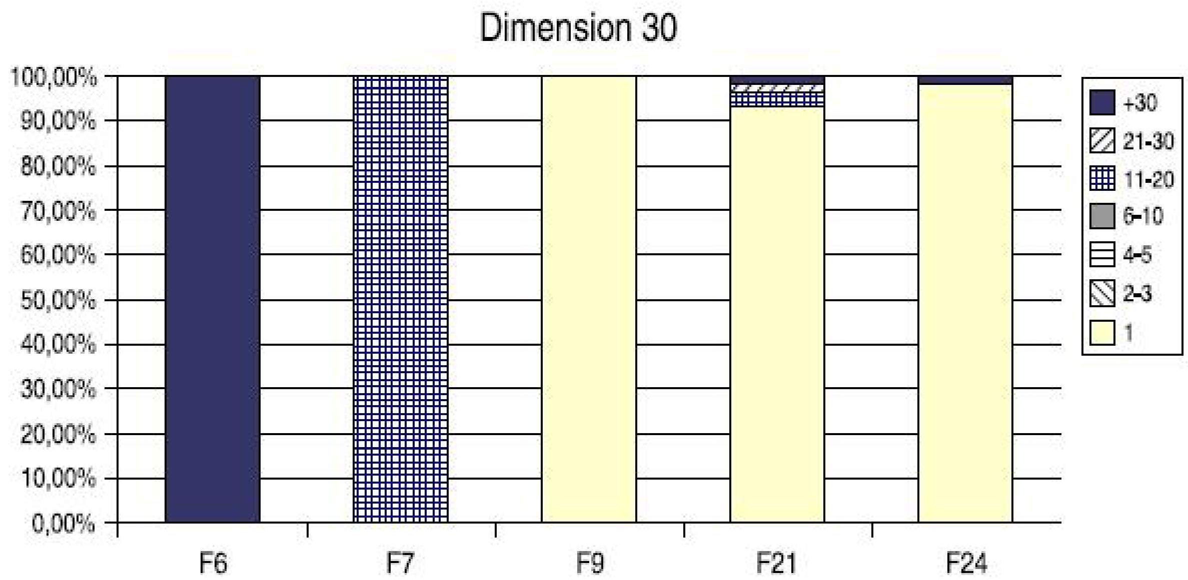


Figure 8: Percentages of LS chains with different lengths ($D = 30$)

Milestone: CEC'2005 Real Parameter Optimization Session and Benchmark

MA-CMA-Chains: Local search adaptation

D. Molina, M. Lozano, C. García-Martínez, F. Herrera, Memetic Algorithms for Continuous Optimization Based on Local Search Chains. *Evolutionary Computation,* 18(1), 2010, 27–63

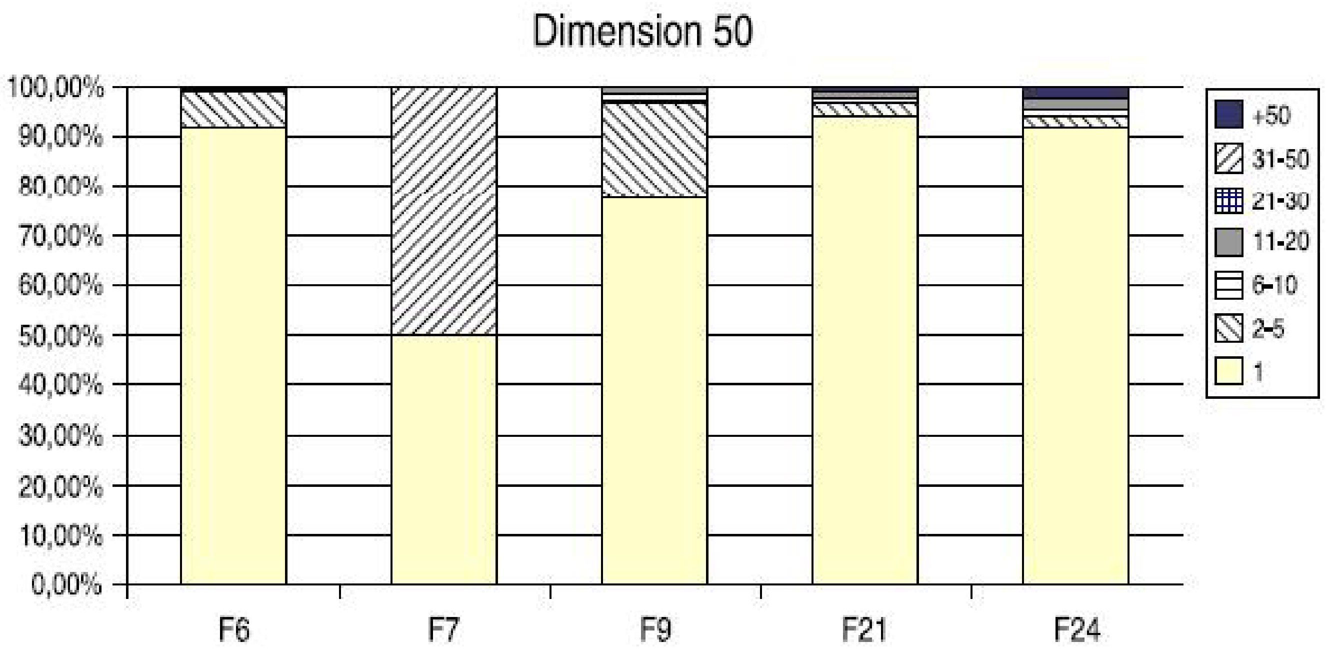


Figure 9: Percentages of LS chains with different lengths ($D = 50$)

Milestone: CEC'2005 Real Parameter Optimization Session and Benchmark

MA-CMA-Chains: Local search adaptation

D. Molina, M. Lozano, C. García-Martínez, F. Herrera, Memetic Algorithms for Continuous Optimization Based on Local Search Chains. *Evolutionary Computation,* 18(1), 2010, 27–63

Comparison with State-of-the-Art MACOs

D	$R+$ (MA-LSCh-CMA)	$R-$ (DEahcSPX)	Critical value	Sig. differences?
10	135	75	52	No
30	169.5	40.5	52	Yes
50	176.5	33.5	52	Yes

Table 7: DEahcSPX versus MA-LSCh-CMA (Wilcoxon's test with p-value = 0.05)

Noman, N. and Iba, H. (2008). Accelerating differential evolution using an adaptive local search. *IEEE Transactions on Evolutionary Computation.* 12:1 (2008)107–125.

Milestone: CEC'2005 Real Parameter Optimization Session and Benchmark

MA-CMA-Chains: Local search adaptation

D. Molina, M. Lozano, C. García-Martínez, F. Herrera, **Memetic Algorithms for Continuous Optimization Based on Local Search Chains.** ***Evolutionary Computation,*** **18(1), 2010,**

Comparison with the Winner of the CEC2005 Competition: G-CMA-ES

D	$R+$ (MA-LSCh-CMA)	$R-$ (G-CMA-ES)	Critical value (p=0.05/p=0.1)	Sig. dif.? (p=0.05)	Sig. dif.? (p=0.1)
10	32.5	177.5	52/60	Yes	Yes
30	**139**	71	52/60	No	No
50	154	56	52/60	No	Yes

Table 8: G-CMA-ES versus MA-LSCh-CMA (Wilcoxon's test with p-value = 0.05 and p-value=0.1)

Auger, A. and Hansen, N. (2005a). A restart CMA evolution strategy with increasing population size. In ***Proc. of the 2005 IEEE Congress on Evolutionary Computation, pages*** **1769-1776.**

S. García, D. Molina, M. Lozano, F. Herrera, A Study on the Use of Non-Parametric Tests for Analyzing the Evolutionary Algorithms' Behaviour: A Case Study on the CEC'2005 Special Session on Real Parameter Optimization. ***Journal of Heuristics,*** *doi: 10.1007/s10732-008-9080-4****, 15 (2009) 617-644***

Milestone: CEC'2005 Real Parameter Optimization Session and Benchmark

OTHER SPECIAL TRACKS

A GECCO 2009 Workshop for Real-Parameter Optimization: Black-Box Optimization Benchmarking (BBOB) 2009. **GECCO 2009, Montreal, Canada, July 8-12 2009.** Organizers: Anne Auger, Hans-Georg Beyer, Nikolaus Hansen, Steffen Finck, Raymond Ros, Marc Schoenauer, and Darrell Whitley.

A GECCO 2010 Workshop for Real-Parameter Optimization: Black-Box Optimization Benchmarking (BBOB) 2010. **GECCO 2010, Portland, USA, July 7-11 2010.** Organizers: Anne Auger, Hans-Georg Beyer, Steffen Finck, Nikolaus Hansen, Petr Posik, Raymond Ros.

Contents

Large Scale Global Optimization

Nowadays, the ability to tackle high-dimensional problems is crucial to many real problems (bio-computing, data mining, etc.), arising high-dimensional optimization problems as a very interesting field of research.

The ability of being scalable for high-dimensional problems becomes an essential requirement for modern optimization algorithm approaches.

G-CMA-ES presents good results with a low/medium number of variables but its drawback is associated to the scalability – More than 100 variables

Large Scale Global Optimization

Special Session & Competition on Large Scale Global Optimization at CEC 2008.

Workshop for Evolutionary Algorithms and other Metaheuristics for Continuous Optimization Problems - A Scalability Test at ISDA 2009.

Special Session & Competition on Large Scale Global Optimization at CEC 2010.

Winner: ***Algorithm: MA-SSW-Chains***

MA-SW-Chains: Memetic Algorithm Based on Local Search Chains for Large Scale Continuous Global Optimization

D. Molina, M. Lozano, F. Herrera

Evolutionary Computation, 2010. WCCI 2010 IEEE World Congress on Computational Intelligence. IEEE Congress on July, 18-23, 2010 Page(s): 3153 - 3160 .

Large Scale Global Optimization

Special Issue of Soft Computing:
Scalability of Evolutionary Algorithms and other Metaheuristics for Large Scale Continuous Optimization Problems
Volume 15, Number 11, 2011

http://sci2s.ugr.es/EAMHCO/#LSCOP-special-issue-SOCO

6. Complementary Material: SOCO Special Issue on Large Scale Continuous Optimization Problems

- A set of **19 scalable function optimization problems** were provided:
    - **6 Funcionts: F1-F6 of the CEC'2008 test suite**. A detailled description may be found in: K. Tang, X. Yao, P. N. Suganthan, C. MacNish, Y. P. Chen, C. M. Chen, and Z. Yang. Benchmark Functions for the CEC'2008 Special Session and Competition on Large Scale Global Optimization. Technical Report, Nature Inspired Computation and Applications Laboratory, USTC, China, 2007. (Source code).
    - **5 Shifted Functions: Schwefel's Problem 2.22 (F7), Schwefel's Problem 1.2 (F8), Extended f10 (F9), Bohachevsky (F10), and Schaffer (F11)**. (Description) (Source code).
    - **8 Hybrid Composition Functions (F12-F19*)**: They are non-separable functions built by combining two functions belonging to the set of functions F1-F11 (Description) (Source code).

The study was made with dimensions **D = 50**, **D = 100**, **D=200**, **D=500**, and **D = 1,000**. The maximum number of fitness evaluations is **5,000·D**.
Each run stops when the maximal number of evaluations is achieved.

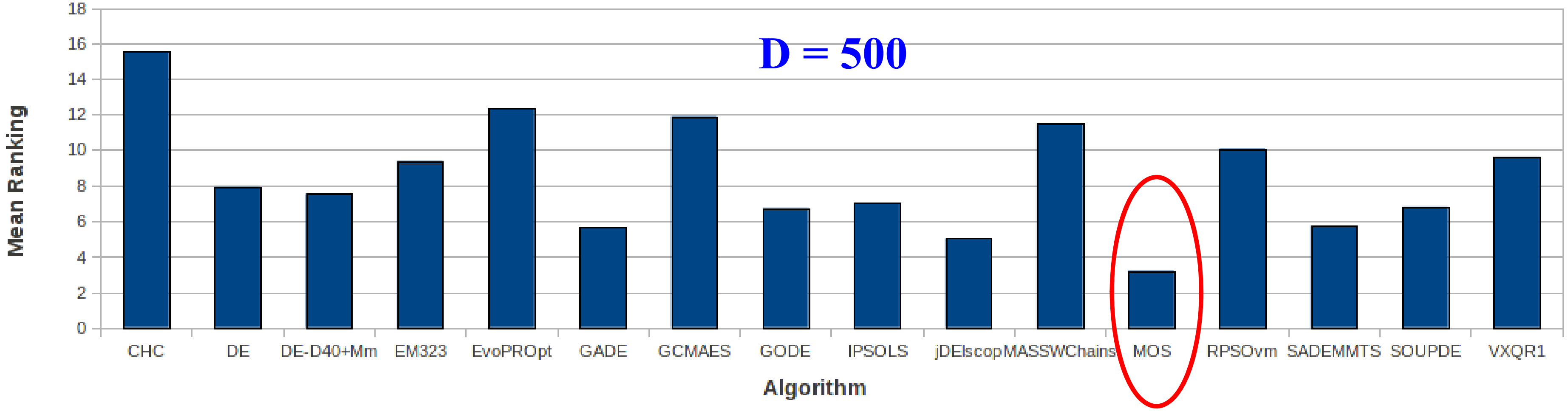
Large Scale Global Optimization

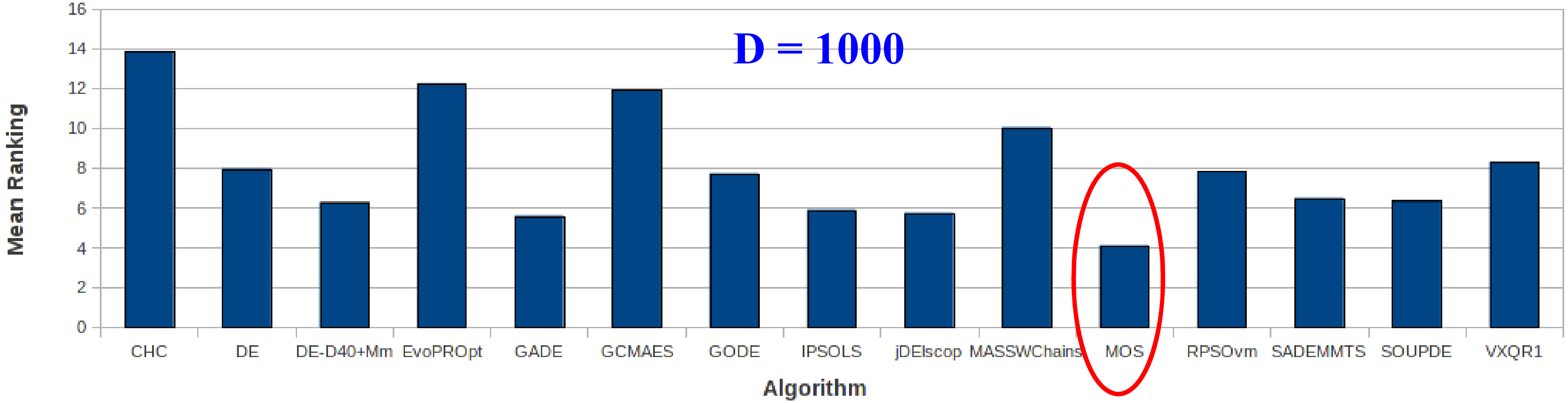
Special Issue of Soft Computing: Scalability of Evolutionary Algorithms and other Metaheuristics for Large Scale Continuous Optimization Problems Volume 15, **Number 11, 2011** **(7 DE approaches)**

P01 - ***SOUPDE*** Shuffle Or Update **Parallel** **Differential Evolution** for Large Scale Optimization
P02 - ***DE-D^40+M^m*** Role Differentiation and Malleable Mating for **Differential Evolution**: An Analysis on Large Scale Optimisation
P03 -***GODE*** Enhanced Opposition-Based **Differential Evolution** for Solving High-Dimensional Continuous Optimization Problems
P04 - ***GaDE*** Scalability of Generalized Adaptive **Differential Evolution** for Large-Scale Continuous Optimization
P05 - ***jDElscop*** Self-adaptive **Differential Evolution** Algorithm using Population Size Reduction and Three Strategies
P06 - **SaDE-MMTS** Self-adaptive **Differential Evolution with Multi-trajectory Search** for Large Scale Optimization
P07 - ***MOS*** A MOS-based Dynamic **Memetic** **Differential Evolution** Algorithm for Continuous Optimization A Scalability Test **(best results)**
P08 - ***MA-SSW-Chains*** **Memetic Algorithms Based on Local Search Chains** for Large Scale Continuous Optimisation Problems: MA-SSW-Chains
P09 - ***RPSO-vm*** **Restart Particle Swarm Optimization** with Velocity Modulation: A Scalability Test
P10 - **Tuned IPSOLS** An Incremental **Particle Swarm** for Large-Scale Optimization Problems: An Example of Tuning-in-the-loop (Re)Design of Optimization Algorithms
P11 -***multi-scale PSO*** Multi-Scale **Particle Swarm Optimization** Algorithm
P12 - ***EvoPROpt*** **Path Relinking** for Large Scale Global Optimization
P13 - ***EM323*** EM323 : A **Line Search based algorithm** for solving high-dimensional continuous non-linear optimization problems
P14 – ***VXQR*** VXQR: Derivative-free unconstrained optimization based on **QR factorizations**

Large Scale Global Optimization

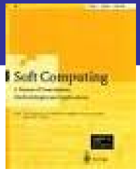
Special Issue of Soft Computing: Scalability of Evolutionary Algorithms and other Metaheuristics for Large Scale Continuous Optimization Problems Volume 15, Number 11, 2011





A MOS-based Dynamic Memetic Differential Evolution Algorithm for Continuous Optimization A Scalability Test. *A. LaTorre, S. Muelas, J.M. Peña.* Soft Computing, 15, pages: 2187-2199, 2011.

Large Scale Global Optimization



Special Issue of Soft Computing: Scalability of Evolutionary Algorithms and other Metaheuristics for Large Scale Continuous Optimization Problems Volume 15, Number 11, 2011

The algorithm with best values is MOS, in the following Wilcoxon's test we compare this one with the other algorithms,

D = 500

Algorithm	MOS value	Other value	Critical value p-value 5% error	Sig. differences?
CHC	189,5	0,5	46	Yes
DE	172	18	46	Yes
DE-D40+Mm	157	33	46	Yes
EM323	176	14	46	Yes
EvoPROpt	189,5	0,5	46	Yes
GADE	138	52	46	No
G-CMA-ES	166,5	23,5	46	Yes
GODE	167,5	22,5	46	Yes
IPSOLS	109	81	46	No
JDElscop	143,5	46,5	46	Yes
MASSWChains	182,5	7,5	46	Yes
RPSOvm	176	14	46	Yes
SADEMMTS	132,5	57,5	46	Yes
SOUPDE	157	33	46	Yes
VXQR1	163,5	26,5	46	Yes

Large Scale Global Optimization

Special Issue of Soft Computing: Scalability of Evolutionary Algorithms and other Metaheuristics for Large Scale Continuous Optimization Problems Volume 15, Number 11, 2011

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GADE	138	52	46	No
G-CMA-ES	170,5	19,5	46	Yes
GODE	159	31	46	Yes
IPSOLS	95	95	46	No
JDElscop	153	37	46	Yes
MASSWChains	163.5	26,5	46	Yes
RPSOvm	178	18	46	Yes
SADEMMTS	136,5	53,5	46	No
SOUPDE	167,5	22,5	46	Yes
VXQR1	160,5	29,5	46	Yes

Contents

Real-world Numerical Optimization Problems

Special Track: Competition: Testing Evolutionary Algorithms on Real-world Numerical Optimization Problems CEC'2011, **New Orleans, USA, Jun 5 - 8, 2011.** Organizer: P.N. Suganthan.

4. Special Sessions and Workshops: Problem definitions and contributions (pdf files) http://sci2s.ugr.es/EAMHCO/#SS

1. **Parameter Estimation for Frequency-Modulated (FM) Sound Waves**
2. **Lennard-Jones Potential Problem**
3. **The Bifunctional Catalyst Blend Optimal Control Problem**
4. **Optimal Control of a Non-Linear Stirred Tank Reactor**
5. **Tersoff Potential Function Minimization Problem**
6. **Spread Spectrum Radar Polly phase Code Design**
7. **Transmission Network Expansion Planning (TNEP) Problem**
8. **Large Scale Transmission Pricing Problem**
9. **Circular Antenna Array Design Problem**
10. **Dynamic Economic Dispatch (DED) Problem**
11. **Static Economic Load Dispatch (ELD) Problem**
12. **Hydrothermal Scheduling Problem**
13. **Messenger: Spacecraft Trajectory Optimization Problem**
14. **Cassini 2: Spacecraft Trajectory Optimization Problem**

13 Algorithms participate in the Special Track

Real-world Numerical Optimization Problems

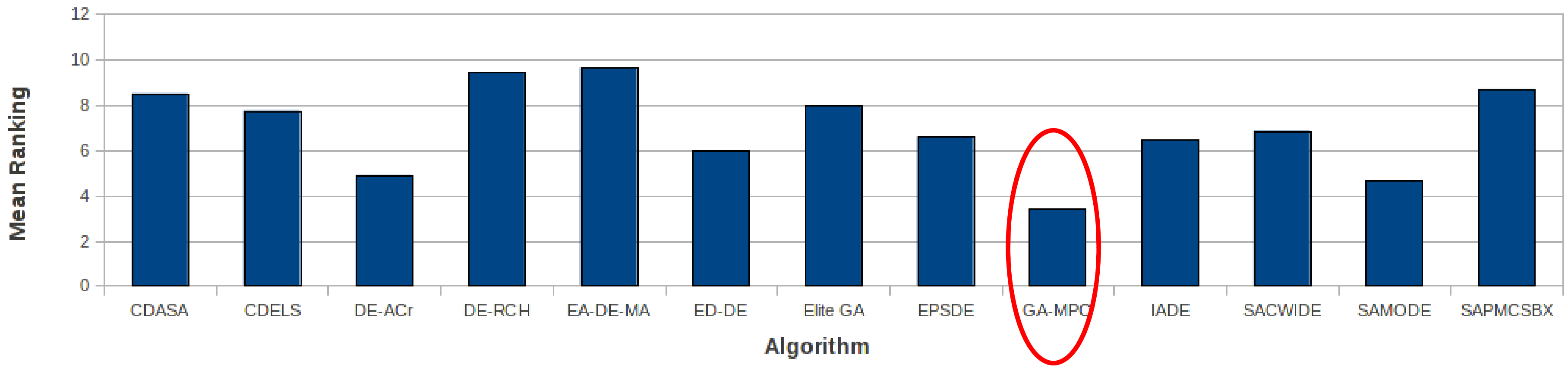
Special Track: Competition: Testing Evolutionary Algorithms on Real-world Numerical Optimization Problems CEC'2011, **New Orleans, USA, Jun 5 - 8, 2011.** Organizer: P.N. Suganthan.

4. Special Sessions and Workshops: Problem definitions and contributions (pdf files)
http://sci2s.ugr.es/EAMHCO/#SS (9 DE approaches)

1. ***Algorithm: Hybrid DE-RHC***
2. ***Algorithm: GA-MPC (*GA with a New Multi-Parent Crossover)**
3. ***Algorithm: SAMODE (*Differential Evolution with Multiple Strategies)**
4. ***Algorithm: Elite GA (*Genetic Algorithm)**
5. ***Algorithm: IADE (*Adaptive Differential Evolution Algorithm)**
6. ***Algorithm: ED-DE (*Estimation of Distribution and Differential Evolution Cooperation)**
7. ***Algorithm: EA-DE-MA (*Hybrid EA-DE-Memetic Algorithm)**
8. ***Algorithm: CDASA (*Continuous Differential Ant-Stigmergy Algorithm)**
9. ***Algorithm: SAPMCSBX (*Modified SBX and Adaptive Mutation)**
10. ***Algorithm: SACWIDE (*Self Adaptive Cluster Based and Weed Inspired Differential Evolution)**
11. ***Algorithm: DE-Acr (*Hybrid DE Algorithm With Adaptive Crossover Operator)**
12. ***Algorithm: EPSDE (*Ensemble Differential Evolution)**
13. ***Algorithm: CDELS (*Modified Differential Evolution with Local Search)**

Real-world Numerical Optimization Problems

Special Track: Competition: Testing Evolutionary Algorithms on Real-world Numerical Optimization Problems CEC'2011, **New Orleans, USA, Jun 5 - 8, 2011.** : P.N. Suganthan.



Algorithm: GA-MPC

GA with a New Multi-Parent Crossover for Solving IEEE-CEC2011 Competition Problems

Saber M. Elsayed; Ruhul A. Sarker; Daryl L. Essam

IEEE Congress on Evolutionary Computation, 2011. Jun, 5-8, 2011 Page(s): 1034 - 1040

STEP 4: For each three consecutive individuals, If $u \in [0,1] < cr$

i) Rank these three individuals from $f(x_i) \leq f(x_{i+1}) \leq f(x_{i+2})$

ii) If one of the selected individuals is the same to another, then replace one of them with a random individual from the selection pool.

iii) Calculate $\beta = N(\mu, \sigma)$

iv) Generate three offspring (o_i):

$$o_1 = x_1 + \beta \times (x_2 - x_3)$$
$$o_2 = x_2 + \beta \times (x_3 - x_1)$$
$$o_3 = x_3 + \beta \times (x_1 - x_2)$$

Real-world Numerical Optimization Problems

Special Track: Competition: Testing Evolutionary Algorithms on Real-world Numerical Optimization Problems CEC'2011, **New Orleans, USA, Jun 5 - 8, 2011.** : P.N. Suganthan.

The algorithm with best values is GA-MPC, in the following Wilcoxon's test we compare this one with the other algorithms.

Algorithm	GA-MPC value	Other value	Critical value p-value 5% error	Sig. differences?
CDASA	242,5	10,5	65	Yes
CDE-LS	239	14	65	Yes
DE-ACr	158,5	94,5	65	No
DE-RCH	242,5	10,5	65	Yes
EA-DE-MA	235,5	17,5	65	Yes
ED-DE	230,5	22,5	65	Yes
Elite GA	229,5	23,5	65	Yes
EPSDE	235	18	65	Yes
IADE	222,5	30,5	65	Yes
SACWIDE	224,5	28,5	65	Yes
SAMODE	202	51	65	Yes
SAPMCSBX	242,5	10,5	65	Yes

Algorithm: GA-MPC: GA with a New Multi-Parent Crossover for Solving IEEE-CEC2011 Competition Problems
Saber M. Elsayed; Ruhul A. Sarker; Daryl L. Essam
Evolutionary Computation, 2011. IEEE Congress on Jun, 5-8, 2011 Page(s): 1034 - 1040

Contents

Non Rigorous Experiments: Local vs Global Comparison

It is usual to find a paper with a novel proposal:

"Advanced xxx algorithm"

For example: **Advanced PSO, advanced DE ….**

Authors compare the new proposal "Advanced xxx algorithm" with the basic "xxx algorithm" or recent "xxx algorithms" that are far from the state of the art.

The proposal "Advanced xxx algorithm" is better than previous ones (of course) and authors claim on the **"high quality of the proposal"**

From the local point of view is good but ... But the proposal "Advanced xxx algorithm" is far from the state of the art (G-CMAES, MA-CMA-Chais, AMALGAM – SO)

Non Rigorous Experiments:

Local vs Global Comparison

Examples for comparison:

SaDE: A. K. Qin, V. L. Huang, P. N. Suganthan, Differential evolution algorithm with strategy adaptation for global numerical optimization, IEEE Transactions on Evolutionary Computation, vol. 13, number 2, pp 398–417. 2009.

JADE: J. Zhang, A. C. Sanderson, JADE: Adaptive differential evolution with optional external archive, IEEE Transactions on Evolutionary Computation, vol. 13, number 5, pp. 945–958. 2009.

DEGL: S. Das, A. Abraham, U. K. Chakraborty, A. Konar, Differential evolution using a neighborhood-based mutation operator, IEEE Transactions on Evolutionary Computation, vol. 13,
number 3, pp 526–553. 2009.

Frankestein PSO: MA. Montes de Oca, T. Stützle, M. Birattari, M. Dorigo, Frankenstein's PSO: A Composite Particle Swarm Optimization Algorithm IEEE Transactions on Evolutionary Computation, Vol 13:5 (2009) pp. 1120-1132

OLPSO: Z-H Zhan, J. Zhang, Y. Li, Y-H. Shi, Orthogonal Learning Particle Swarm Optimization, IEEE Transactions on Evolutionary Computation, (2011)

Non Rigorous Experiments: Local vs Global Comparison

G-CMA-ES Vs	R^+	R^-	P-value
Frankenstein PSO	278.0	22.0	6.39E-5
OLPSO Global	310.0	15.0	8.166E-6
SADE	263.0	37.0	6.498E-4
DEGL	325.0	0.0	5.960E-8
JADE	298.0	27.0	7.498E-5

Table 1: Results obtained by the Wilcoxon test for algorithm G-CMA-ES (D=10)

G-CMA-ES Vs	R^+	R^-	P-value
Frankenstein PSO	286.5	38.5	4.030E-4
OLPSO Global	325.0	0.0	5.960E-8
SADE	217.0	83.0	0.0564
DEGL	277.0	48.0	0.0013
JADE	216.5	108.5	0.1524

Table 2: Results obtained by the Wilcoxon test for algorithm G-CMA-ES (D=30)

G-CMA-ES Vs	R^+	R^-	P-value
Frankenstein PSO	276.0	24.0	9.084E-5
OLPSO Global	281.0	44.0	8.082E-4
SADE	205.0	120.0	0.2457
DEGL	276.0	49.0	0.0015
JADE	217.0	108.0	0.148

Table 3: Results obtained by the Wilcoxon test for algorithm G-CMA-ES (D=50)

Non Rigorous Experiments: Local vs Global Comparison

Of course, the two following kind of studies are important :

A) To propose new advances inside of techniques (DE, PSO, …), but authors must try to reach the state of the art.

B) New optimization frameworks, as a first idea on a new research branch, are welcome: (third generation?)

Estimation of Distribution Algorithms

Chang Wook Ahn, Ramakrishna, R.S. (2008). **On the scalability of real-coded bayesian optimization algorithm**. IEEE Transaction of Evolutionary Computation 12(3), 307-322 doi: 10.1109/TEVC.2007.902856.

Central Force Optimization

Formato, R.A. (2007). **Central Force Optimization: A New Metaheuristic with Applications in Applied Electromagnetics**. Progress In Electromagnetics Research 77, 425-491 doi: 10.2528/PIER07082403.

Non Rigorous Experiments:
Local vs Global Comparison

B) New optimization frameworks, as a first idea on a new research branch, are welcome:

Artificial Bee Colony Optimization

Karaboga, D., Basturk, B. (2007). **A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm**. Journal of Global Optimization, 39, 459-471 doi: 10.1007/s10898-007-9149-x.

Variable mesh optimization

A. Puris, R. Bello, D. Molina, F. Herrera, **Variable mesh optimization for continuous optimization problems**. *Soft Computing - A Fusion of Foundations, Methodologies and Applications (2011) 1-15, doi: 10.1007/s00500-011-0753-9*, ***in press (2011)***.

Now it is necessary to advance in the development of new/novel proposals inside of these frameworks, making them competitive with the state of the art.

Contents

Current trends

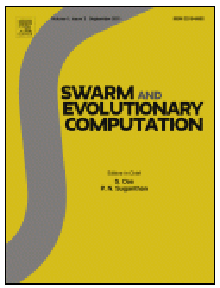
There are different areas of research that focus the attention of researchers in "evolutionary parameter optimization":

- **The algorithms' scalability: High dimensional problems**

- **Multi-modal problems with multiple solutions**

Recent review

Real-parameter evolutionary multimodal optimization — A survey of the state-of-the-art
Swarm and Evolutionary Computation, 1:2 (2011), *71-88*
Swagatam Das, Sayan Maity, Bo-Yang Qu, P.N. Suganthan



Current trends

There are different areas of research that focus the attention of researchers in "evolutionary parameter optimization":

- **Constraint optimization**

Recent event: CEC10 Special Session / Competition on Evolutionary Constrained Real Parameter single objective optimization

- **Multi-objective optimization**

The last high quality algorithm (state of the art): **MOEA/D Homepage**
http://dces.essex.ac.uk/staff/qzhang/webofmoead.htm

Q. Zhang and H. Li, **MOEA/D:** A Multi-objective Evolutionary Algorithm Based on Decomposition, IEEE Trans. on Evolutionary Computation, vol.11, no. 6, pp712-731 2007.

H. Li and Q. Zhang, Multiobjective Optimization Problems with Complicated Pareto Sets, **MOEA/D** and NSGA-II, IEEE Trans on Evolutionary Computation, vol. 12, no 2, pp 284-302, April/2009

Q. Zhang, W. Liu, E. Tsang and B. Virginas, Expensive Multiobjective Optimization by **MOEA/D** with Gaussian Process Model, IEEE Trans on Evolutionary Computation, vol. 14, no.3, pp 456-474, 2010.

Current trends

There are different areas of research that focus the attention of researchers in "evolutionary parameter optimization":

- **New frameworks for Evolutionary parameter optimization and the development of advanced approaches to compete with the state of the art.**

- **Memetic Algorithms as the extension of hybrid approaches (new frameworks and local search).**

Recent high quality methods are MAs: MA-CMA-Chains (Genetic Algorithm and CMAES as local search, **standar dimension) MOS** (Dynamic Memetic Differential Evolution , **large scale optimization)**

Contents

Final Comments

- **Many real-world problems may be formulated as optimization problems of parameters with variables in continuous domains (parameter optimization problems).**

- **The development of high quality evolutionary algorithms (improving known or developing new algorithms) allows us to tackle a large number of real-world applications.**

- **It is very important to understand stochastic search in continuous and high-dimensional search spaces to advance in the topic.**

Final Comments

Website: Evolutionary Algorithms and other Metaheuristics for Continuous Optimization Problems
http://sci2s.ugr.es/EAMHCO/

Thematic Public Websites

Evolutionary Algorithms and other Metaheuristics for Continuous Optimization Problems

EAs & MHs Continuous Optimization

This **Website** is devoted to a Evolutionary Algorithms and other Metaheuristics for Continuous Optimization Problems. It is maintained by M. Lozano, D. Molina, C. García-Martínez, F. Herrera following the next **summary**:

1. Introduction
2. Pioneer and Outstanding Contributions
3. Books and Special Issues
4. Special Sesions and Workshops
5. Large Scale Optimization Problems
6. Complementary Material: SOCO Special Issue on Large Scale Continuous Optimization Problems
7. Software
8. Slides
9. Test Functions and Results
10. Statistical Test Based Methodologies for Algorithm Comparisons
11. Future Events