Results of the 2017 IEEE CEC Competition on Niching Methods for Multimodal Optimization

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IEEE CEC 2017 Competition on Niching Methods

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Introduction

Introduction

- Many real-world problems are "multi-modal" by nature, i.e., multiple satisfactory solutions exist
- Niching methods: promote and maintain formation of multiple stable subpopulations within a single population
  - Aim: maintain diversity and locate multiple globally optimal solutions.
- Challenge: Find an efficient optimization algorithm, which is able to locate multiple global optimal solutions for multi-modal problems with various characteristics.

Competition: CEC 2013/2015/2016/2017

Provide a common platform that encourages fair and easy comparisons across different niching algorithms.

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

- 20 benchmark multi-modal functions with different characteristics
- 5 accuracy levels: $\varepsilon \in \{10^{-1}, 10^{-2}, 10^{-3}, 10^{-4}, 10^{-5}\}$
- The benchmark suite and the performance measures have been implemented in: C/C++, Java, MATLAB, (Python soon)

Benchmark function set

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

Id	Dim.	# GO	Name	Characteristics
F_1	1	2	Five-Uneven-Peak Trap	Simple, deceptive
F_2	1	5	Equal Maxima	Simple
F_3	1	1	Uneven Decreasing Maxima	Simple
F_4	2	4	Himmelblau	Simple, non-scalable, non-symmetric
F_5	2	2	Six-Hump Camel Back	Simple, not-scalable, non-symmetric
F_6	2,3	18,81	Shubert	Scalable, #optima increase with D, unevenly distributed grouped optima
F_7	2,3	36,216	Vincent	Scalable, #optima increase with D, unevenly distributed optima
F_8	2	12	Modified Rastrigin	Scalable, #optima independent from D, symmetric
F_9	2	6	Composition Function 1	Scalable, separable, non-symmetric
F_{10}	2	8	Composition Function 2	Scalable, separable, non-symmetric
F_{11}	2,3,5,10	6	Composition Function 3	Scalable, non-separable, non-symmetric
F_{12}	2,3,5,10	8	Composition Function 4	Scalable, non-separable, non-symmetric

Peak Ratio (PR) measures the average percentage of all known global optima found over multiple runs:

$$\mathrm{PR} = \frac{\sum_{run=1}^{NR} \#\text{ of Global Optima}_i}{(\#\text{ of known Global Optima}) * (\#\text{ of runs})}$$

Who is the winner:

- The participant with the highest average Peak Ratio performance on all benchmarks wins.
- In all functions the following holds: the higher the PR value, the better

Participants

Participants

Submissions to the competition:

- (SSGA-DMRTS-DDC: SSGA-1) Steady State Genetic Algorithm with the Dynamic Modified Restricted Tournament Selection Method and the Dynamic Distance Criterion [1]
- (SSGA-DMRTS-DDC-F: SSGA-2) Steady State Genetic Algorithm with a static (dimensionality-dependent) Modified Restricted Tournament Selection Method and the Dynamic Distance Criterion

  by Camila Silva de Magalhães, Lincon Onório Vidal, Matheus Muller Pereira da Silva, Raquel Gomes Gon calves Farias, Helio José Correa Barbosa, and Laurent Emmanuel Dardenne, from UFRJ and LNCC, Brazil

Participants (2)

Implemented algorithms for comparisons:

- (CrowdingDE) Crowding Differential Evolution [3]
- (DE/nrand/1) Niching Differential Evolution algorithms with neighborhood mutation strategies [4]
- (dADE/nrand/1) A Dynamic Archive Niching Differential Evolution algorithm for Multimodal Optimization [5]
- (NEA2) Niching the CMA-ES via Nearest-Better Clustering [6]
- (NMMSO) Niching Migratory Multi-Swarm Optimiser of Fieldsend [2].

In the repository: CMA-ES, IPOP-CMA-ES, DE/nrand/1,2, DECG, DELG, DELS-aj, CrowdingDE, dADE/nrand/1,2, NEA1, NEA2, N-VMO, PNA-NSGAII, A-NSGAII, rlsis, rs-cmsa-es, ascga, nea2+, ...

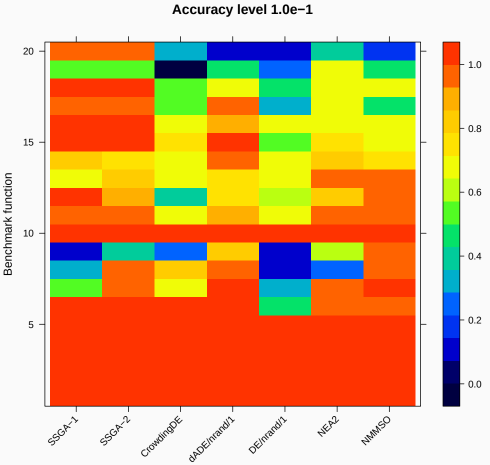
Results

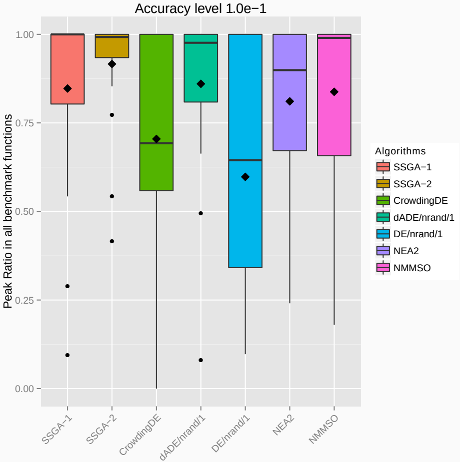
Results

Summary:

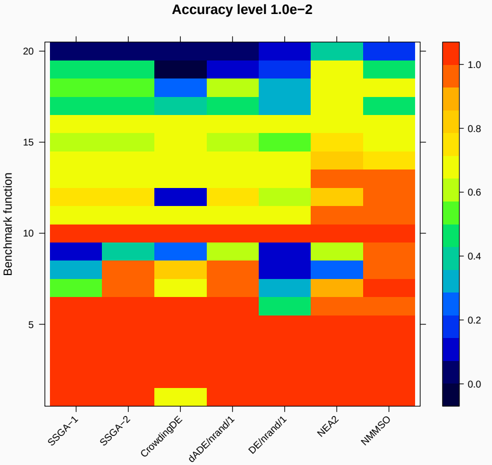
- **2** new search algorithms
- **5** comparators based on the previous competitions @ CEC2013 and CEC2015
- **20** multi-modal benchmark functions
- **5** accuracy levels $\varepsilon \in \{10^{-1}, 10^{-2}, 10^{-3}, 10^{-4}, 10^{-5}\}$
- Results: **per accuracy level & over all accuracy levels**
- In total (CEC2013, CEC2015, CEC2016) 25 algorithms in the repository: `https://github.com/mikeagn/CEC2013`

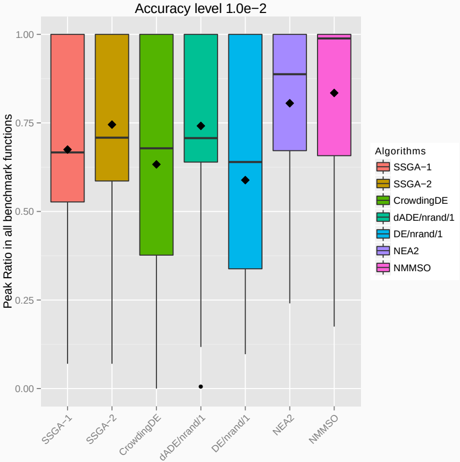
Accuracy level $\varepsilon = 10^{-1}$



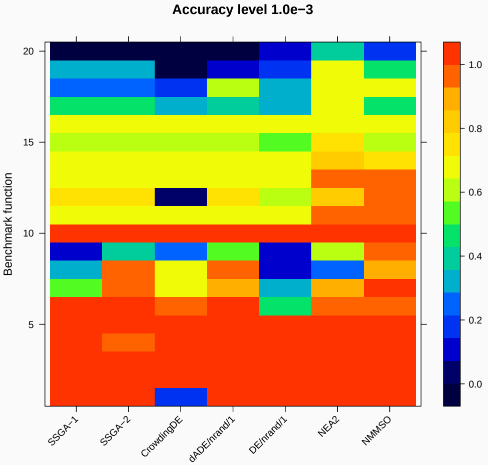


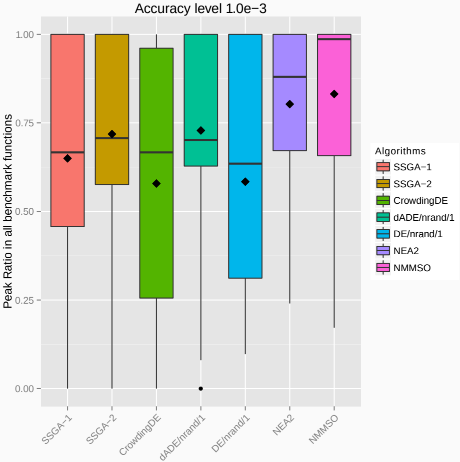
Accuracy level $\varepsilon = 10^{-2}$



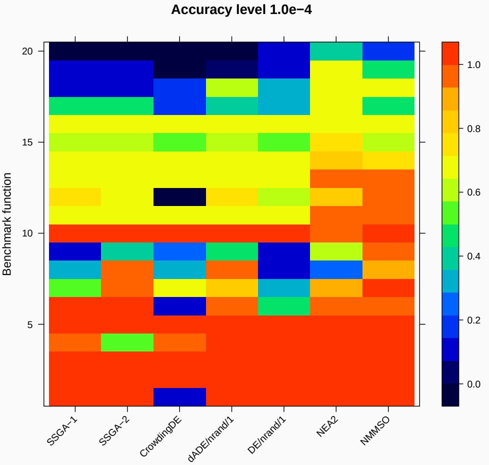


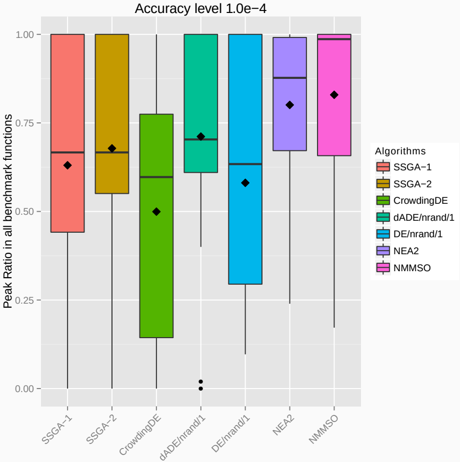
Accuracy level $\varepsilon = 10^{-3}$



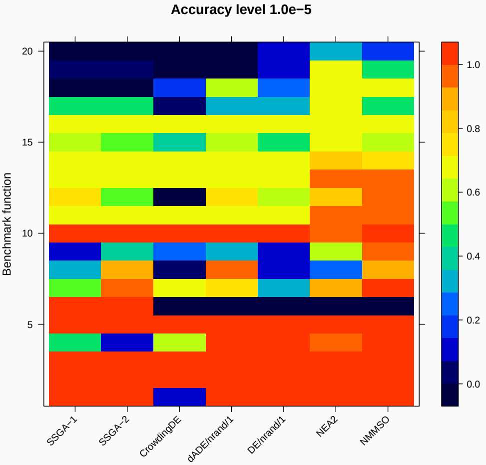


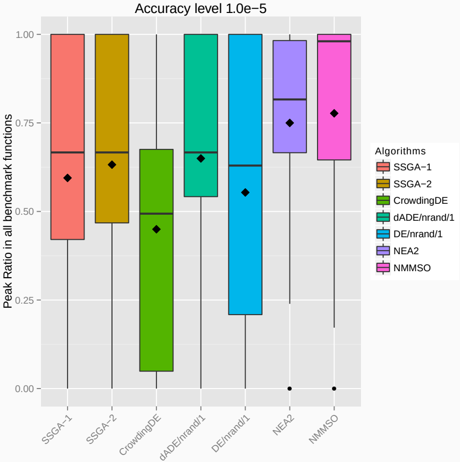
Accuracy level $\varepsilon = 10^{-4}$



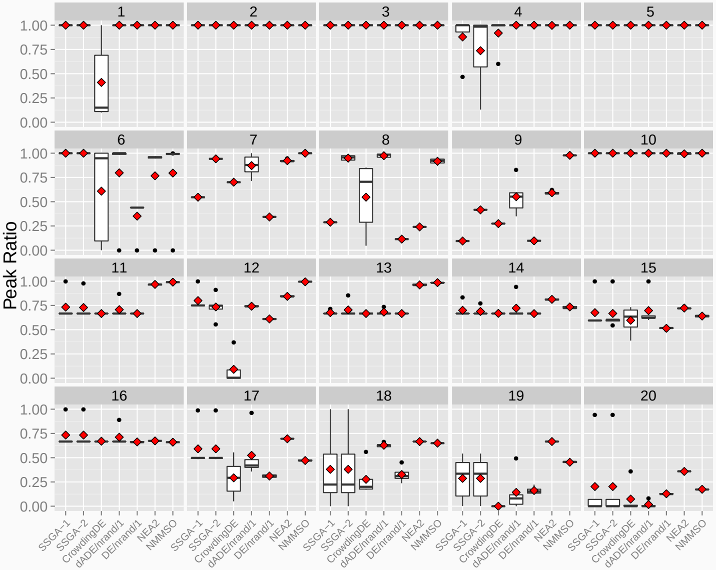


Accuracy level $\varepsilon = 10^{-5}$

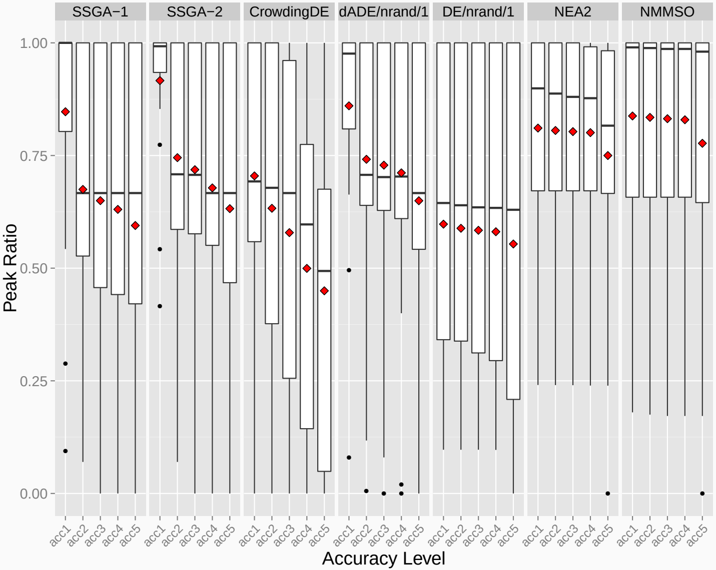




Performance per benchmark across all accuracy levels



Performance per algorithm

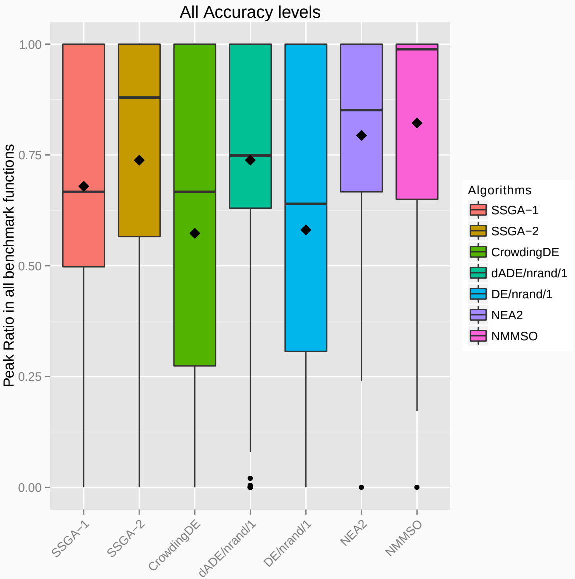


Statistical Analysis

	SSGA-1	SSGA-2	CrowdingDE	dADE/nrand/1	DE/nrand/1	NEA2
SSGA-2	+/=	N/A	N/A	N/A	N/A	N/A
CrowdingDE	+/=	−/−	N/A	N/A	N/A	N/A
dADE/nrand/1	+/=	=/=	+/+	N/A	N/A	N/A
DE/nrand/1	−/−	−/−	=/=	−/−	N/A	N/A
NEA2	+/+	−/−	+/+	+/+	+/+	N/A
NMMSO	+/+	+/+	+/+	+/+	+/+	=/=

- p: Wilcoxon rank-sum test
- p_b: Bonferroni correction
- **+** row wins column,
- **−** row loses from column,
- **=** non-significant differences
- N/A: Not Applicable

Overall performance (1)



Overall performance (2)

	Algorithm	Statistics			Rankings	
		Median	Mean	St.D.	Rank (Median)	Rank (Mean)
2017	SSGA-1	0.6667	0.6794	0.3283	5	5
	SSGA-2	**0.8794**	**0.7381**	0.3013	**2**	4
2015	NMMSO	**0.9885**	**0.8221**	0.2538	**1**	**1**
2013	CrowdingDE	0.6667	0.5731	0.3612	5	7
	DE/nrand/1	0.6396	0.5809	0.3338	7	6
	dADE/nrand/1	0.7488	0.7383	0.3010	4	**3**
	NEA2	**0.8513**	**0.7940**	0.2332	**3**	**2**

Winners

Winners

Ranking based on average PR values (only CEC2017)

1. (**SSGA-DMRTS-DDC-F**: SSGA-2) Steady State Genetic Algorithm with a static (dimensionality-dependent) Modified Restricted Tournament Selection Method and the Dynamic Distance Criterion
2. (**SSGA-DMRTS-DDC**: SSGA-1) Steady State Genetic Algorithm with the Dynamic Modified Restricted Tournament Selection Method and the Dynamic Distance Criterion [1]

Note: The algorithms have not been fine-tuned for the specific benchmark suite!
Note: the new algorithm haven't performed better than state-of-the-art

Summary

Conclusions

Summary

- Two new search algorithms (in total 27 algorithms!)
- Winner: SSGA-DMRTS-DDC-F Steady State Genetic Algorithm with a static (dimensionality-dependent) Modified Restricted Tournament Selection Method and the Dynamic Distance Criterion
  - Competitive against state-of-the-art, (Steady state GA, RTS, dynamic distance criterion, adaptive parameters)

Conclusions (2)

- State-of-the-art algorithms perform very well on the benchmark set
- New algorithms produce competitive and promising performance

Key characteristics of the new algorithms:

- Modified classic niching techniques: Modified RTS, dynamic distance measures
- Usage of adaptive parameter techniques.
- Algorithms: Steady State Genetic Algorithms

Future Work

Possible objectives:

- Re-organize the competitions from scratch
- Enhance the benchmark function set
- Introduce new performance measures

Acknowledgment

We really want to thank for their help:

- The participants :-)

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