Results of the 2016 IEEE WCCI/CEC Competition on Niching Methods for Multimodal Optimization

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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

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

Measures:

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

Submissions to the competition:

- (**rlsis**): Restarted Local Search with Improved Selection of Starting Points, Simon Wessing
- (**rs-cmsa-es**): Benchmarking Covariance Matrix Self Adaption Evolution Strategy with Repelling Subpopulations, Ali Ahrari, Kalyanmoy Deb and Mike Preuss
- (**ascga**): Adaptive species conserving genetic algorithm, Jian-Ping Li, Felician Campean
- (**nea2+**): Niching the CMA-ES via Nearest-Better Clustering: First Steps Towards an Improved Algorithm, Mike Preuss

Participants (2)

Implemented algorithms for comparisons:

- (**CrowdingDE**) Crowding Differential Evolution [7]
- (**DE/nrand/1**) Niching Differential Evolution algorithms with neighborhood mutation strategies [8]
- (**dADE/nrand/1**) A Dynamic Archive Niching Differential Evolution algorithm for Multimodal Optimization [9]
- (**NEA2**) Niching the CMA-ES via Nearest-Better Clustering [10]
- (**NMMSO**) Niching Migratory Multi-Swarm Optimiser [6]

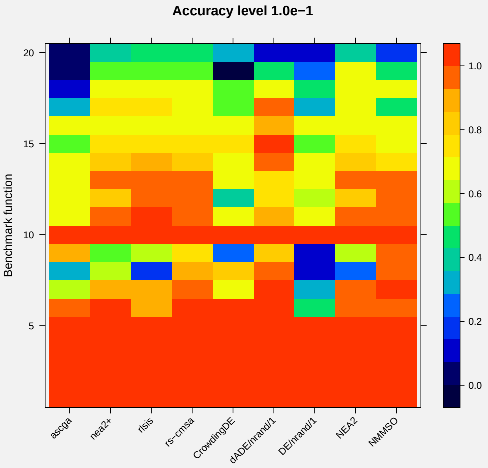
In the repository: CMA-ES, IPOP-CMA-ES, DE/nrand/1,2, DECG, DELG, DELS-aj, CrowdingDE, dADE/nrand/1,2, NEA1, NEA2, N-VMO, PNA-NSGAII, A-NSGAII, ALNM, MEA, MSSPSO, LSEAGP, LSEAEA, NMMSO, etc

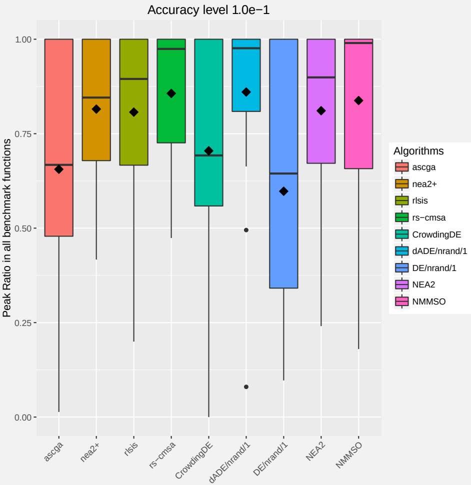
Results

Summary:

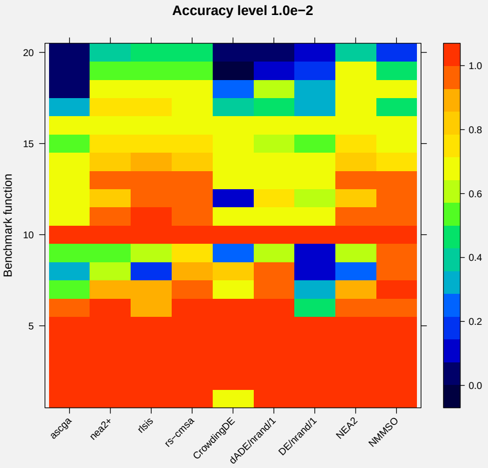
- **4** new search algorithms
- **5** classic comparators (based on CEC 2013, 2015)
- **20** multi-modal benchmark functions
- **5** accuracy levels $\varepsilon \in \{10^{-1}, 10^{-2}, 10^{-3}, 10^{-4}, 10^{-5}\}$
- Results: **per accuracy level & over all accuracy levels**
- In total (CEC2013 & CEC2015) more than 21 algorithms in the repository:
  `https://github.com/mikeagn/CEC2013`

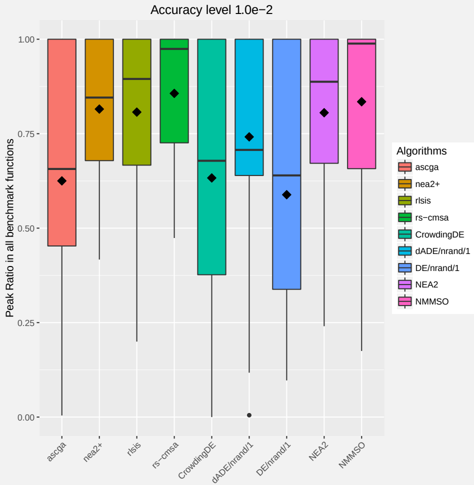
Accuracy level $\varepsilon = 10^{-1}$



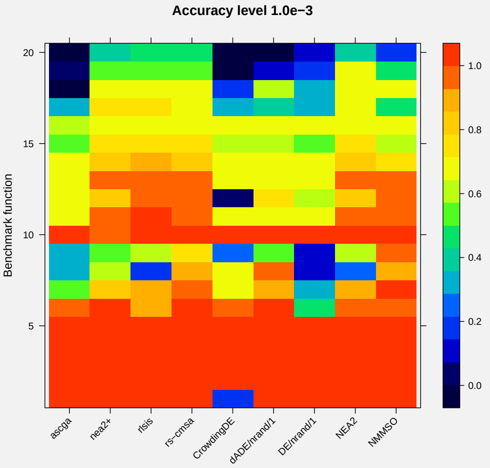


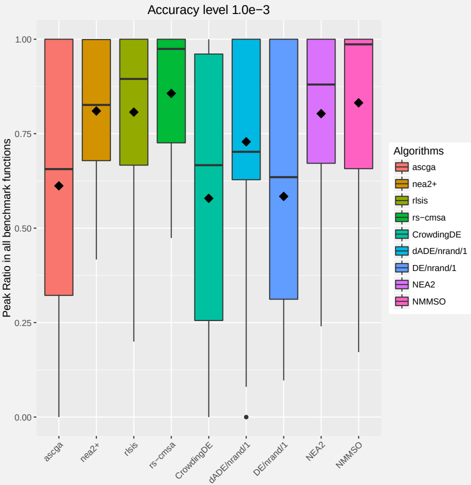
Accuracy level $\varepsilon = 10^{-2}$



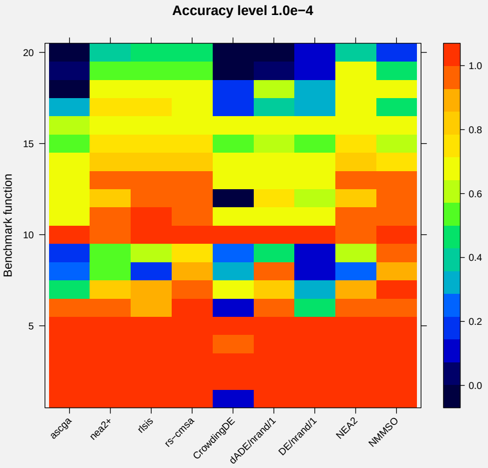


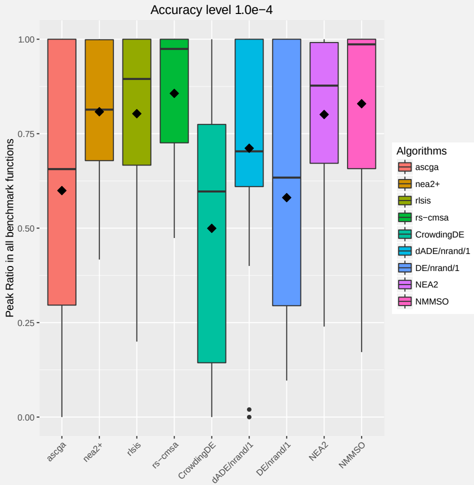
Accuracy level $\varepsilon = 10^{-3}$



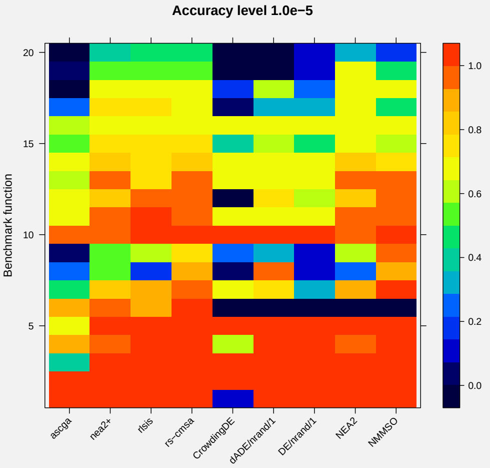


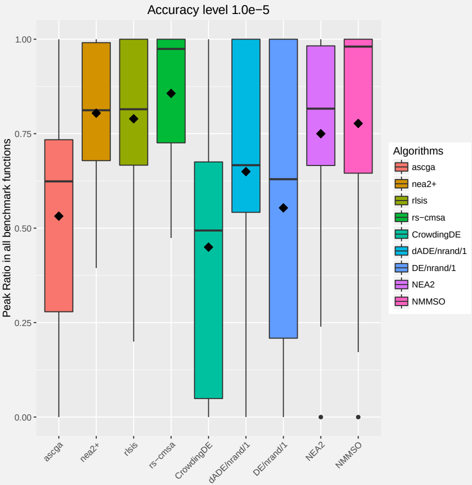
Accuracy level $\varepsilon = 10^{-4}$



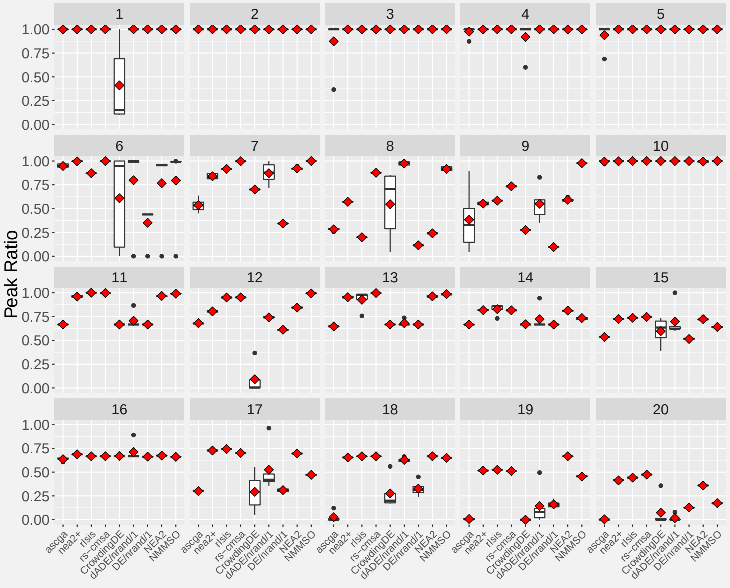


Accuracy level $\varepsilon = 10^{-5}$

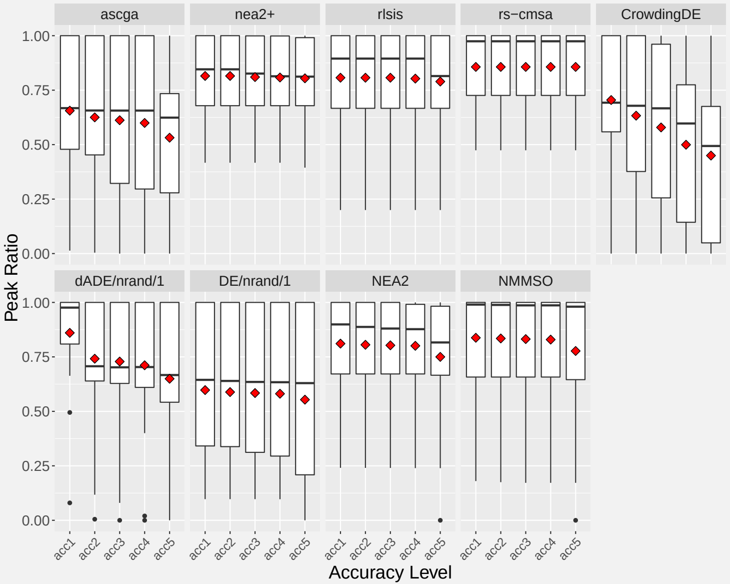




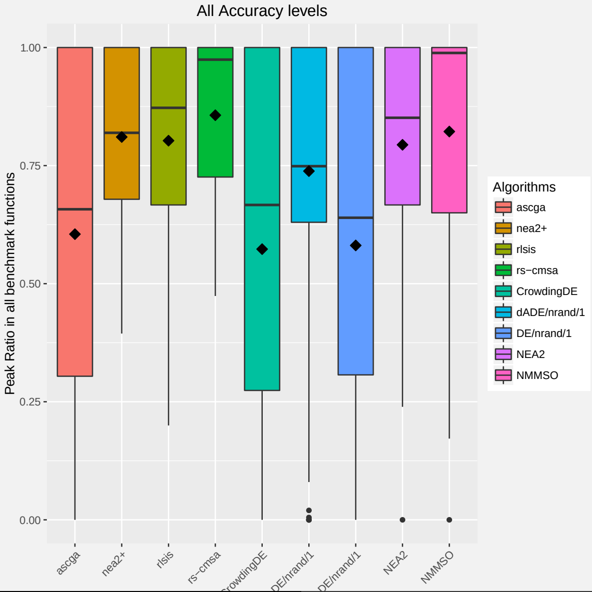
Performance per benchmark across all accuracy levels



Performance per algorithm



Overall performance (1)



Overall performance (2)

	Algorithm	Statistics			
		Mean	Median	St.D.	Rank
CEC2016	ascga	0.604	0.657	0.348	7
	nea2+	**0.810**	0.819	0.190	**3**
	rlsis	0.802	**0.872**	0.225	4
	rs-cmsa	**0.856**	**0.974**	0.174	**1**
CEC2013/5	NMMSO	**0.822**	**0.988**	0.253	**2**
	NEA2	0.794	0.851	0.233	5
	DE/nrand/1	0.580	0.639	0.333	8
	dADE/nrand/1	0.738	0.748	0.301	6
	CrowdingDE	0.573	0.666	0.361	9

Overall performance: CEC2013 + 2015 + 2016

Algorithm	Statistics			
	Mean	Median	St.D.	Rank
rs-cmsa	0.8566	0.9743	0.1746	1
NMMSO	0.8221	0.9885	0.2538	2
nea2+	0.8105	0.8193	0.1902	3
rlsis	0.8027	0.8723	0.2250	4
NEA2	0.7940	0.8513	0.2332	5
LSEAEA	0.7477	0.9030	0.3236	6
dADE/nrand/1	0.7383	0.7488	0.3010	7
LSEAGP	0.7302	0.7900	0.3268	8
CMA-ES	0.7137	0.7550	0.2807	9
N-VMO	0.6983	0.7140	0.3307	10
dADE/nrand/2	0.6931	0.7150	0.3174	11
ALNM	0.6594	0.7920	0.3897	12
PNA-NSGAII	0.6141	0.6660	0.3421	13
NEA1	0.6117	0.6496	0.3280	14
DE/nrand/2	0.6082	0.6667	0.3130	15
ascga	0.6048	0.6575	0.3485	16
DE/nrand/1	0.5809	0.6396	0.3338	17
DELS-aj	0.5760	0.6667	0.3857	18
CrowdingDE	0.5731	0.6667	0.3612	19
DELG	0.5706	0.6667	0.3925	20
DECG	0.5516	0.6567	0.3992	21
IPOP-CMA-ES	0.3625	0.2600	0.3117	22
MEA	0.3585	0.2075	0.3852	23
A-NSGAII	0.3275	0.0740	0.4044	24
MSSPSO	0.2188	0.0000	0.3913	25

Winners

Ranking based on average PR values (only CEC2016)

1. (**rs-cmsa-es**): Benchmarking Covariance Matrix Self Adaption Evolution Strategy with Repelling Subpopulations, Ali Ahrari, Kalyanmoy Deb and Mike Preuss
2. (**nea2+**): Niching the CMA-ES via Nearest-Better Clustering: First Steps Towards an Improved Algorithm, Mike Preuss
3. (**rlsis**): Restarted Local Search with Improved Selection of Starting Points, Simon Wessing
4. (**ascga**): Adaptive species conserving genetic algorithm, Jian-Ping Li, Felician Campean

Note: The algorithms have not been fine-tuned for the specific benchmark suite!

Conclusions

Summary

- Four new search algorithms (in total 25 algorithms!)
- Winner: **rs-cmsa-es:** Benchmarking Covariance Matrix Self Adaption Evolution Strategy with Repelling Subpopulations, Ali Ahrari, Kalyanmoy Deb and Mike Preuss
  - Competitive on average performance, (CMA-ES, repelling strategy)
  - CMA-ES: Strong local searcher to accurately locate global optima
  - Repelling: To avoid wasting effort in already searched areas

Conclusions (2)

- The competition gave a boost to the multi-modal optimization community
- New competitive and very promising approaches

Key characteristics of the algorithms:

- Usage of local models to maintain diversity and exploit locally the neighborhoods
- Methodologies: repelling, restarts, surrogates
- Algorithms: CMA-ES, Evolutionary Algorithms, Multi-swarms, GAs.

Future Work

Possible objectives:

- Re-organize the competitions in future
- Enhance the benchmark function set
- Introduce new performance measures
- Further automate the experimental design and results output
- Boost multi-modal optimization community

Acknowledgment

We really want to thank for their help:

- The participants :-)

Stay tuned!

- IEEE CIS Task Force on Multi-Modal Optimization
- `http://www.epitropakis.co.uk/ieee-mmo/`

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(-: Thank you very much for your attention :-)

Questions ???

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