Results of the 2016 GECCO Competition on Niching Methods for Multimodal Optimization

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Outline

Introduction

- Numerical optimization is probably one of the most important disciplines in optimization
- 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

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, (R 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

GECCO Competition (I)

Largely follows the procedures of the 2013/2015 CEC niching competitions, adopt new performance criteria:

Improved Scenarios

- Include information on the resources (time, function evaluations) needed to find the global optima, not only the fraction of successes within a given time period (number of evaluations), and
- Take into account the size of the final solution set, and reward small sets that mostly consist of the sought optima only.

GECCO Competition (II)

Three different Scenarios (performance evaluation):

- **Scenario I**: Adopt the CEC2013/2015 competition ranking procedure (based on average Peak Ratio), to facilitate straight forward comparisons with all previous competition entries.
- **Scenario II**: Adopt the (static) F1 measure to take into account the recall and precision of the final solution sets
- **Scenario III**: Adopt the (dynamic) F1 measure integral over the whole runtime to take into account the computational efficiency of the submitted algorithm

Ranking based on average values across all problems/accuracy levels of the aforementioned measures are used to decide the winner.

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 for GECCO 2016 Competition on Multimodal Optimization, 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
- (**nmmso**) Niching Migratory Multi-Swarm Optimiser, J. Fieldsend

Participants (2)

Implemented algorithms for comparisons:

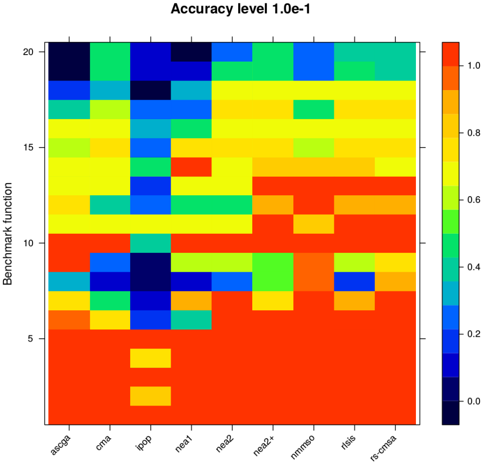
- (**CMA-ES**) The classic CMA-ES with restarts
- (**IPOP-CMA-ES**) The classic IPOP-CMA-ES
- (**NEA1,NEA2**) Niching the CMA-ES via Nearest-Better Clustering

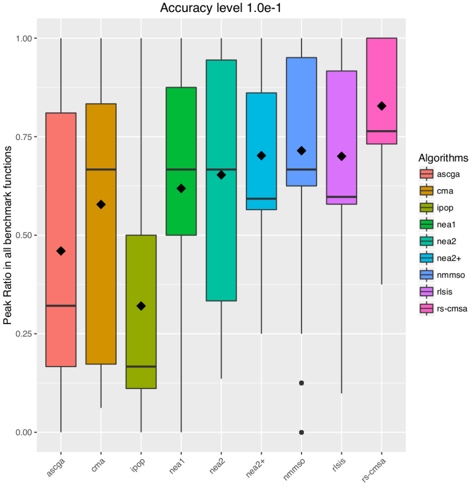
Results

Summary:

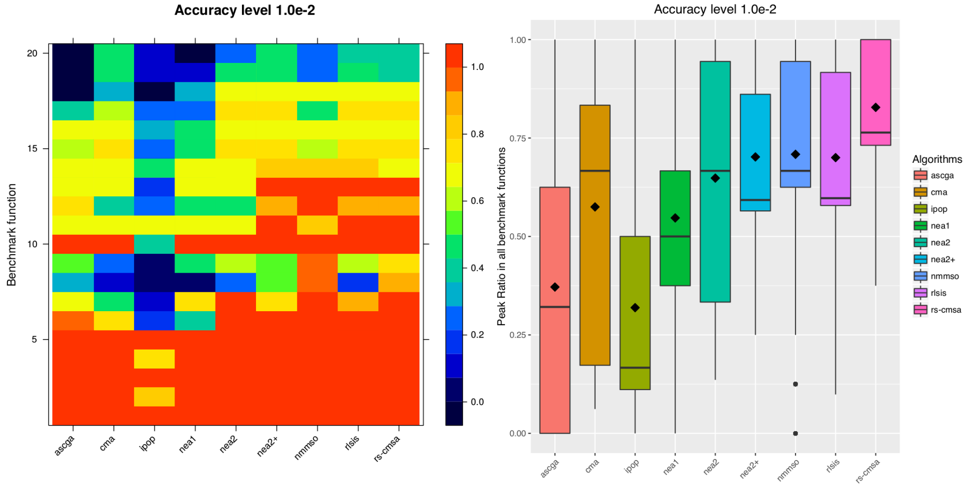
- **5** new search algorithms
- **4** classic algorithm comparators
- **20** multi-modal benchmark functions
- **5** accuracy levels $\varepsilon \in \{10^{-1}, 10^{-2}, 10^{-3}, 10^{-4}, 10^{-5}\}$
- Results: **per accuracy level & over all accuracy levels**
- Latest version always in the repository: `https://github.com/mikeagn/CEC2013`

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

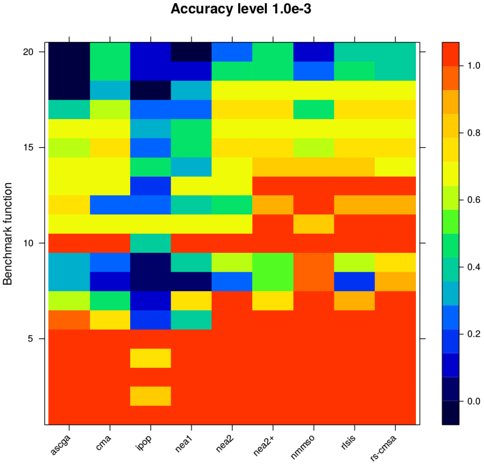


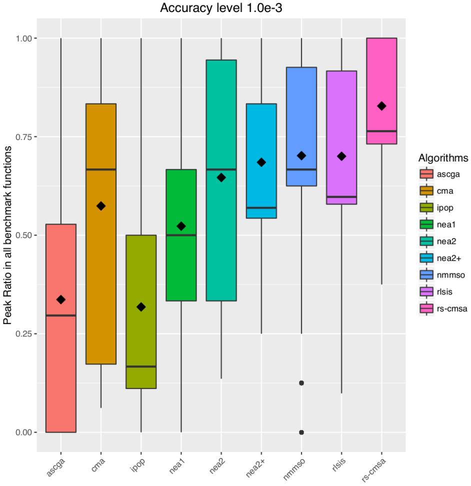


Scenario I: Accuracy level $\varepsilon = 10^{-2}$

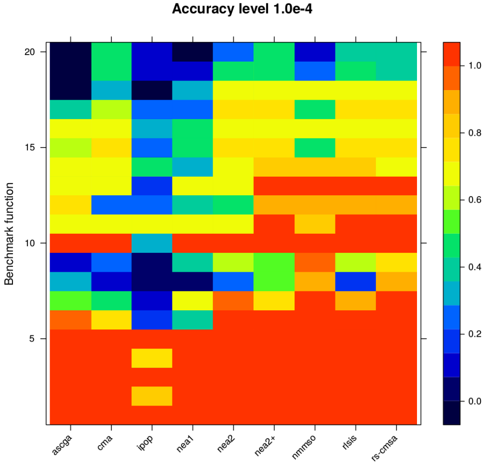


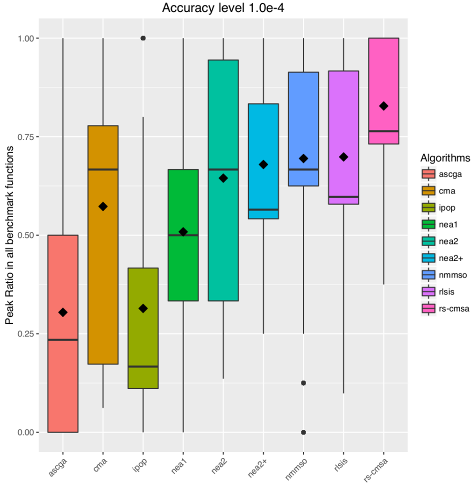
Scenario I: Accuracy level $\varepsilon = 10^{-3}$



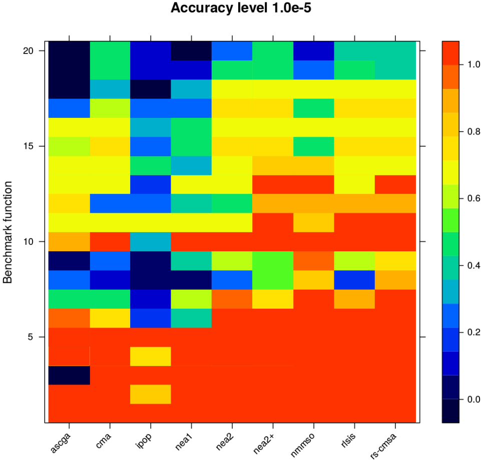


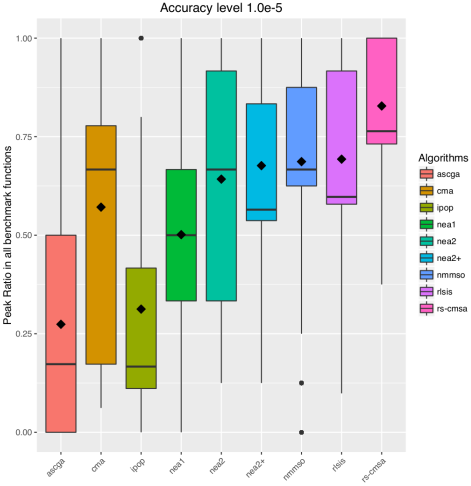
Scenario I: Accuracy level $\varepsilon = 10^{-4}$



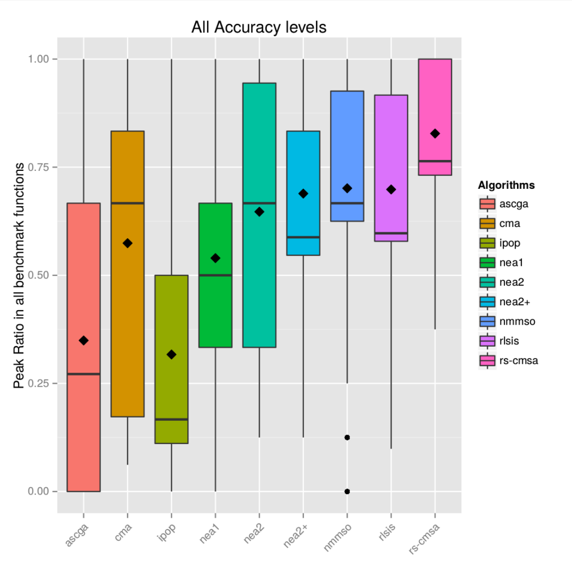


Scenario I: Accuracy level $\varepsilon = 10^{-5}$

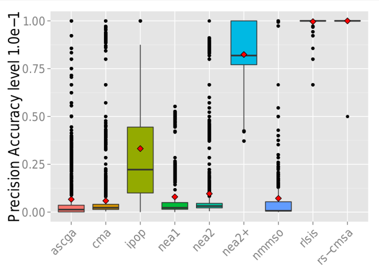


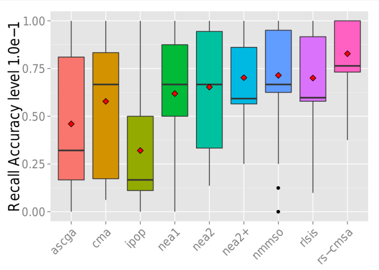


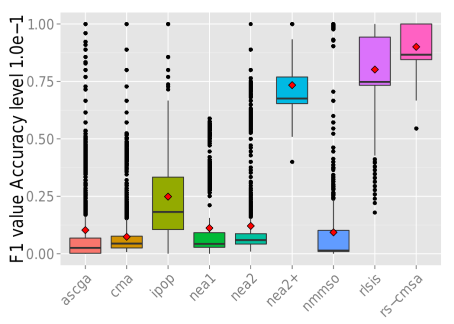
Scenario I: Overall performance



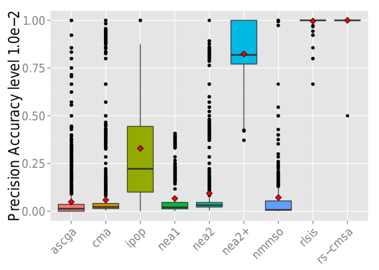
Scenario II: Accuracy level $\varepsilon = 10^{-1}$

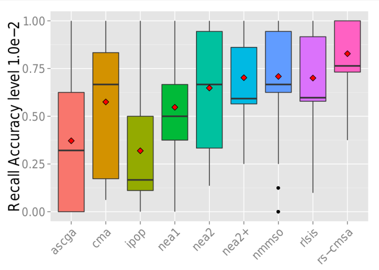


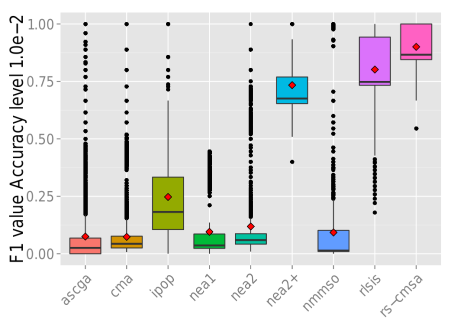




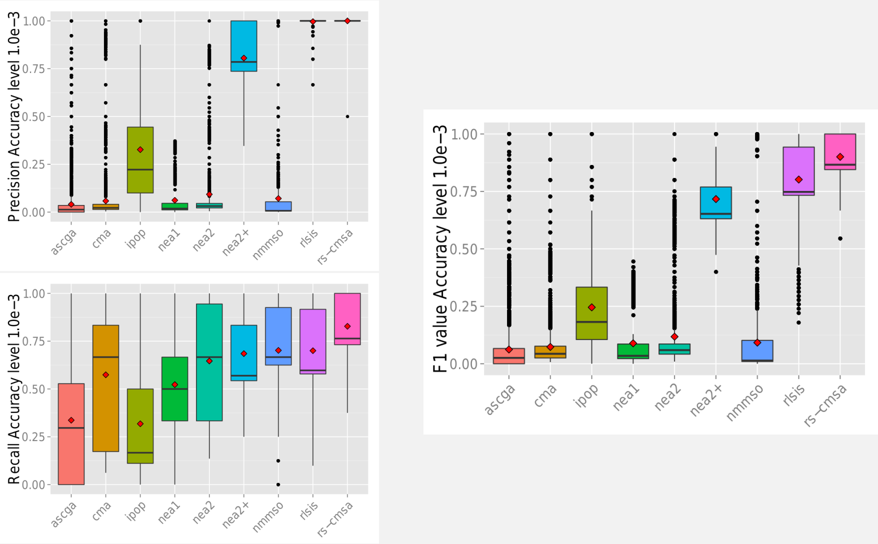
Scenario II: Accuracy level $\varepsilon = 10^{-2}$



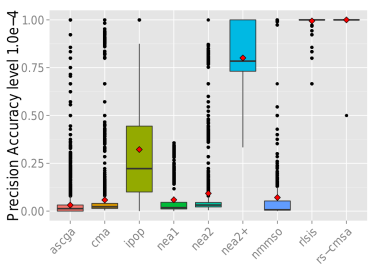


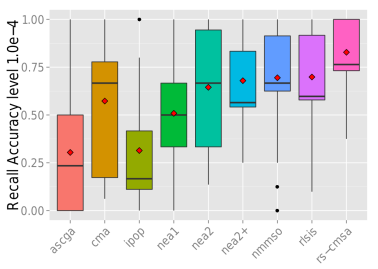


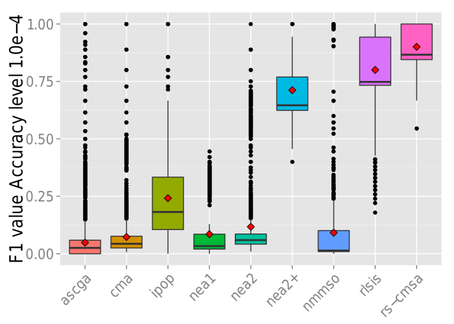
Scenario II: Accuracy level $\varepsilon = 10^{-3}$



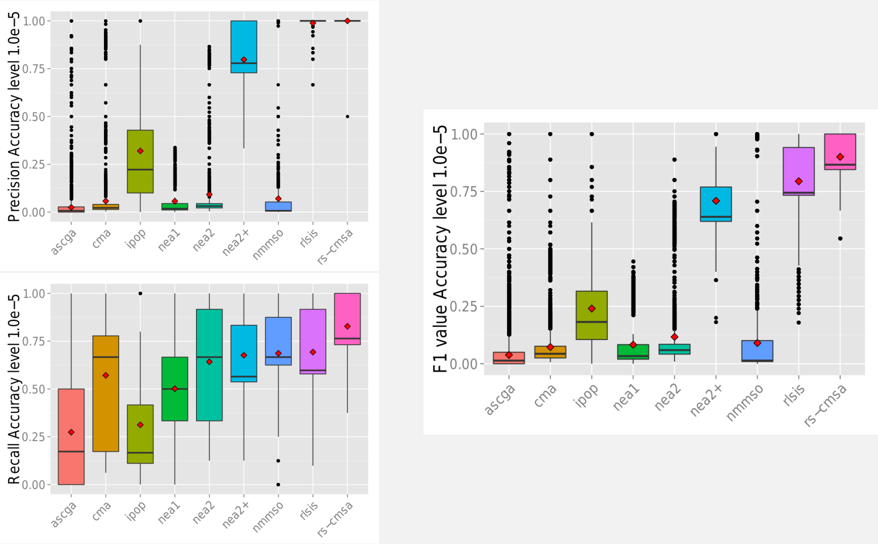
Scenario II: Accuracy level $\varepsilon = 10^{-4}$



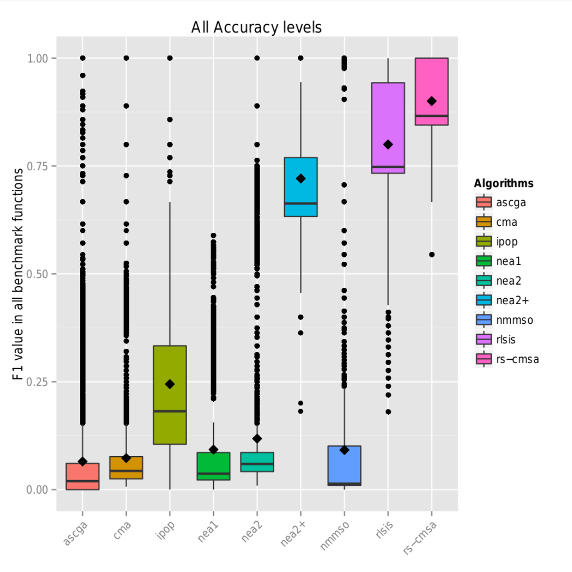




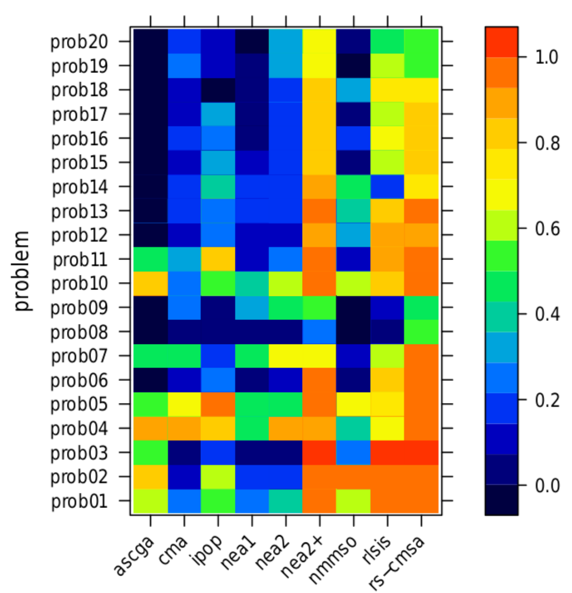
Scenario II: Accuracy level $\varepsilon = 10^{-5}$



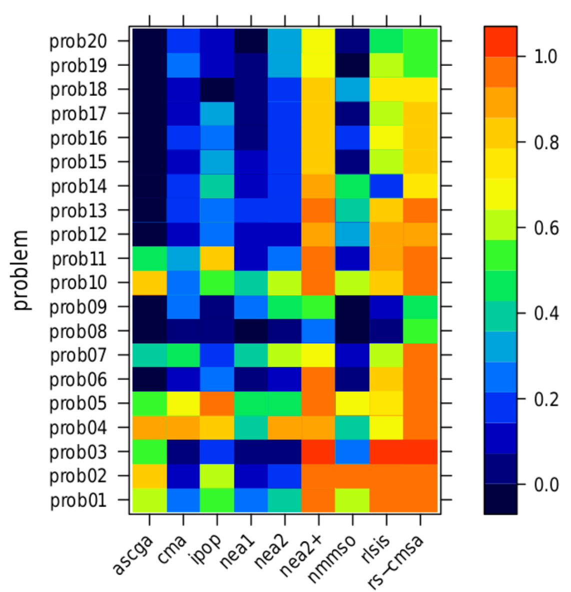
Scenario II: Overall performance



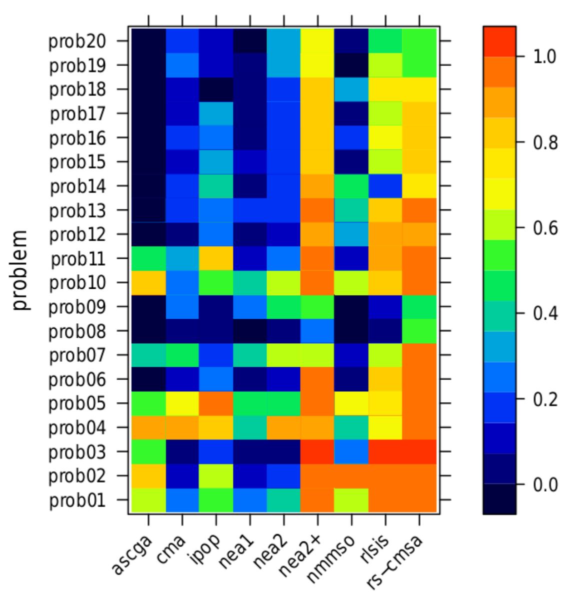
Scenario III: Accuracy level $\varepsilon = 10^{-1}$



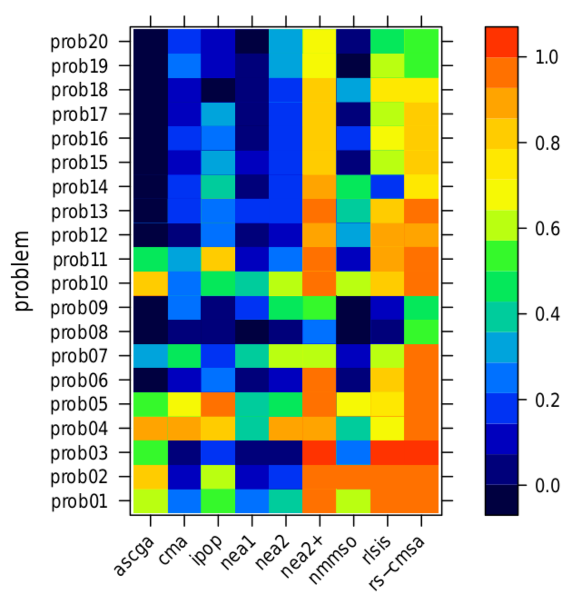
Scenario III: Accuracy level $\varepsilon = 10^{-2}$



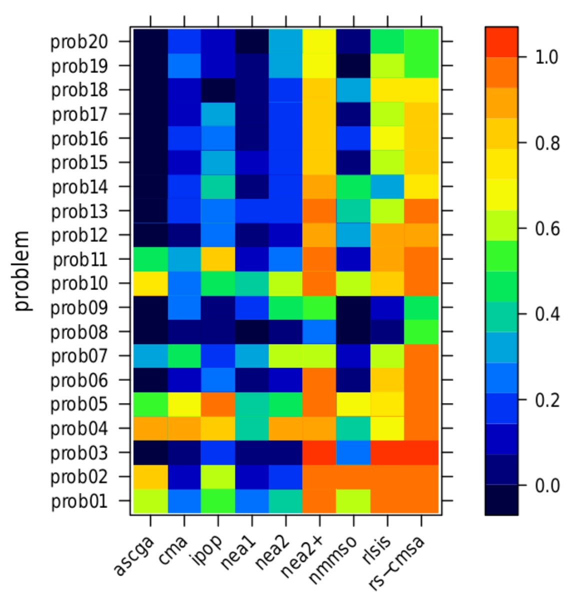
Scenario III: Accuracy level $\varepsilon = 10^{-3}$



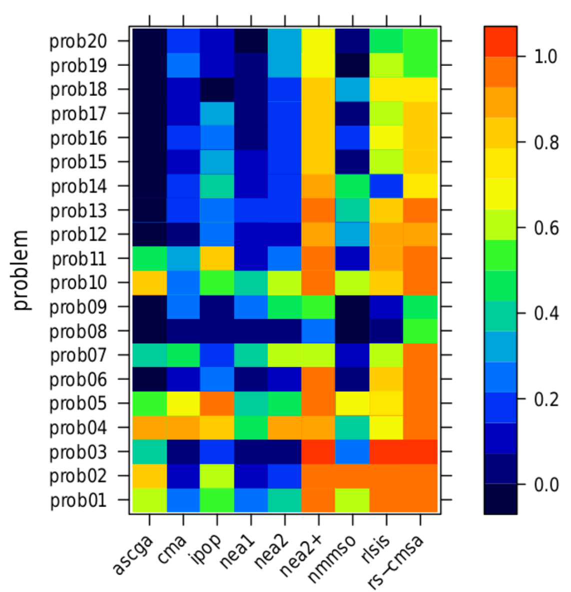
Scenario III: Accuracy level $\varepsilon = 10^{-4}$



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



Scenario III: Overall performance



Overall performance

Alg.	Sc.I	Rank	Sc.II	Rank	Sc.III	Rank	Mean Rank	Final Rank
ascga	0.349	5	0.065	5	0.236	4	4.666	**5**
nea2+	0.688	4	0.720	3	0.811	2	3.000	**3**
nmmso	0.701	2	0.091	4	0.218	5	3.666	**4**
rlsis	0.698	3	0.799	2	0.663	3	2.666	**2**
rs-cmsa	0.827	1	0.900	1	0.839	1	1.000	**1**

Winners

Overall ranking on all scenarios

1. (**rs-cmsa-es**): Covariance Matrix Self Adaption Evolution Strategy with Repelling Subpopulations, Ali Ahrari, Kalyanmoy Deb and Mike Preuss
2. (**rlsis**): Restarted Local Search with Improved Selection of Starting Points, Simon Wessing
3. (**nea2+**): Niching the CMA-ES via Nearest-Better Clustering: First Steps Towards an Improved Algorithm, Mike Preuss
4. (**nmmso**) Niching Migratory Multi-Swarm Optimiser, J. Fieldsend
5. (**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

- Five search algorithms in new Scenarios
- Winner: **rs-cmsa-es:** Covariance Matrix Self Adaption Evolution Strategy with Repelling Subpopulations
  - Best on average performance, (CMA-ES, Repelling Sub-populations)
- Places 2 and 3:
  - **rlsis:** Restarted Local Search with Improved Selection of Starting Points
  - **nea2+:** Niching the CMA-ES via Nearest-Better Clustering (improved)

Conclusions (2)

- The competition provides a boost to the multi-modal optimization community
- New competitive and very promising approaches in new performance scenarios

Key characteristics of the algorithms:

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

Future Work

Possible objectives:

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

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

Questions ???

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