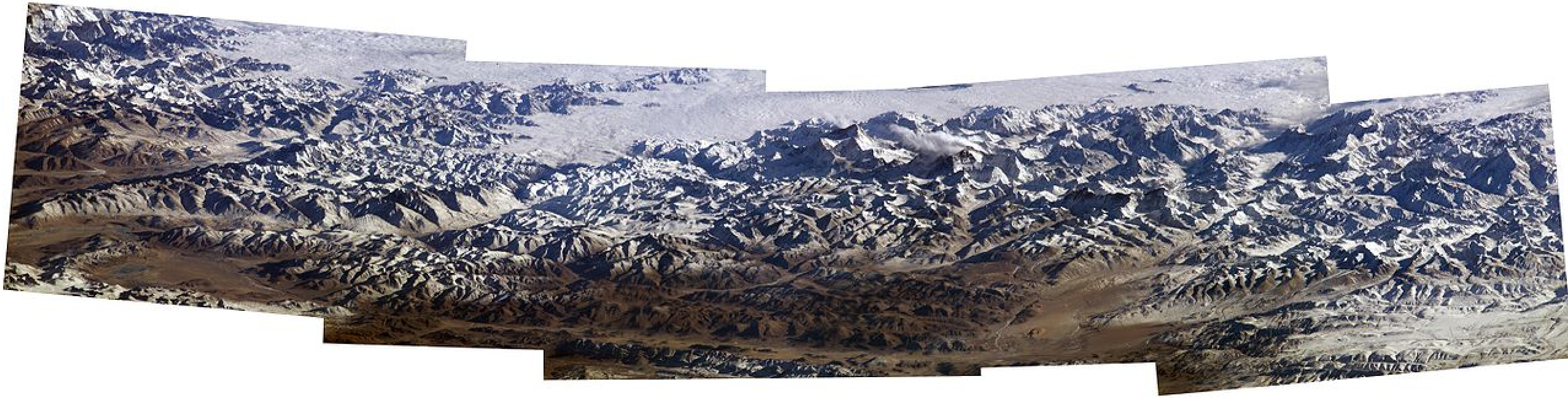
Westfälische Wilhelms-Universität Münster

European Research Center for Information Systems

MULTIMODAL OPTIMIZATION

MIKE PREUSS.

WHAT ARE WE DEALING WITH?



SOME GENERAL NOTES

- more questions than answers in Multimodal Optimization (MMO)
- field not well defined
- basic terms not well defined
- similarities to Multi-Objective Optimization (MOO)
- huge bulk of literature
- Evolutionary Computation (EC) people focus on EC approaches

- consider this as “request for comments”
- suggestions for future work appreciated
- better: you start to do interesting MMO stuff

OUTLINE

- why multimodal optimization (MMO)?
- abstraction: niching and a model EA
- different scenarios and their measures
- taxonomy of methods
- results/competition/software
- the future

why multimodal optimization (MMO)?

ATTEMPTING A DEFINITION

In a multimodal optimization task, the main purpose is to find multiple optimal solutions (global and local), so that the user can have a better knowledge about different optimal solutions in the search space and as and when needed, the current solution may be switched to another suitable optimum solution.

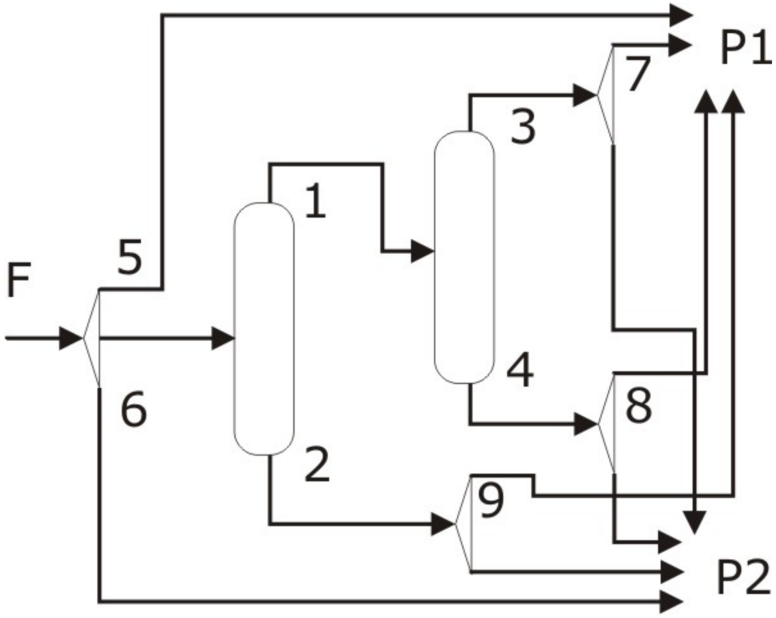
Deb, Saha: Multimodal Optimization Using a Bi-Objective Evolutionary Algorithm, ECJ, 2012

main tasks:

- alternative solutions
- problem knowledge

SEPARATION PROCESS OPTIMIZATION

REAL-WORLD EXAMPLES



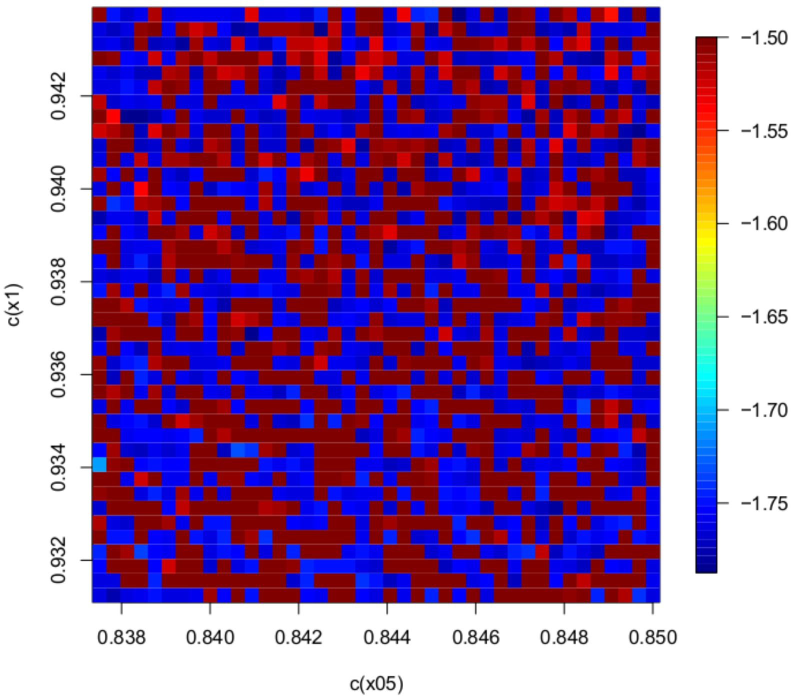
- many solutions invalid, looks like Rastrigin problem

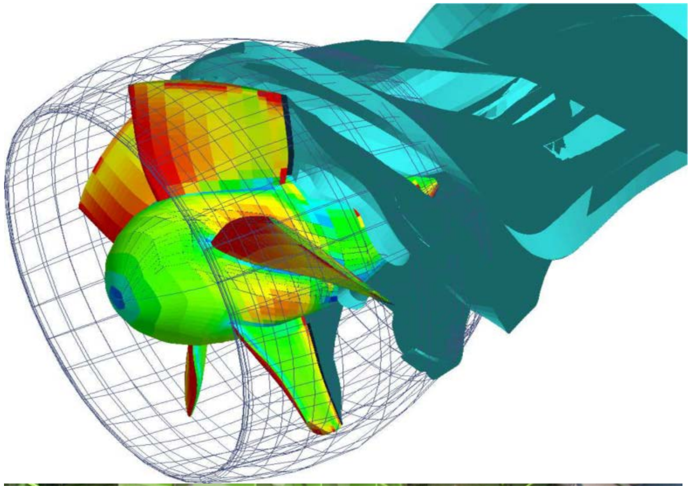
Henrich, Bouvy, Kausch, Lucas, Preuss, Rudolph, Roosen. Economic optimization of non-sharp separation sequences by means of evolutionary algorithms. In *Computers & Chemical Engineering*, Volume 32, Issue 7, pp. 1411-1432. Elsevier, 2008.

LINEAR-JET OPTIMIZATION

REAL-WORLD EXAMPLES

Rudolph, Preuss, Quadflieg. Two-layered surrogate modeling for tuning metaheuristics. In *ENBIS/EMSE Conference Design and Analysis of Computer Experiments*, 2009

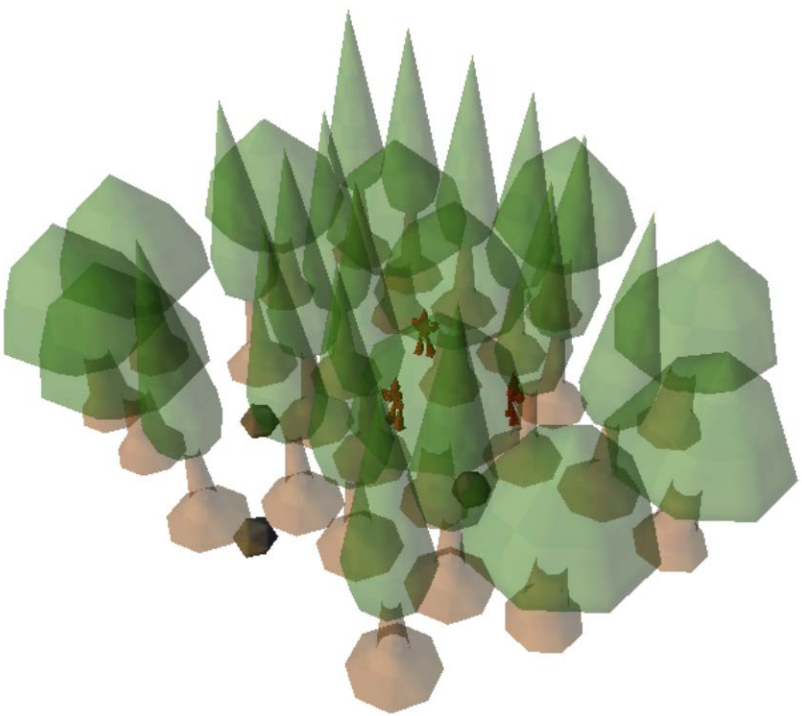


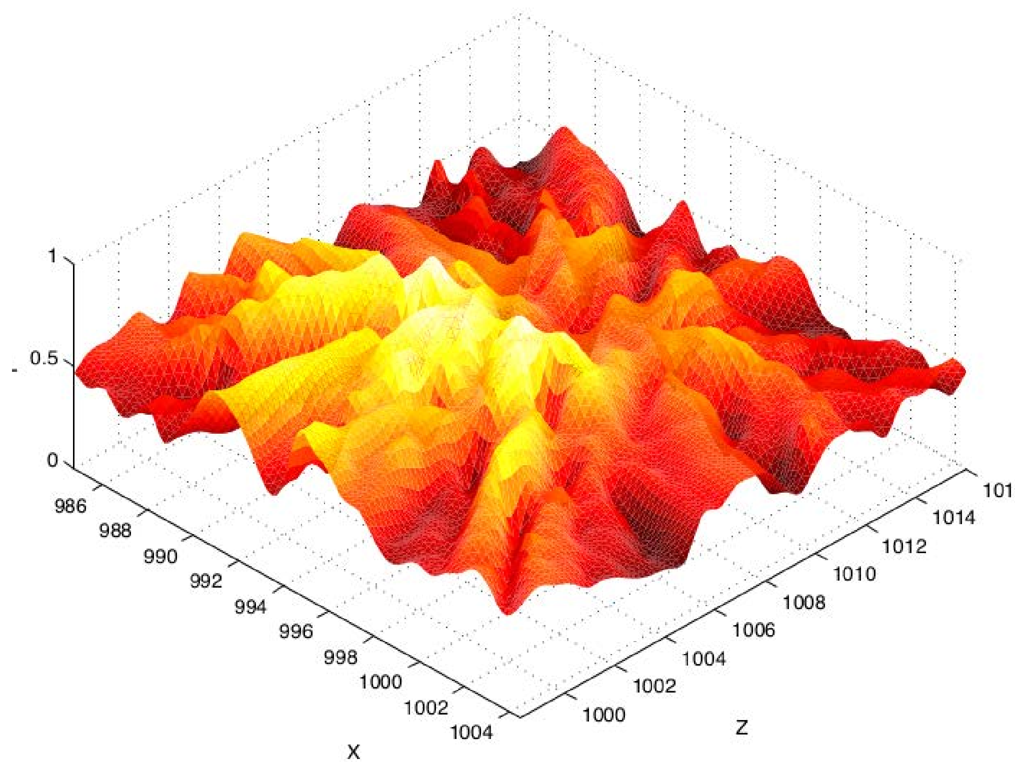


CAMERA POSITIONING

REAL-WORLD EXAMPLES

Preuss, Burelli, Yannakakis. Diversified Virtual Camera Composition. In EvoApplications 2012, pp. 265-274. Springer, 2012





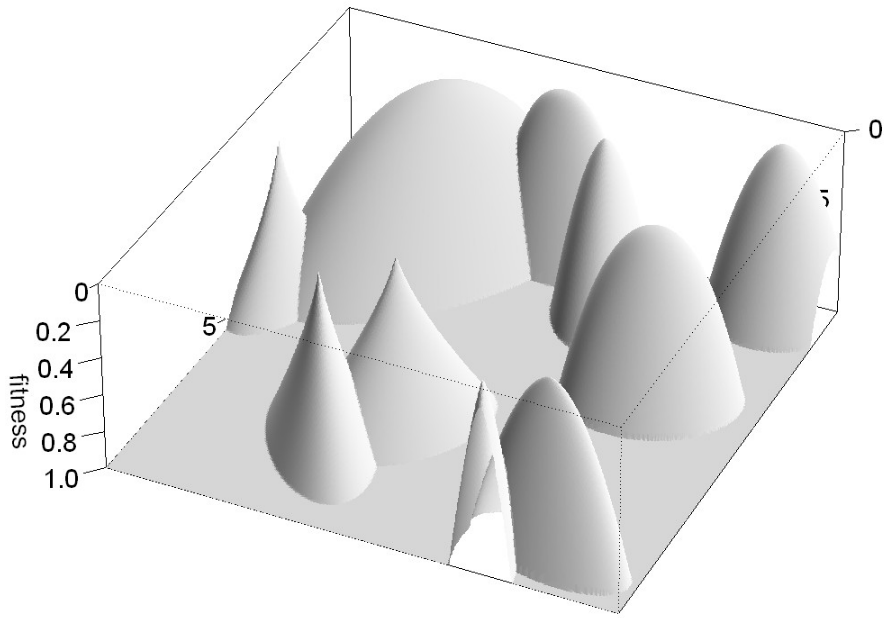
MAIN RESEARCH QUESTIONS

- in which situations are MMO methods actually better than "usual" EC optimization algorithms?
  - problems
  - performance measures
  - external conditions, e.g. runtime
- among different MMO methods, which one shall we choose?
- what are the limits for further improvement?

assumption: successful MMO needs distribution of solutions into different basins of attraction, this resembles the *niching* idea

abstraction: niching and a model EA

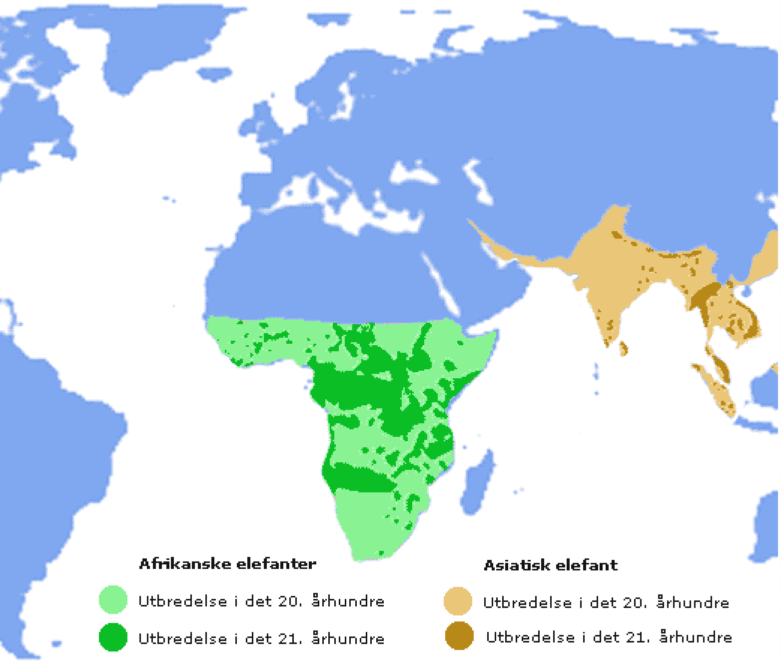
NICHING

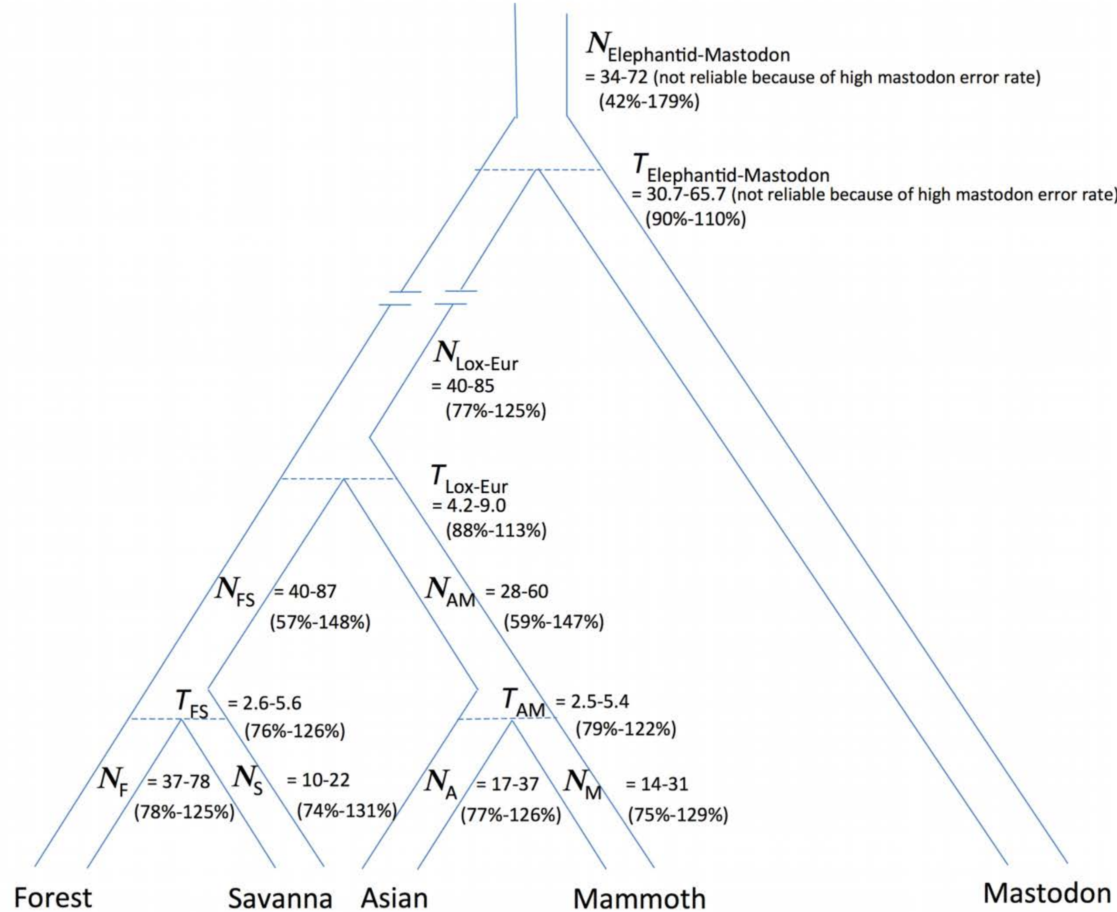


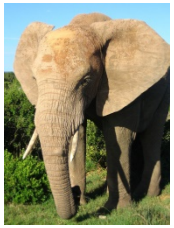
“Niching in EAs is a two-step procedure that a) concurrently or subsequently distributes individuals onto distinct basins of attraction and b) facilitates approximation of the corresponding (local) optimizers.”

(Preuss, BIOMA 2006)

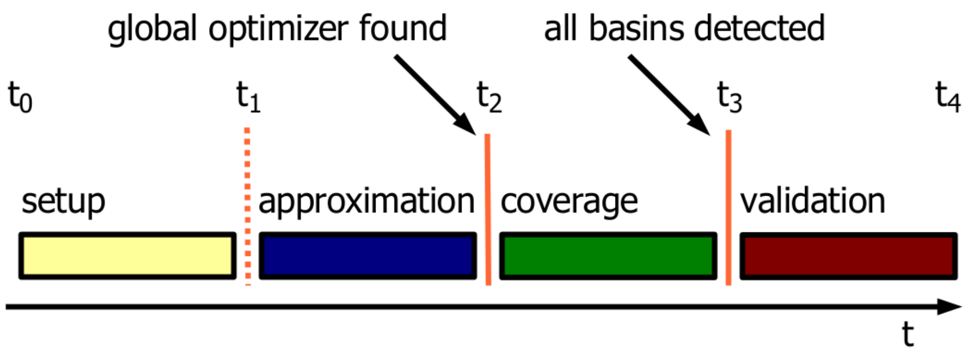
NICHING/SPECIATION

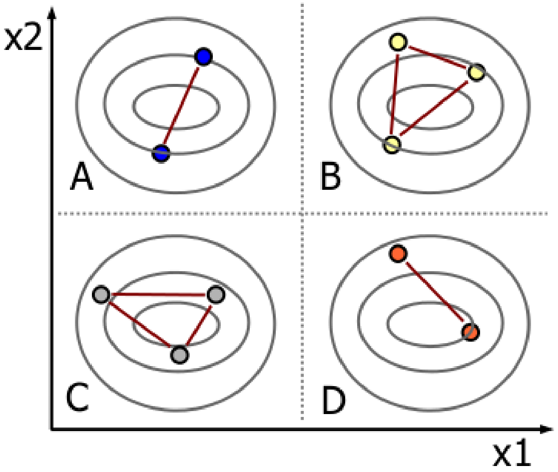




OPTIMIZATION PHASES

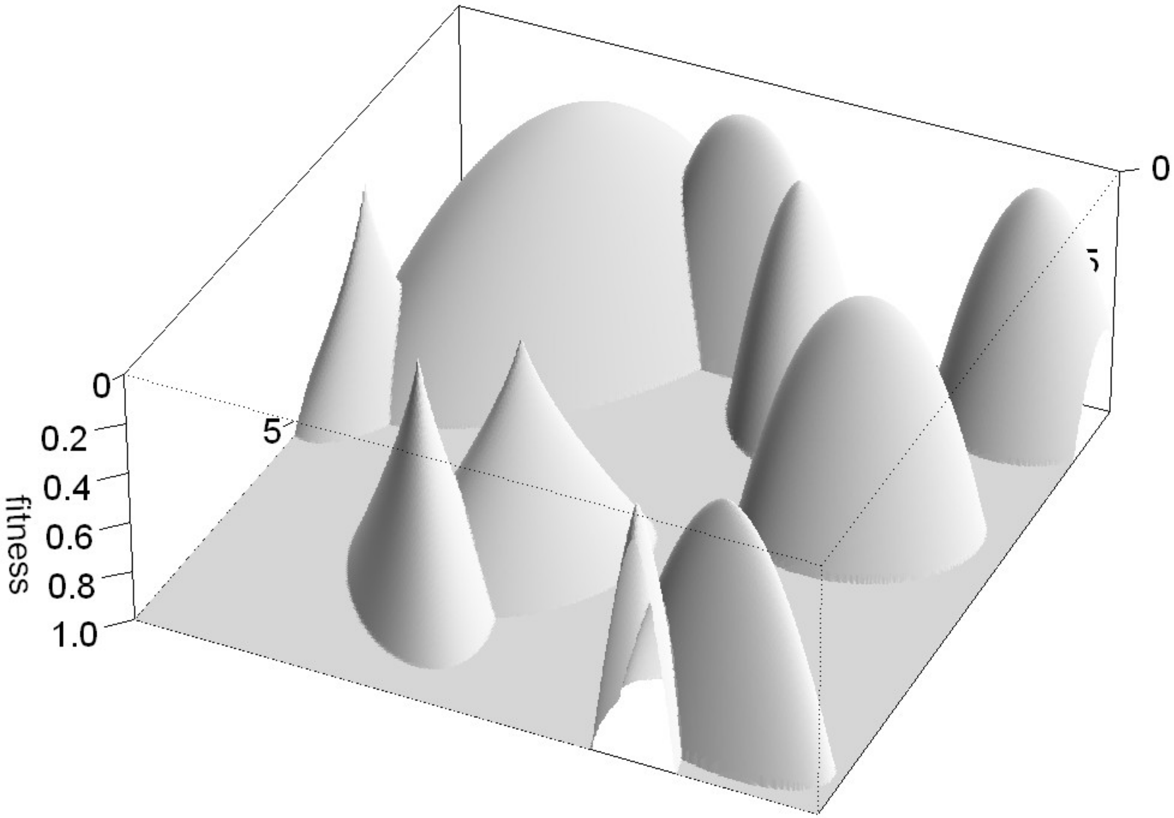




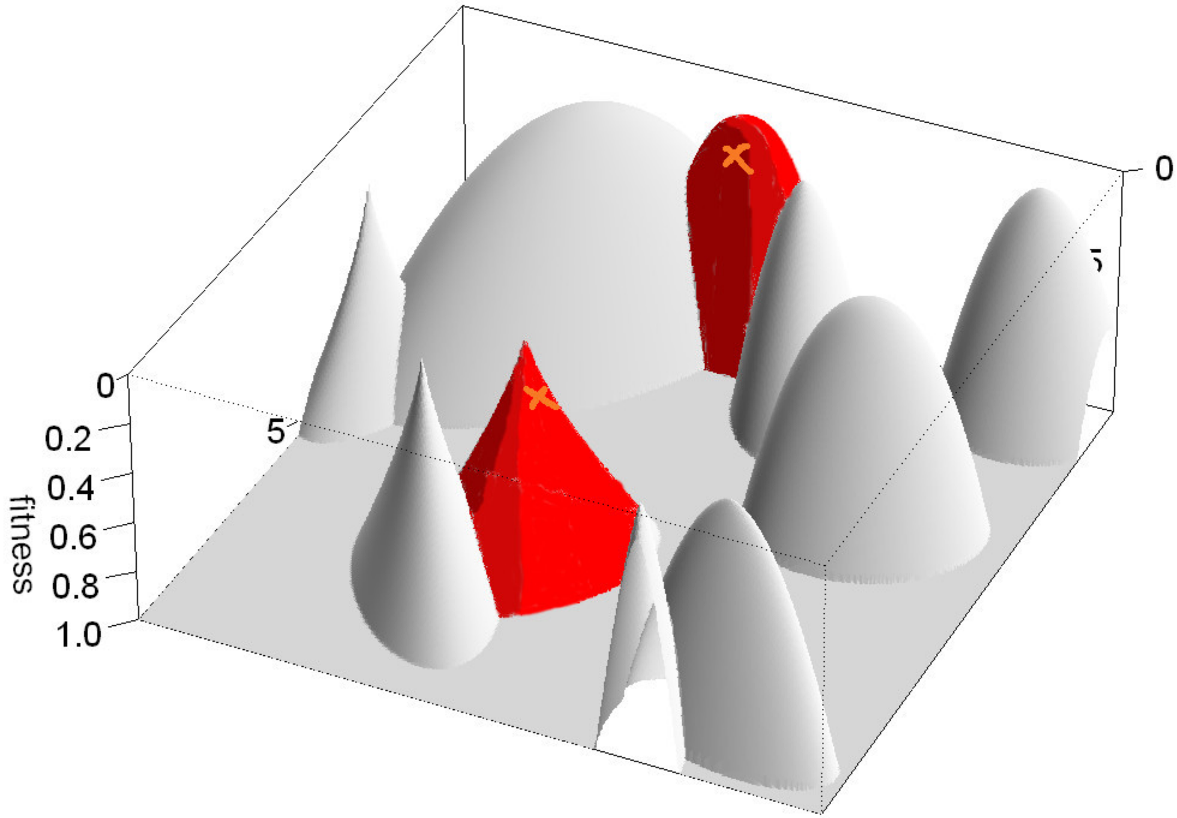
Redundancy for repeated local search and b basins (Beasley 1993):

$$R = \sum_{i=1}^{b} \frac{1}{i} \overset{b>3}{\approx} \gamma + \ln b \qquad with \quad \gamma \approx 0.5772$$

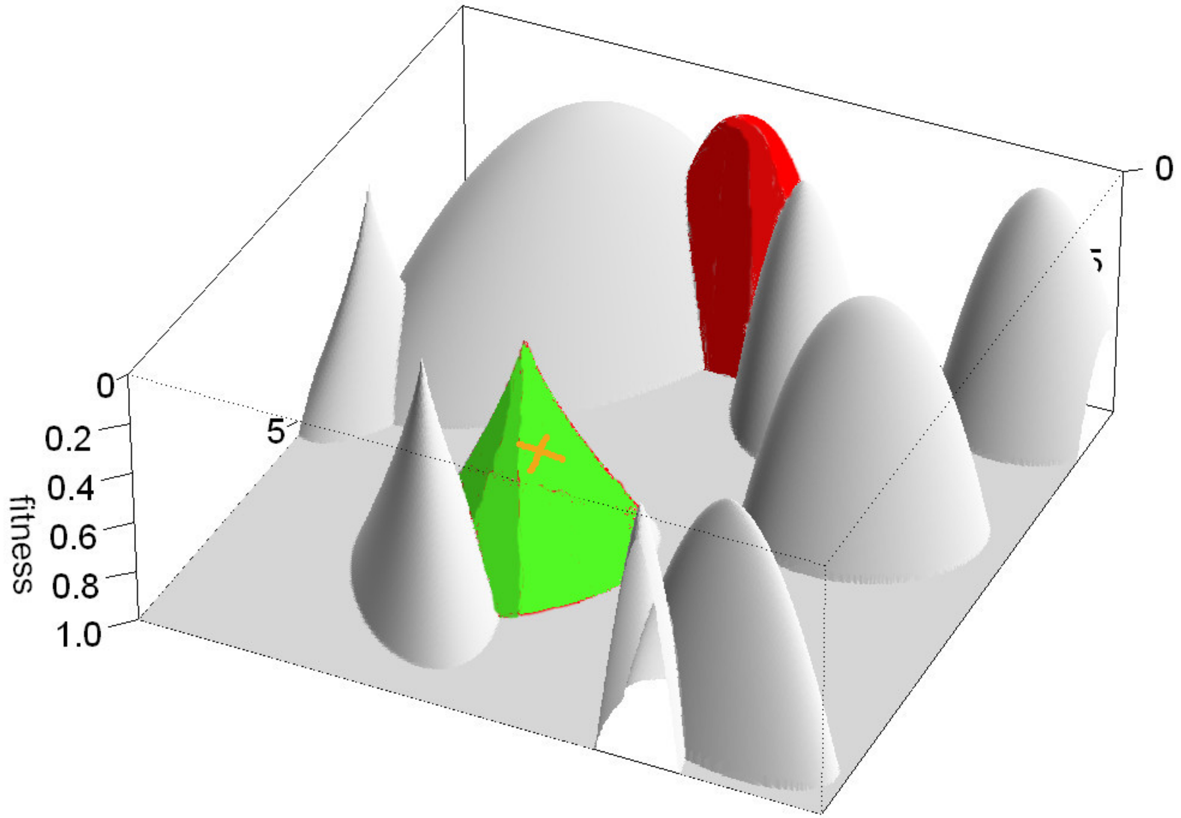
BASIN IDENTIFICATION/BASIN RECOGNITION



BASIN IDENTIFICATION



BASIN RECOGNITION



PROBABILISTIC IDENTIFICATION/RECOGNITION

- basin identification relies on detecting if two solutions are located in the same basin (binary)
- basin recognition: is the basin of a certain solution known?
- no perfect knowledge: probabilistic approach

$$p_{BI}(\mathbf{x}_1, \mathbf{x}_2) \qquad\qquad p_{BR}(\mathbf{x}_1)$$

- these express sensitivity (we do not have information about unvisited areas)

$$\text{sensitivity} := \frac{\sum \text{true positives}}{\sum \text{true positives} + \sum \text{false negatives}}$$

SIMULATION

Algorithm 1: Niching model algorithm

repeat
  randomly distribute solutions over c of b basins;
  basin identification: detect if solutions belong to same basin with probability $p_{BI}(\mathbf{x}_1, \mathbf{x}_2)$;
  select one solution per basin $= c$ solutions;
  forall the *c solutions* **do**
    if *basin of c not known (probability for recognition $p_{BR}(\mathbf{x}_1)$)* **then**
      execute local search from chosen solution;
until *all basins visited)*;

- question: how many local searches necessary to find the global optimum (t2), or
- or to visit all basins at least once (t3)?

COUPON COLLECTOR'S PROBLEM (CCP)








given a set of 8 collector's cards, and we randomly get 3,

- how many iterations until we get one specific card? (2.67)
- or obtain all existing cards? (6.58 iterations)

EXACT RESULTS

P(BI) = 1, P(BR) = 0

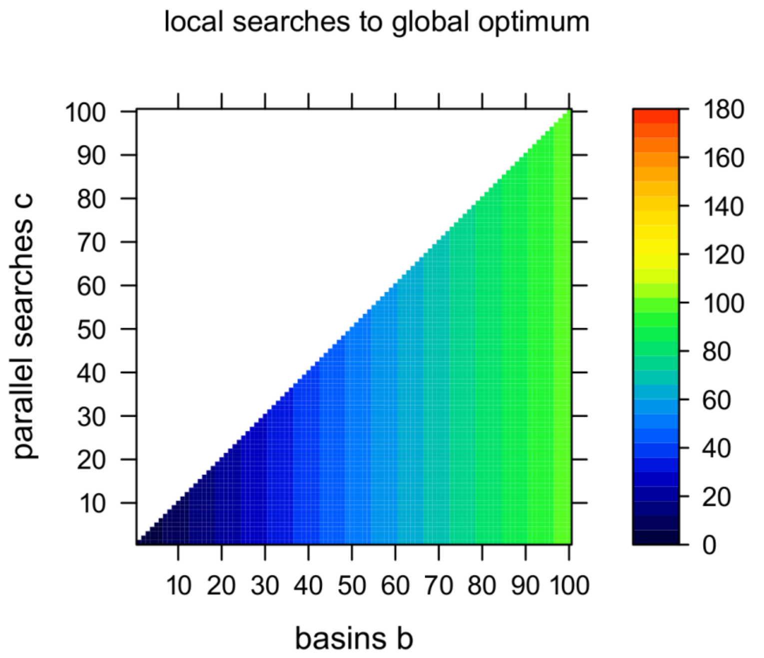
- under the assumption of equal probabilities (for single cards/basins), this can be computed
- formula of (Stadje. The collector's problem with group drawings. Advances in Applied Probability, 22(4):866–882, 1990):

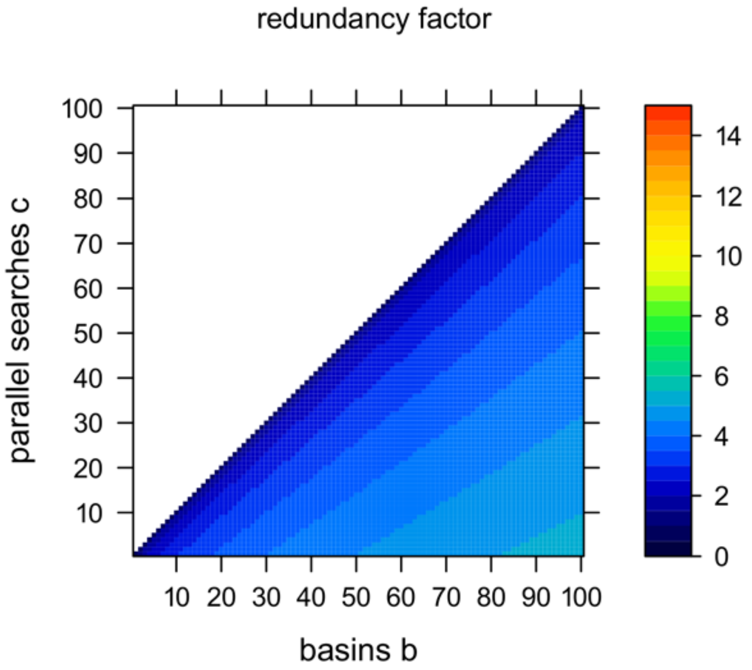
$n = l = 1$ for t_2 und $n = l = b$ for t_3:

$$E(Z(b,l,n,c)) = \binom{b}{c} \sum_{j=0}^{n-1} (-1)^{n-j+1} \binom{l}{j} \binom{j-j-1}{l-n} \left[\binom{b}{c} - \binom{b-l+j}{c} \right]^{-1}$$

- b = cards/basins per drawing,
- c = number of cards/basins
- n = desired elements of desired set, l = desired set size

EXACT RESULTS





for t_2 $(l = n = 1)$ we obtain:

$$E(Z(b,c)) = \binom{b}{c}\left[\binom{b-1}{c-1}\right]^{-1} = \frac{b}{c}$$

THIS IS SHOCKING!

- under the equal basin size assumption, obtaining the global optimum (t2) needs on average b local searches!
- so basin identification does not make sense?

but:

- what about basin recognition?
- equal basin sizes not realistic
- we cannot know if we have reached t2
- situation changes if we want multiple solutions

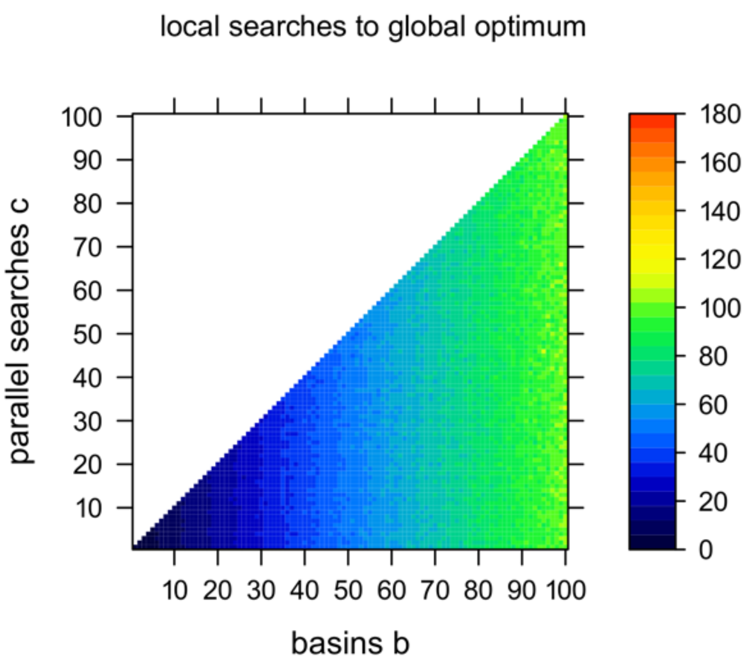
SUMMARIZING THE SIMPLE CASES

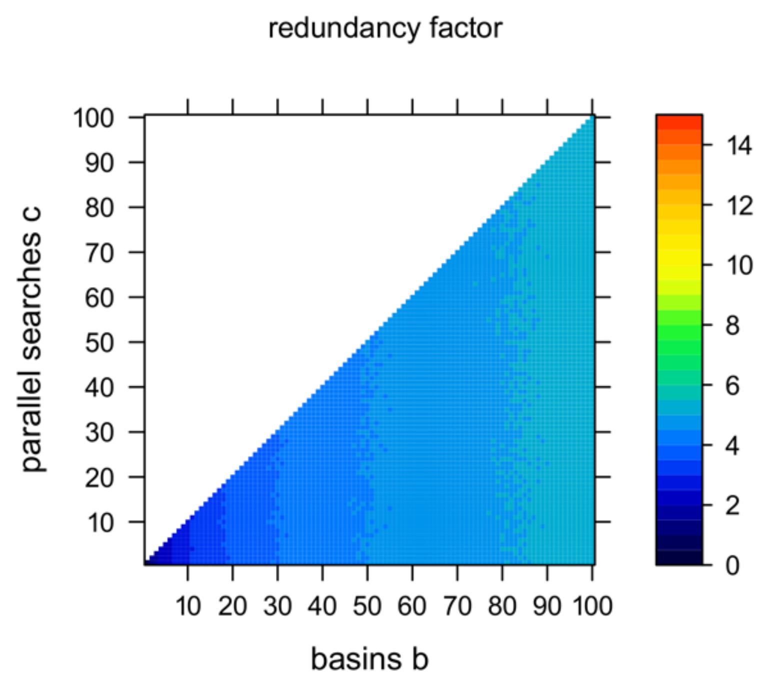
- we leave out perfect BR, no BI, seems unreasonable
- even under ideal circumstances, not much gain for t2
- but BI/BR help for t3:
- rationale for multimodal optimization

BI/BR accuracy	$E(t_2)/b$	$E(t_3)/b$
no BI, no BR	1	$R = \sum_{i=1}^{b} \frac{1}{i} \overset{b>3}{\approx} \gamma + \ln b$
perfect BI, no BR	1 from Stadje equation	Stadje equation
perfect BI and BR	0.5	1

- more complex cases (unequal basin sizes, PBI/PBR not 0 or 1) have to be simulated

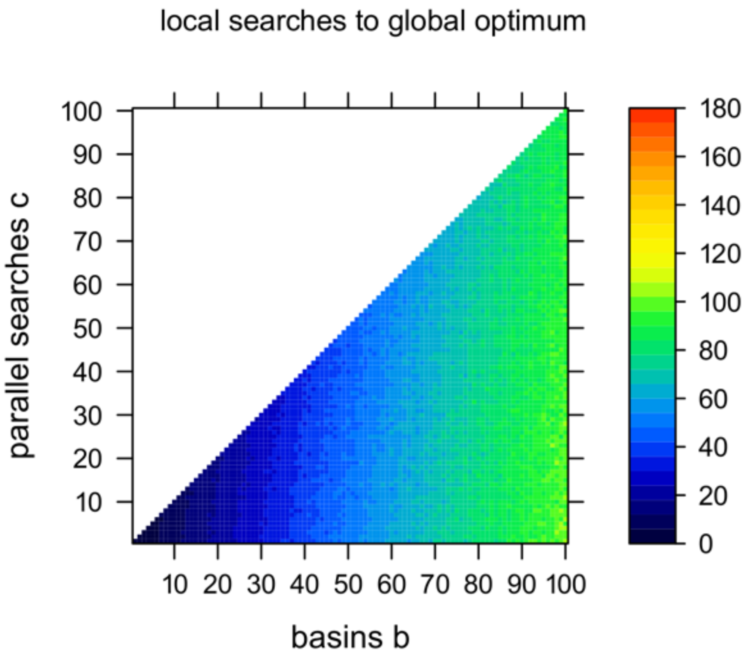
SIMULATION: EQUAL BASIN SIZES

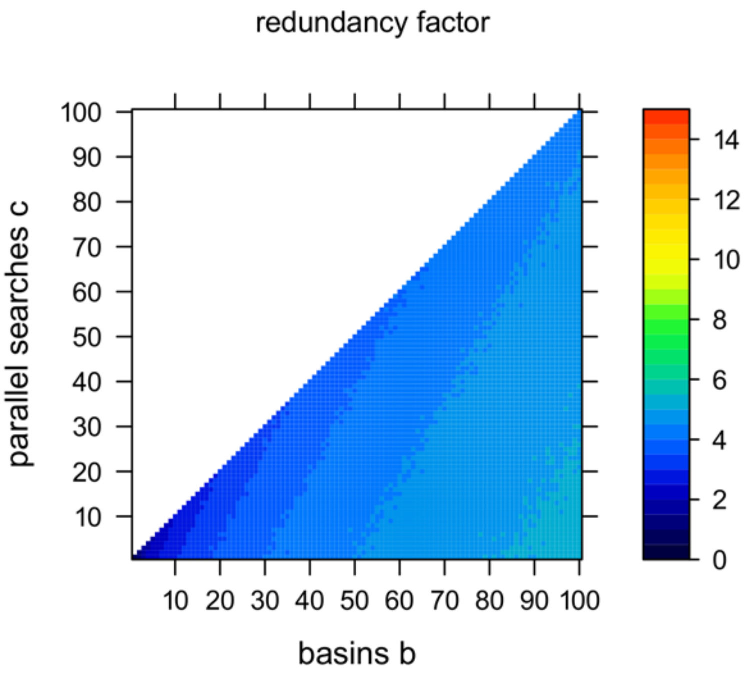




P(BI) = 0, P(BR) = 0

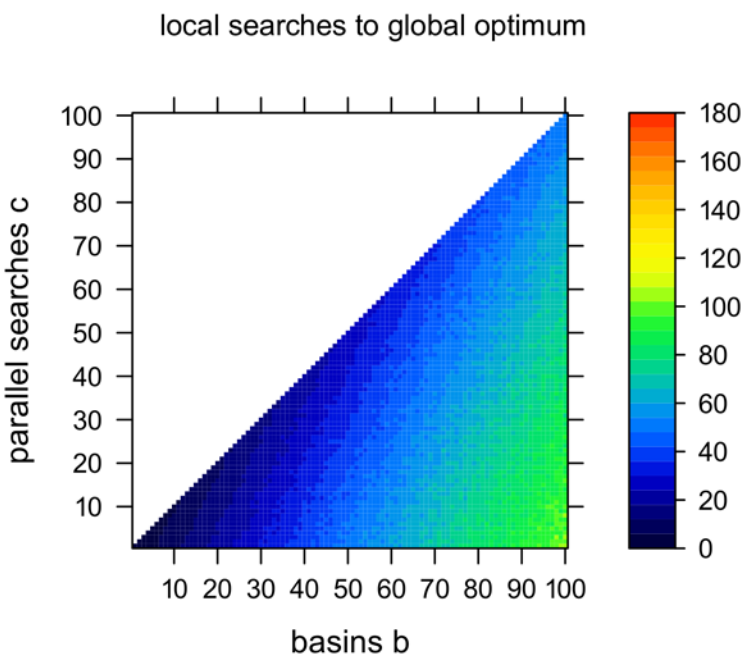
SIMULATION: EQUAL BASIN SIZES

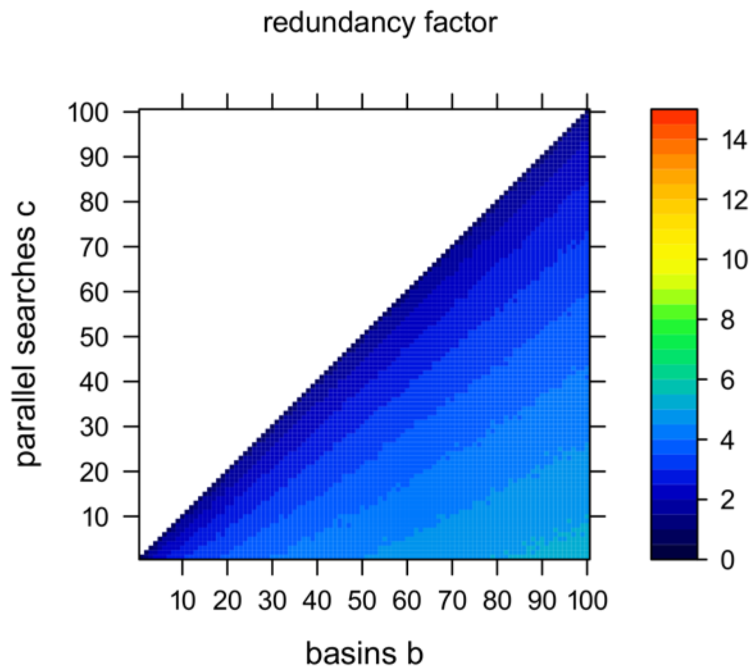




P(BI) = 0.5, P(BR) = 0

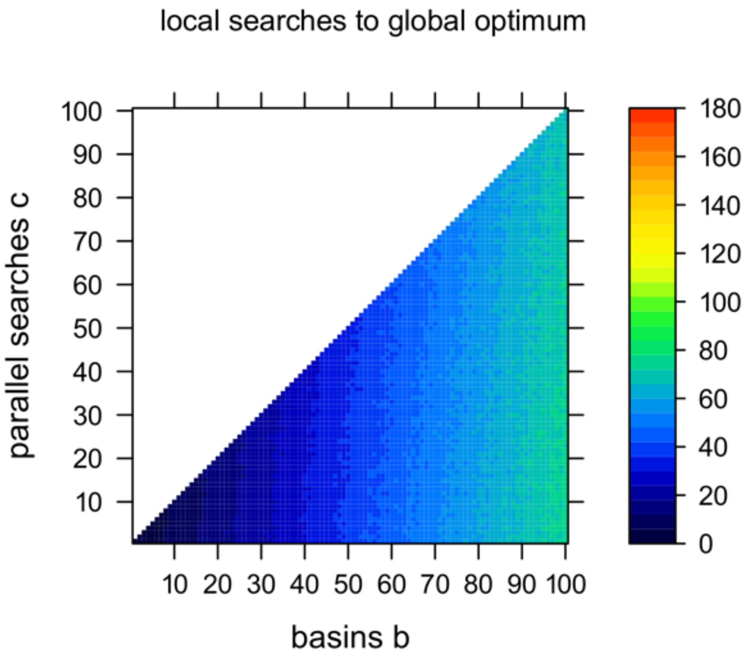
SIMULATION: EQUAL BASIN SIZES

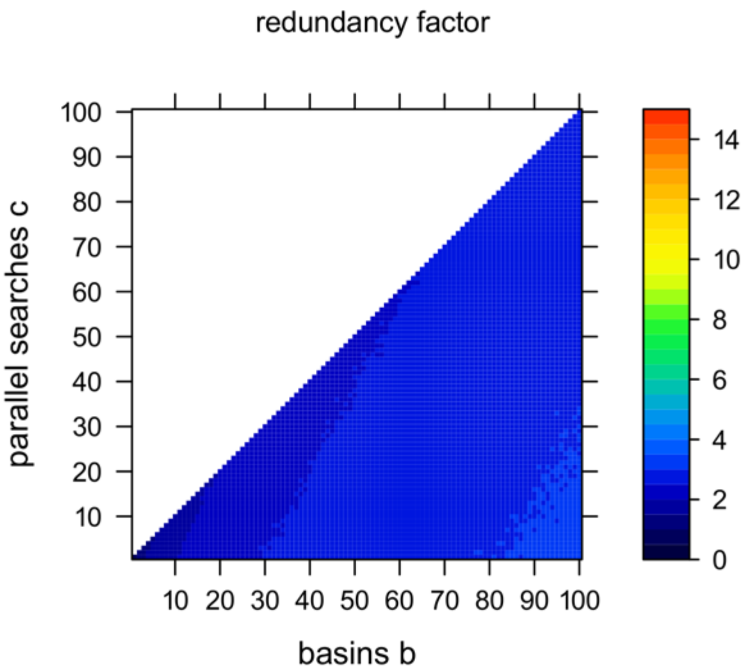




P(BI) = 1, P(BR) = 0 (this is the theoretically tractable case, the difference comes from instant stopping when reaching t2)

SIMULATION: EQUAL BASIN SIZES



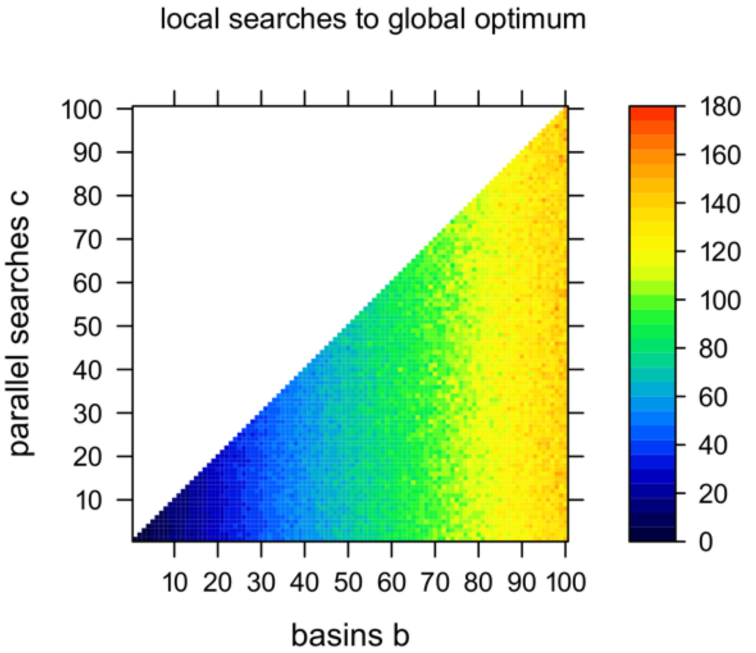


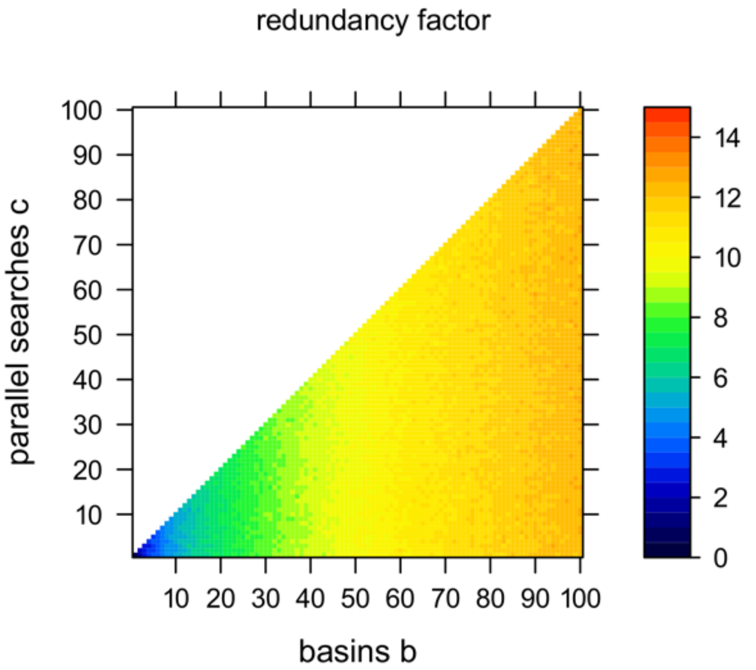
P(BI) = 0.5, P(BR) = 0.5

UNEQUAL BASIN SIZES?

- why should we care?
- because size differences grow exponentially in dimensions
- 10D with 2:1 per dim makes a volume difference of 1024:1
- however, basin identification/basin recognition may be very difficult with large size differences
- we simulate abstract 1:10 size difference

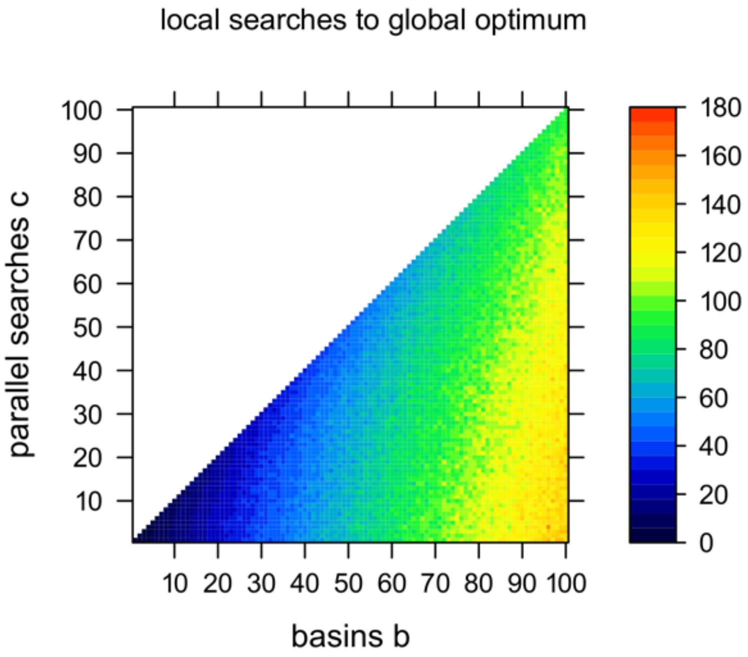
SIMULATION: UNEQUAL BASIN SIZES

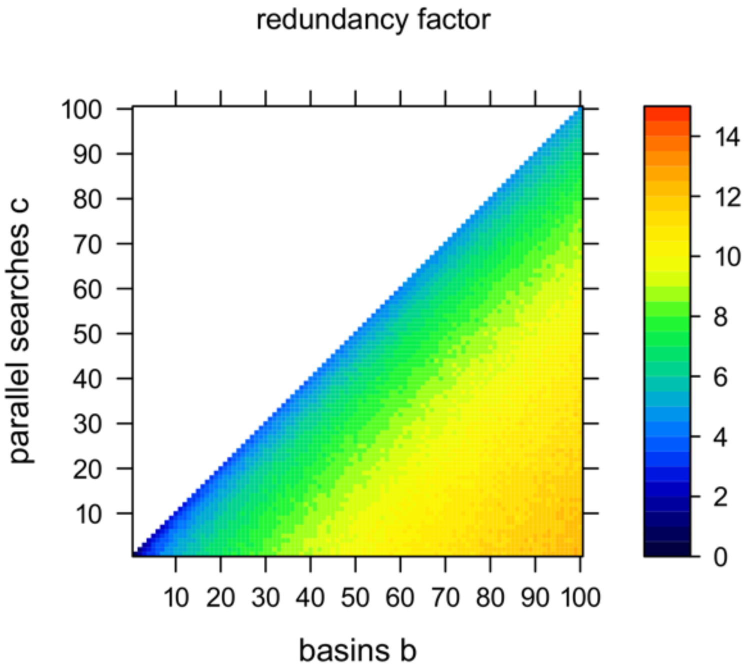




P(BI) = 0, P(BR) = 0

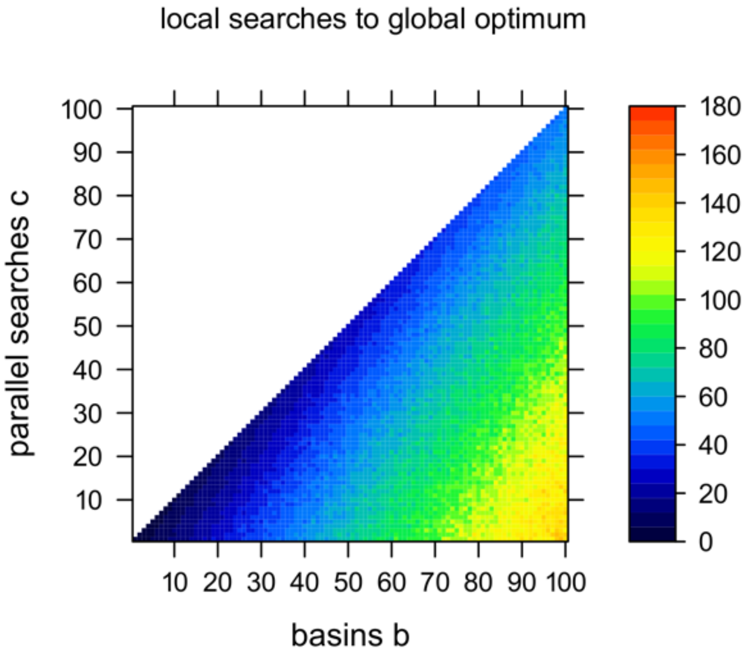
SIMULATION: UNEQUAL BASIN SIZES

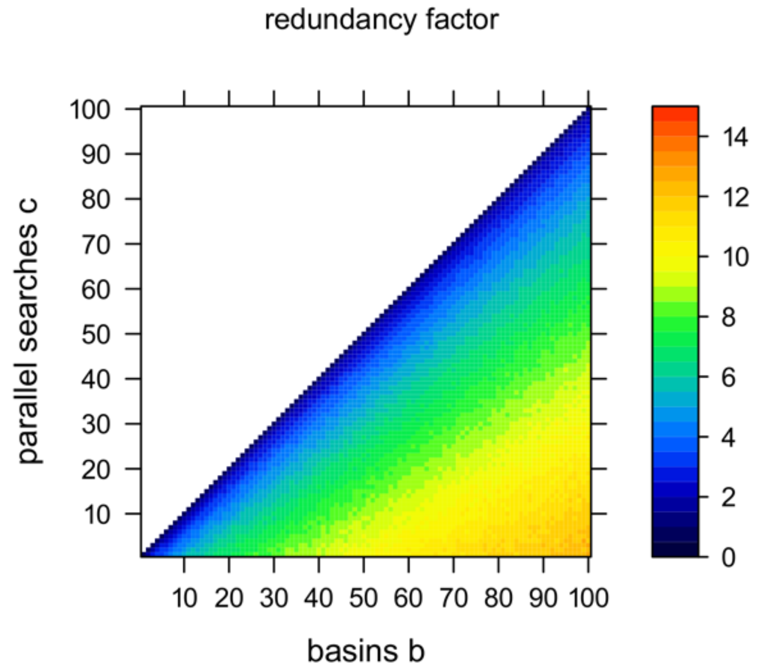




P(BI) = 0.5, P(BR) = 0

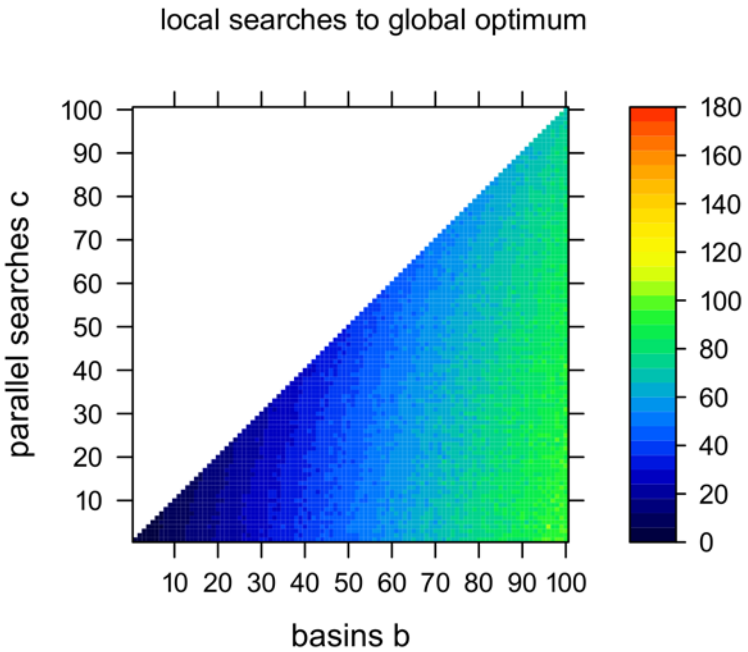
SIMULATION: UNEQUAL BASIN SIZES

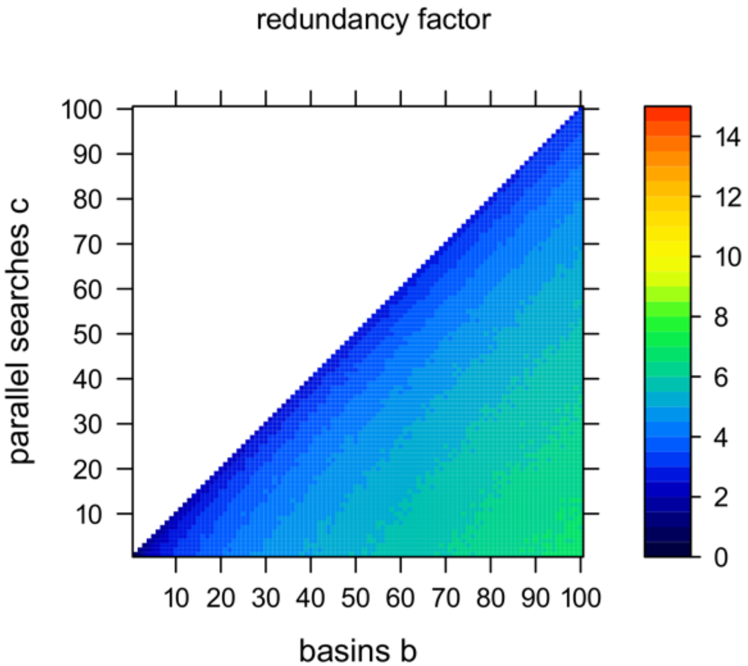




P(BI) = 1, P(BR) = 0

SIMULATION: UNEQUAL BASIN SIZES





P(BI) = 0.5, P(BR) = 0.5

MODEL EA FINDINGS

- there are limits to possible improvements
- **for equal basin sizes, t2 cannot really be improved**
- t3 can be improved a lot
- for unequal basin sizes, t2 and t3 are improved by BI/BR
- basin recognition (needs archive) is more important than basin identification

different scenarios and their measures

MULTIMODAL OPTIMIZATION SCENARIOS

one-global: looking for the global optimum only

all-global: find all preimages of the global optimum

- the problems of the CEC 2013 niching competition belong here

all-known: find all preimages of known optima, (local or global)

good-subset: locate a small subset of preimages of all optima that is well distributed over the search space

ONE-GLOBAL

- the BBOB (black-box optimization benchmark) established the expected runtime (ERT)

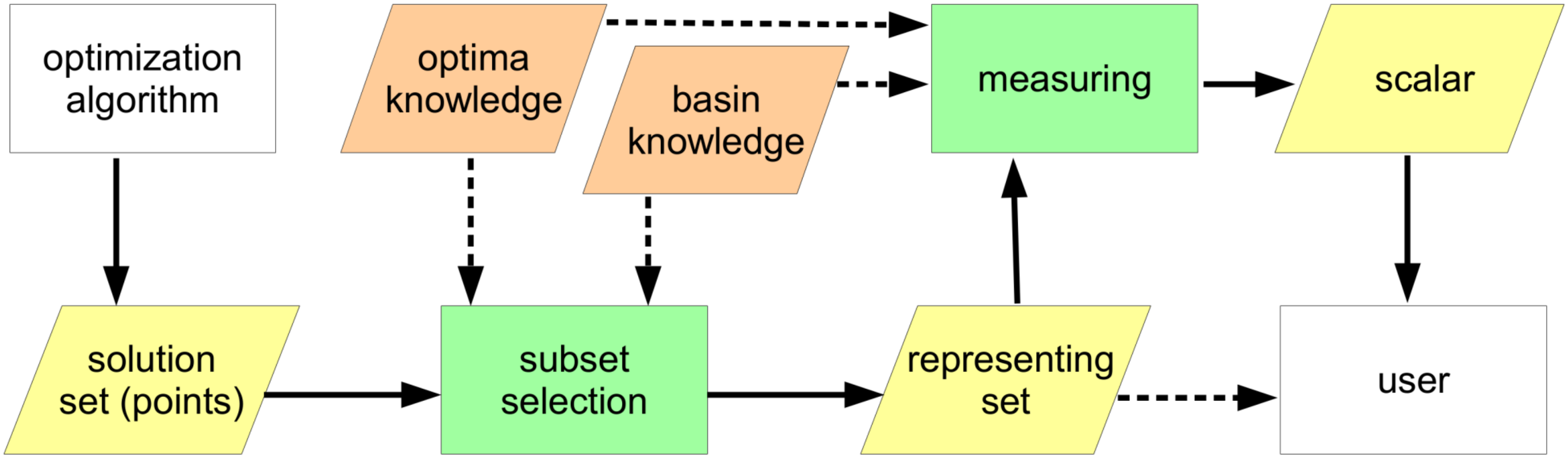
$$\mathrm{ERT}(f_{\mathrm{target}}) = \mathrm{RT}_S + \frac{1-p_s}{p_s}\mathrm{RT}_{\mathrm{US}}$$

- MMO not really well suited to **one-global** scenario
- this could also be applied to other scenarios, need to redefine targets

MEASURING PROCESS

2 main components:

- subset selection
- measuring



MEASURES

indicator	short	requires $f(\vec{x})$	subset sel.	optima known	basins known	param.
sum of distances	SD					
SD to nearest neighbor	SDNN					
Solow-Polasky diversity	SPD					✓
average objective value	AOV	✓				
peak ratio	PR		✓	✓		✓
quantity-adjusted PR	QAPR			✓		✓
peak distance	PD		✓	✓		
augmented PD	APD	✓	✓	✓		
peak accuracy	PA	✓	✓	✓		
averaged Hausdorff distance	AHD			✓		✓
augmented AHD	AAHD	✓		✓		✓
basin ratio	BR		✓	✓	✓	
quantity-adjusted BR	QABR			✓	✓	
basin accuracy	BA	✓	✓	✓	✓	
representative 5 selection	R5S	✓				

mostly used currently in literature (also for CEC'2013):

- peak ratio (PR), but this is problematic

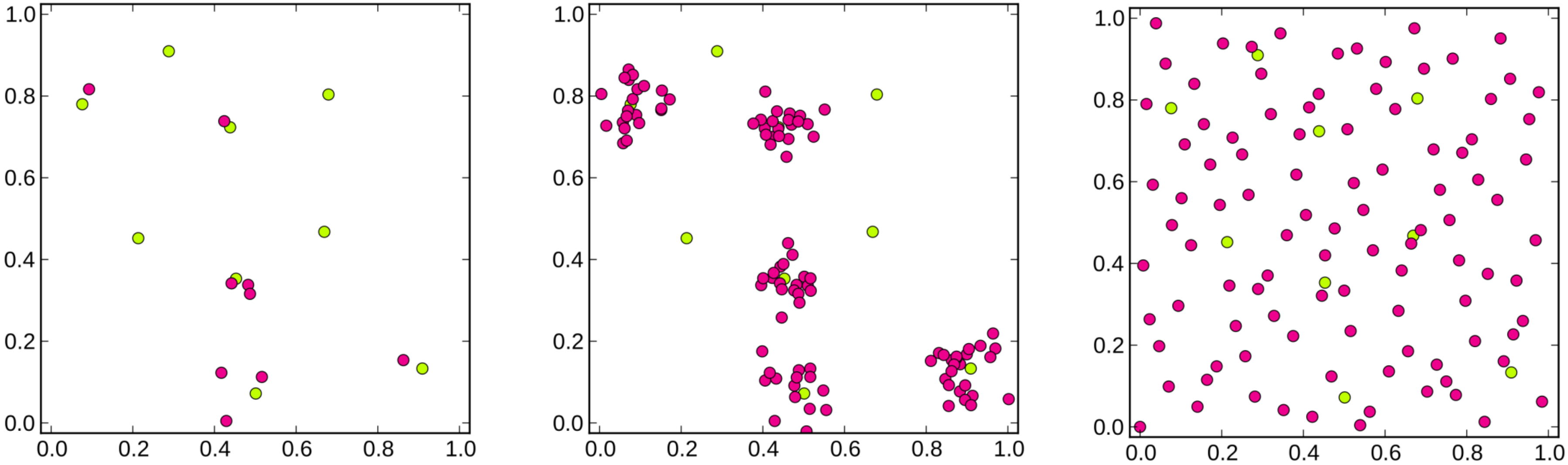
RECENT FINDINGS ON MMO MEASURING

MUCH OF WHICH IS RELATED TO MULTI-OBJECTIVE MEASURING

- Solow-Polasky diversity measure heavily dependent on critical parameter
- result set size taken into account by quantity adjustment
- peak distance (PD) and averaged Hausdorff distance (AHD) can be “augmented” by adding objective values as dimension
- AHD penalizes solutions far away from any optimum
  -> trend to smaller result sets
- similar measures for basins (basin ratio, basin accuracy) can be defined if basins are known

Preuss, Wessing. Measuring Multimodal Optimization Solution Sets with a View to Multiobjective Techniques. In *EVOLVE IV*, pp. 123–137, Springer, 2013

DIFFERENT SCENARIOS



- approximation set, parallel local search, maximal exploration
- note that PR measures for the left two are similar
- PR measure for the right should be good if radius not too small

PEAK RATIO CRITIQUE

- several parameters have to be set properly (e.g. radius)
- aggregation of binary measure (gradual improvement not rewarded)
- does not respect result set distribution (reached optima may all be in a small region)
- does not penalize huge result sets

→ we need alternatives

PEAK DISTANCE (PD)

$$\mathrm{PD}(\mathcal{P}) := \frac{1}{k}\sum_{i=1}^{k} d_{\mathrm{nn}}(\vec{z}_i, \mathcal{P})$$

- introduced in slightly different form in

Stoean, Preuss, Stoean, Dumitrescu. Multimodal optimization by means of a topological species conservation algorithm. IEEE TEC 14(6) (2010) 842-864

- for every optimum, looks for nearest element in population P
- similar to inverted generational distance as known in MOO
- large result sets are not penalized (needs subset selection)
- no parameter needed, gradual improvement measured

AVERAGED HAUSDORFF DISTANCE

$$\begin{aligned}\mathrm{AHD}(\mathcal{P}) &:= \Delta_p(\mathcal{P},\mathcal{Q}) \\ &= \max\left\{\left(\frac{1}{k}\sum_{i=1}^{k} d_{\mathrm{nn}}(\vec{z}_i,\mathcal{P})^p\right)^{1/p}, \left(\frac{1}{\mu}\sum_{i=1}^{\mu} d_{\mathrm{nn}}(\vec{x}_i,\mathcal{Q})^p\right)^{1/p}\right\}.\end{aligned}$$

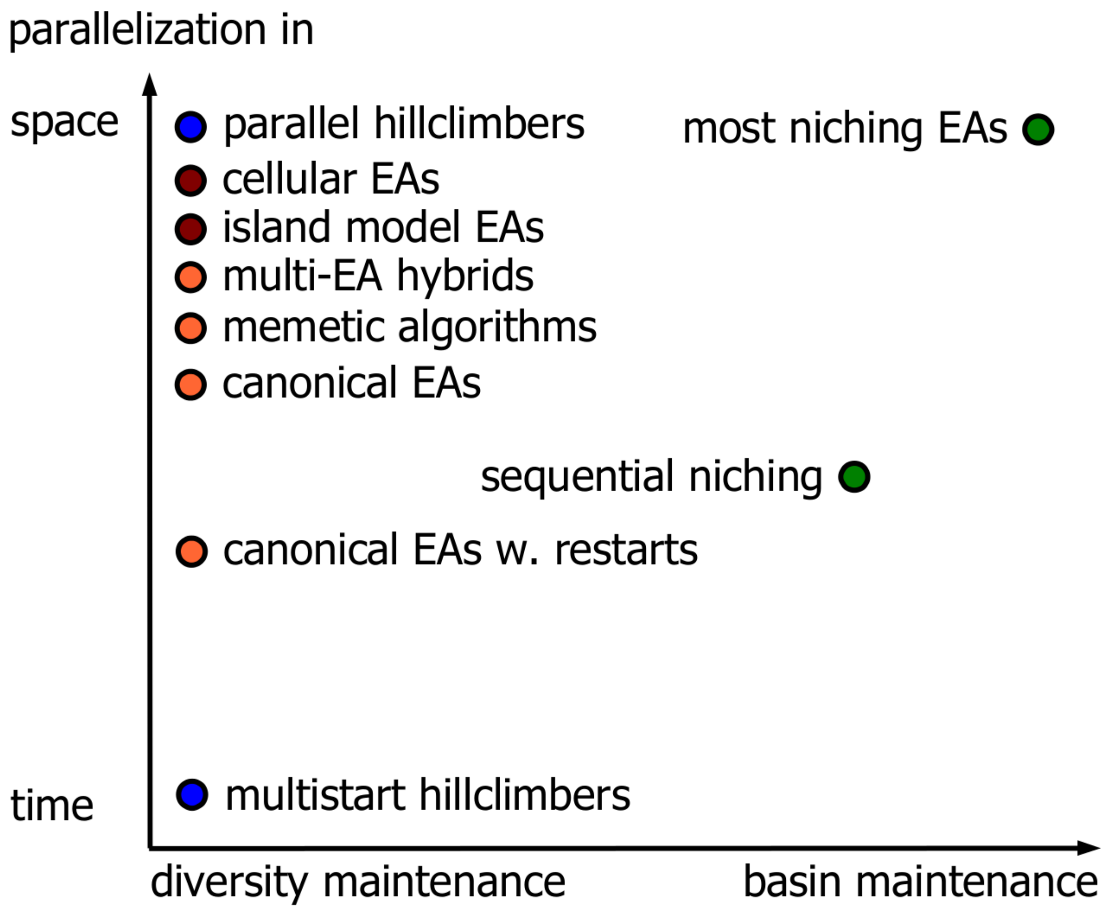
$$\begin{aligned}\mathrm{AHD}(\mathcal{P}) &\overset{p=1}{:=} \Delta_p(\mathcal{P},\mathcal{Q}) \\ &= \max\left\{\frac{1}{k}\sum_{i=1}^{k} d_{\mathrm{nn}}(\vec{z}_i,\mathcal{P}), \frac{1}{\mu}\sum_{i=1}^{\mu} d_{\mathrm{nn}}(\vec{x}_i,\mathcal{Q})\right\}.\end{aligned}$$

- we set p=1 here (parameter used to penalize outliers)
- max of peak distance and reverse component (for every solution, find nearest optimum)
- originally introduced for multi-objective optimization (MOO) in

Schütze, Esquivel, Lara, Coello Coello: Using the averaged hausdorff distance as a performance measure in evolutionary multiobjective optimization. IEEE Transactions on Evolutionary Computation 16(4) (2012) 504-522

taxonomy of methods

GENERAL METHOD OVERVIEW



WHAT NICHING CAN DO

- we assume that some sort of niching is necessary for MMO
- niching is meant as paradigm used to "organize search with respect to basins of attraction"
- it helps to avoid 2 problems:

"Type I Error, Local search will be repeated in some region of attraction.

Type II Error, Local search will not start in some region of attraction even if a sample point has been located in that region of attraction."

this statement comes from an early global optimization work:

Ali, Storey. Topographical multilevel single linkage. Journal of Global Optimization, 5(4):349–358, 1994.

NICHING BASED CLASSIFICATION

A. Explicit basin identification: mapping from search space to basins for determining the basin any location in the search space belongs to

B. Basin avoidance (implicit basin identification or basin recognition): avoid search in known regions

C. Diversity maintenance: spread out search while ignoring topology. Also constrained information exchange without explicit relation bot basins, e.g., by subpopulations or mating restrictions

NICHING BASED TAXONOMY I

year	method name	author	class	dist.	obj.	k var	basic technique
1970	alg. of Becker and Lago	Becker	A	✓	i	✓	density based clustering
1973	Törn's LC algorithm	Toern	A	✓	i	✓	density based clustering
1975	crowding	DeJong	C				local selection
1984	single linkage GOA	Timmer	A	✓	i	✓	single linkage clustering
1984	multi level single linkage	Timmer	A	✓	✓	✓	topological & single-link
1987	sharing	Goldberg	C				selection modification
1992	topographical GO	Toern	A	✓	✓	✓	topological
1993	sequential niching	Beasley	B			✓	derating
1993	adaptive clustering	Yin	A	✓			k-means
1994	tagging	Spears	C			✓	randomized
1996	dynamic peak identificat.	Miller	A	✓	i	✓	single-link
1996	clearing	Petrowski	A	✓	i	✓	single-link
1998	UEGO	Jelasity	A	✓	✓	✓	topological & single-link
1998	SGA-CL	Hanagandi	A	✓	i	✓	density based/Törn LC
1999	hill-valley method	Ursem	A		✓	✓	topological
1999	shifting balance GA	Oppacher	B	✓		✓	island location control
1999	classificat. tree speciation	Petrowski	A	✓	✓	✓	topological
1999	dynamic niche method	Gan	A	✓	i	✓	topological
2000	$\kappa(\mu(\tau)/\rho, \lambda)$-ES	Aichholzer	A	✓		✓	complete linkage
2001	DNM wt. hill-valley	Gan	A	✓	✓	✓	topological
2002	NichePSO	Brits	A	✓	✓	✓	stagnation & single-link
2002	DNM/niche linkage	Gan	A	✓	✓	✓	topological & single-link
2002	species conservation	Li	A	✓	i	✓	single-link

NICHING BASED TAXONOMY II

year	method name	author	class	dist.	obj.	k var	basic technique
2003	clustering based niching	Streichert	A	✓		✓	single-link
2004	clustered genetic search	Schaefer	A	✓	i	✓	density based clustering
2005	ES dynamic niching	Shir2005	A	✓	i		single-link
2005	nearest-better clustering	Preuss	A	✓	✓	✓	topological
2005	sample-based crowding	Ando	A		✓	✓	topological
2005	DE species conservation	Li	A	✓	i	✓	single-link
2006	DNM wt. recursive middl.	Yao	A	✓	✓	✓	topological
2006	ES adaptive niching	Shir	A	✓	i		adaptive single-link
2006	adaptive niching PSO	Bird	A	✓		✓	adaptive single-link
2007	fitness-euclidean dist.ratio	Li	A	✓	✓	✓	topological
2007	roaming	Lung	A	✓	✓	✓	topological & single-link
2007	topological species cons.	Stoean	A		✓	✓	topological
2010	ES shape adaptive niching	Shir	A	✓	i		adaptive single-link
2010	topological species cons. 2	Stoean	A	i	✓	✓	topological
2011	dynamic archive	Zhai	A	✓	✓	✓	adapt. s.-link/stagnation
2011	NOAH	Ulrich	C	✓			density based removal
2012	nearest-better clustering 2	Preuss	A	✓	✓	✓	topological
2012	neighborhood based SC	Qu	A	✓	i	✓	single-link
2012	multiobjectivization	Deb	A	✓	✓	✓	topological
2013	dADE/nrand/1	Epitropakis	A	✓	✓	✓	adaptive single-link

SOME FINDINGS

- many early “niching methods” are not class A niching methods
- the number of used techniques is limited: single-link, density based clustering, topological methods, archives appear often
- there are many A methods using distances, objective values and can handle a variable number of optima/basins
- early global optimization methods (e.g. Timmers’ multi-level single linkage) may make good MMO algorithms
- there is nothing like BBOB (many algorithms comparisons) here

SEQUENTIAL NICHING

- parallelizes in time (sequential)
- basically restarted local search
- modifies objective function to avoid known basins (derating)
- related to “tunneling”
- comes with the same problems: basins are not exactly known
  - optima may not be completely hidden
  - new optima may be introduced unintendedly

Beasley, Bull, Martin. A sequential niche technique for multimodal function optimization. Evolutionary Computation, 1(2):101–125, 1993

RADIUS-BASED APPROACHES

- Niching Evolution Strategy (or Niching-CMA-ES) as example
- uses DPI (dynamic peak identification), fittest first ordering
- for every search point, we check if distance to any existing peak is < preset radius
- $(1 \overset{+}{,} \lambda)$ is executed for every peak (in parallel)
- fixed number of niches
- extensions: shape learning, step size / radius coupling

Shir. Niching in Derandomized Evolution Strategies and its Applications in Quantum Control. PhD thesis, Universiteit Leiden, 2008

EARLY GLOBAL OPTIMIZATION METHODS

- multi-level single-linkage (MLSL) uses a method very similar to DPI, but more than 10 years earlier
- a theoretically motivated radius separates "species"
- from an initial sample, local searches are executed to find the optima that belong to the starting set samples
- "detects" the number of optima by itself
- only used as global optimization algorithm, not for MMO

Rinnooy Kan, Boender, Timmer. A stochastic approach to global optimization. Technical Report WP1602-84, 1984.

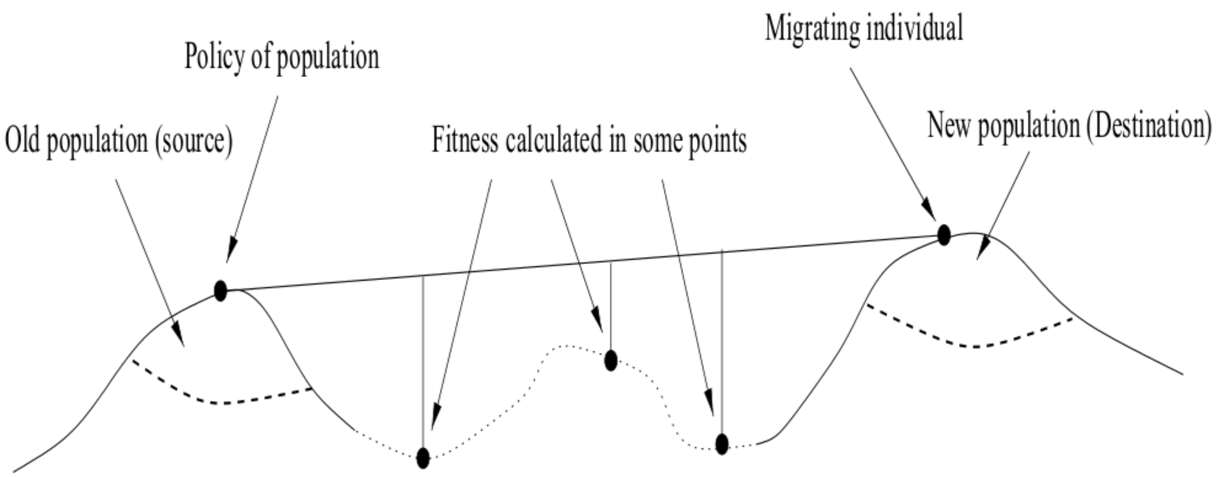
MORE GLOBAL OPTIMIZATION METHODS

- topographical global optimization (TGO) does away with radius
- uses the k-topograph (connect each point to all of k nearest neighbors that are worse) instead
- points without incoming connections are seen as near to local optima, used as start points for local search
- k usually > 8, so that only few local optima can be identified
- some published improvements, never used for MMO

Törn, Viitanen. Topographical global optimization. In Recent Advances in Global Optimization, pp. 384–398. Princeton University Press, 1992

TOPOLOGICAL SEPARATION

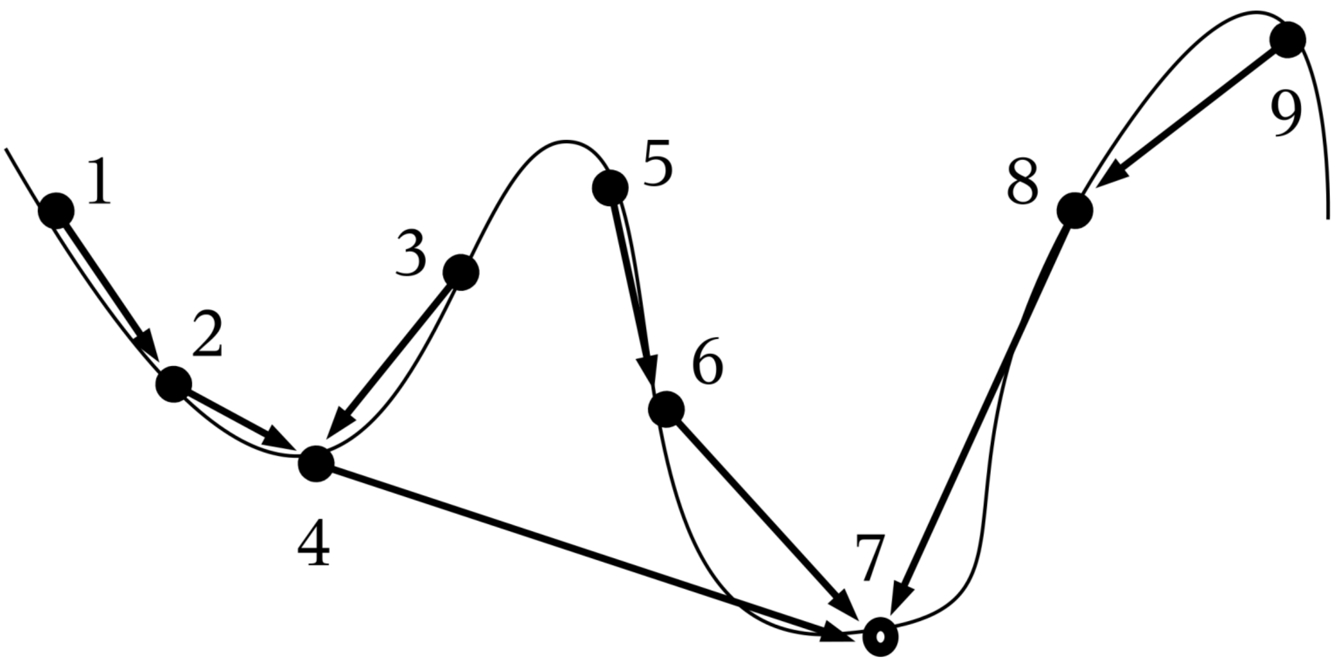
- uses objective values and distances to detect basins
- best known heuristic by Ursem: hill-valley method
- needs additional function evaluations
- limitation: all geometric methods bad in dimensions (>>10D)



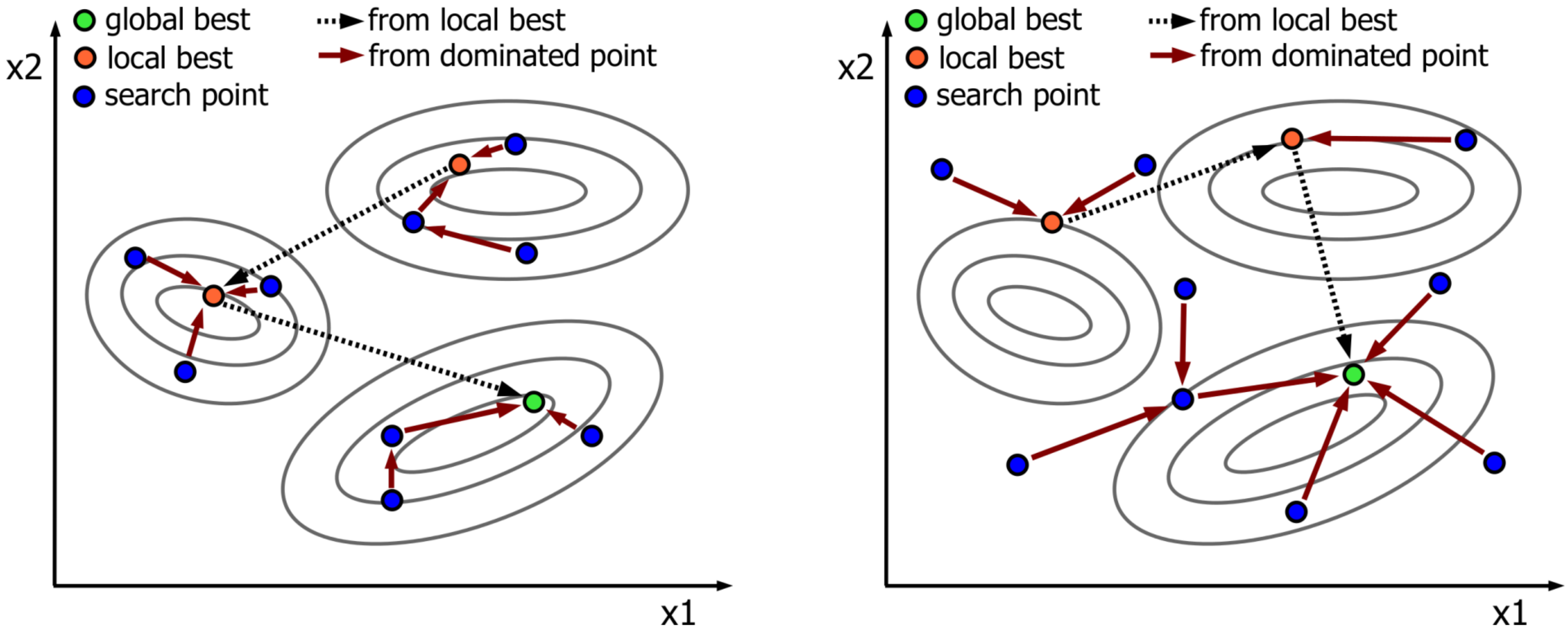
Ursem. Multinational evolutionary algorithms. In Proceedings of the Congress of Evolutionary Computation (CEC-99), pp. 1633–1640, 1999. IEEE Press

NEAREST-BETTER CLUSTERING

- connect every solution to nearest one that is better
- longest edges are connections between optima



NEAREST-BETTER CLUSTERING



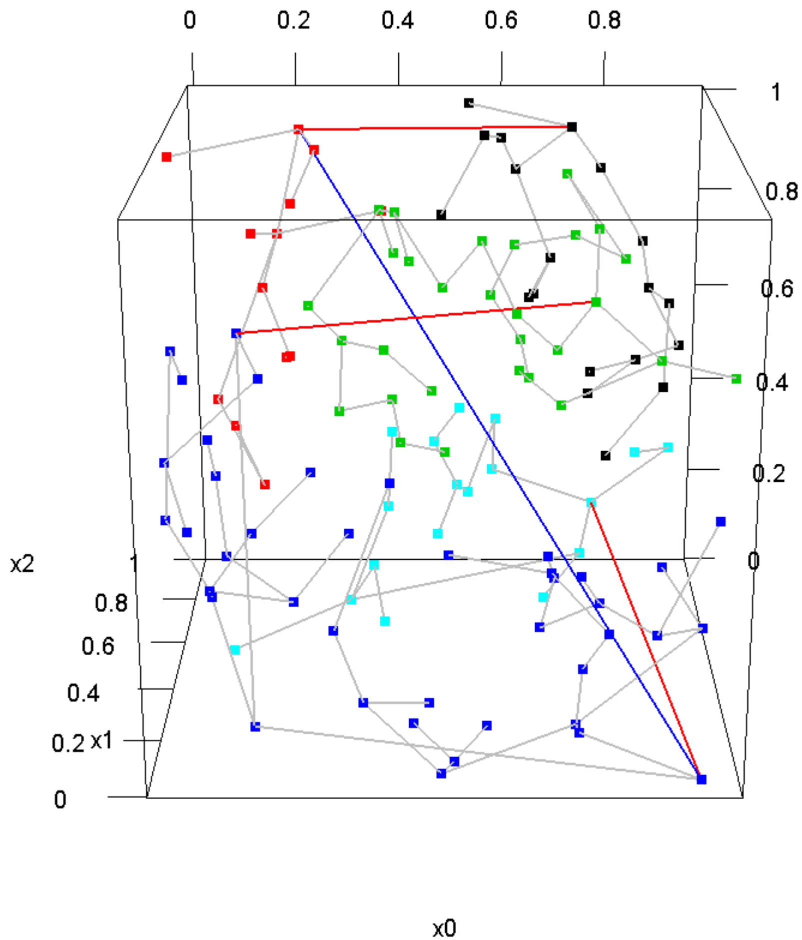
- works with clustered (left) and randomized (right) samples
- needs heuristic to remove “the right” longest edges

NBC ALGORITHM WITH RULE 2

Algorithm 1: Nearest-better clustering (NBC) with rule 2

compute all search points mutual distances;
create an empty graph with num(*search points*) nodes;
`// make spanning tree:`
forall the *search points* **do**
    find nearest search point that is better; create edge to it;
`// cut spanning tree into clusters:`
RULE1: delete edges of length $> \phi \cdot \text{mean}(\textit{lengths of all edges})$;
RULE2: forall the *search points with at least 3 incoming and 1 outgoing edge* **do**
    if $\textit{length(outgoing edge)/median(length(incoming edges))} > b$ **then**
        cut outgoing edge;
`// find clusters:`
find connected components;

NBC EXAMPLE CLUSTERING



NICHING EVOLUTIONARY ALGORITHM 2

ITERATED SEQUENTIAL ALGORITHM TYPE

Algorithm 1: NEA2

```
1 distribute an evenly spread sample over the search space;
2 apply NBC: separate sample into populations according to clusters;
3 forall the populations do
4     run local optimization (e.g. CMA-ES) until stop criterion is hit;
  // start all over:
5 if !termination then
6     goto step 1
```

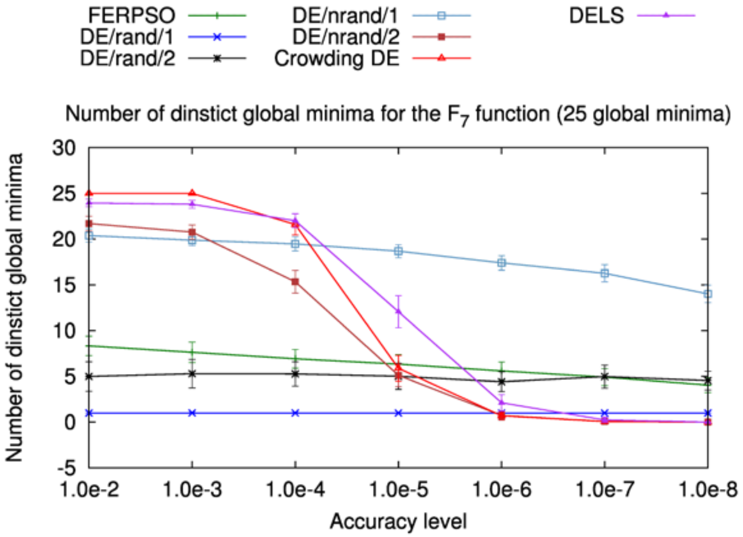
- most flexible with iterations of clustering + local optimization
- can be improved e.g. with archive, but not always successfull
- for real-valued optimization, CMA-ES is used
- not very dependent on parameters

DE -> DE/NRAND/1

WITH MATERIAL PROVIDED BY MICHAEL EPITROPAKIS

- DE/rand/1 already shows ability to "hold" many optima in the population
- instead of an individual we employ its nearest neighbor as base

$$v_{g+1}^{i} = x_{g}^{NN_i} + F(x_g^{r1} - x_g^{r2})$$

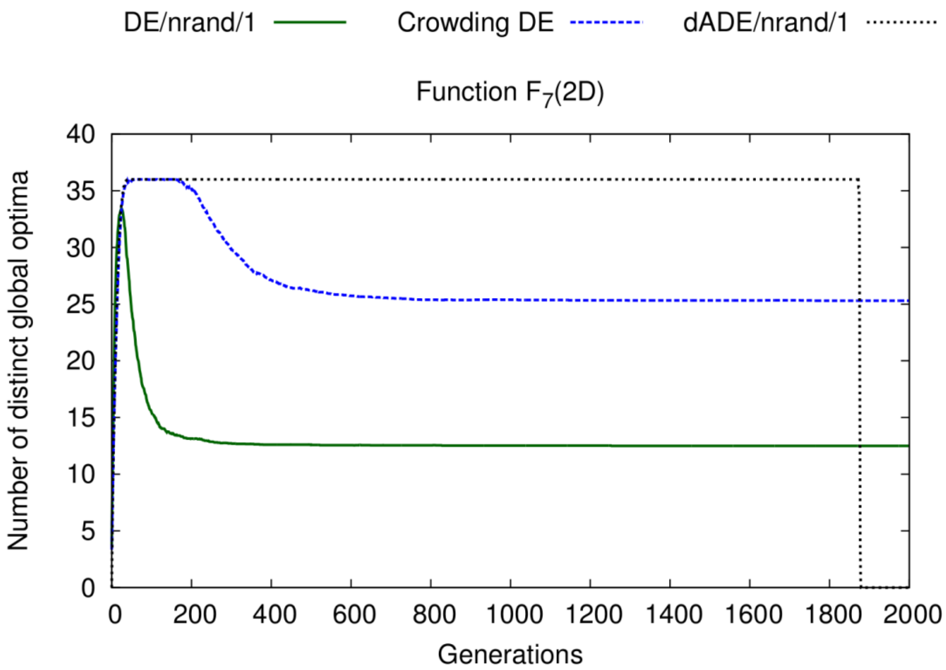


Epitropakis, Plagianakos, Vrahatis. Finding multiple global optima exploiting differential evolution's niching capability. 2011 IEEE Symposium on Differential Evolution (SDE)

DE/NRAND/1 -> DADE/NRAND/1

PARALLEL METHOD

- addition of a parameter adaptation method for F and CR, taken from JADE
- addition of dynamic archive:
- put only better solutions in
- if near better contained, re-initialize individual
- identification radius R adapted during run
- much better performance



Epitropakis, Li, Burke. A Dynamic Archive Niching Differential Evolution Algorithm for Multimodal Optimization. CEC 2013

results/competition/software

TEST PROBLEMS/BENCHMARK SETS

- BBOB collection for global optimization: http://coco.gforge.inria.fr/

- CEC 2013 Niching Competition Problems (20)
  - a collection of known problems in different dimensions, 1D to 20D

  http://goanna.cs.rmit.edu.au/~xiaodong/cec13-niching/competition/

- Preuss/Lasarczyk generator: mixture of polynomials

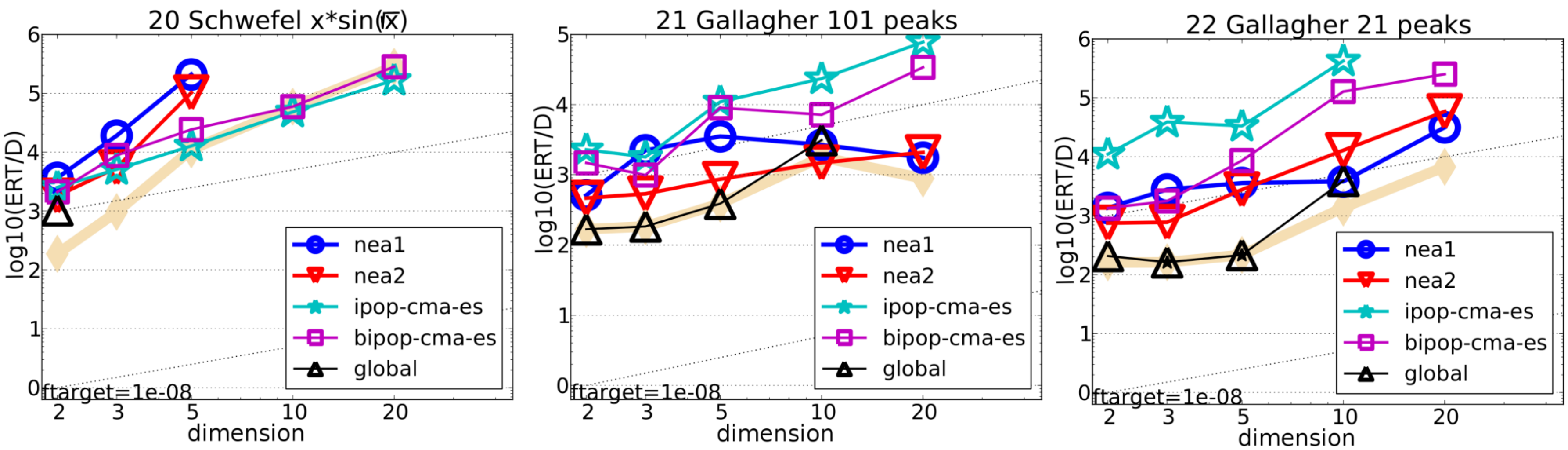
Preuss, Lasarczyk. On the importance of information speed in structured populations. In Proc. PPSN VIII, pp. 91–100, 2004, Springer

- Gallagher/Yuan generator: mixture of gaussian distributions

Gallagher and B. Yuan. A general-purpose tunable landscape generator. IEEE Trans. Evolutionary Computation, 10(5):590–603, 2006

ONE-GLOBAL CASE

SELECTED MULTIMODAL BBOB FUNCTIONS

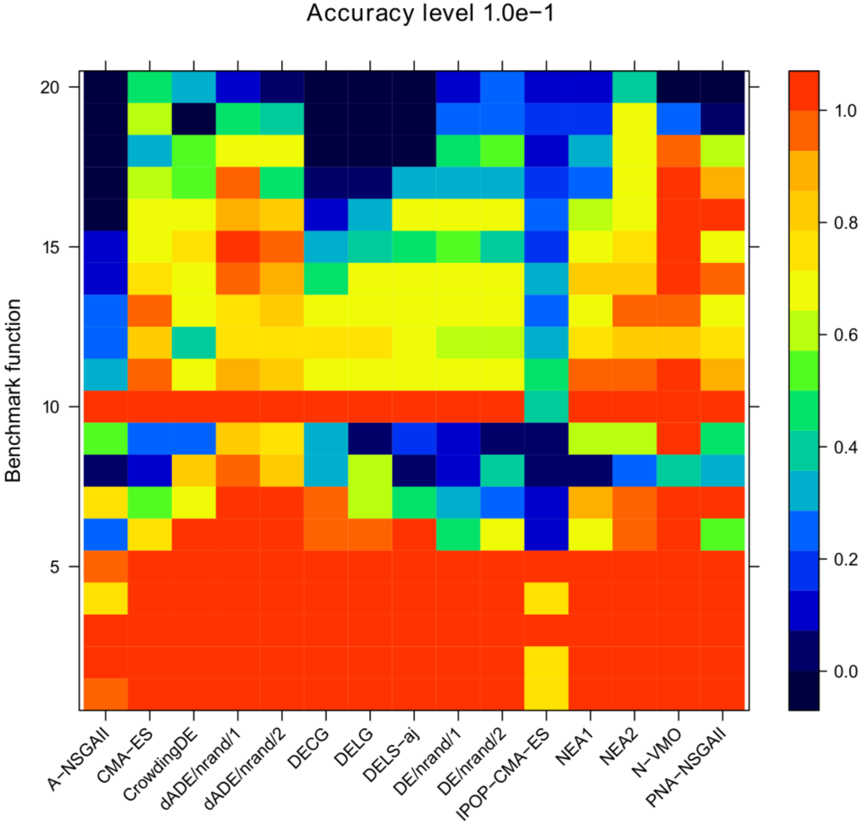


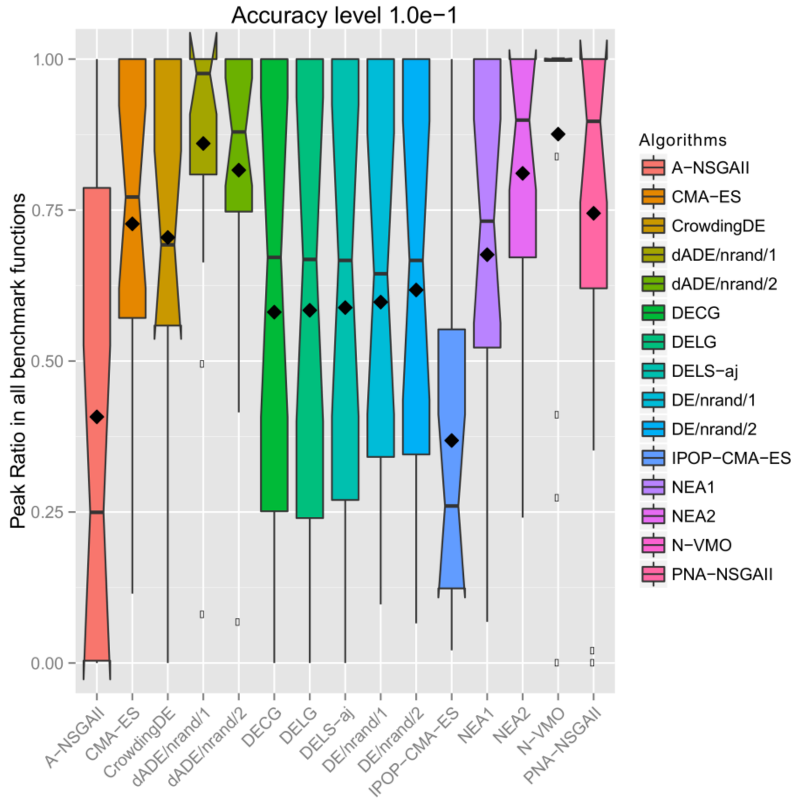
- MMO algorithm can be better than CMA-ES if topology suitable
- however, classical GO methods often better in these cases
- for global optimization, MMO algorithms not the right tool

ALL-GLOBAL CASE

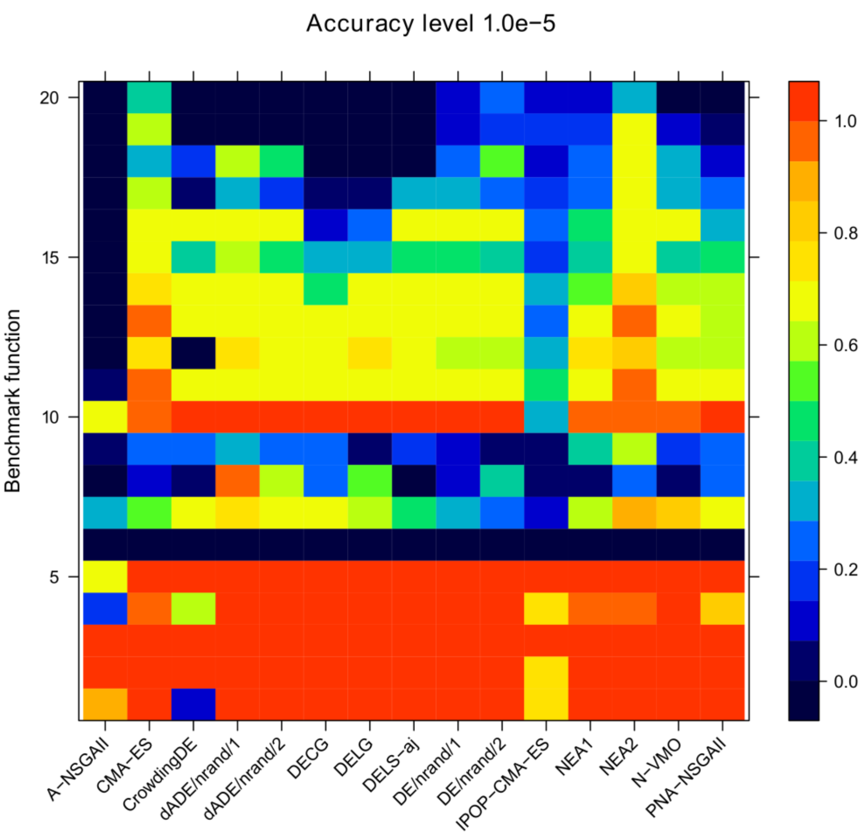
FROM THE CEC 2013 NICHING COMPETITION

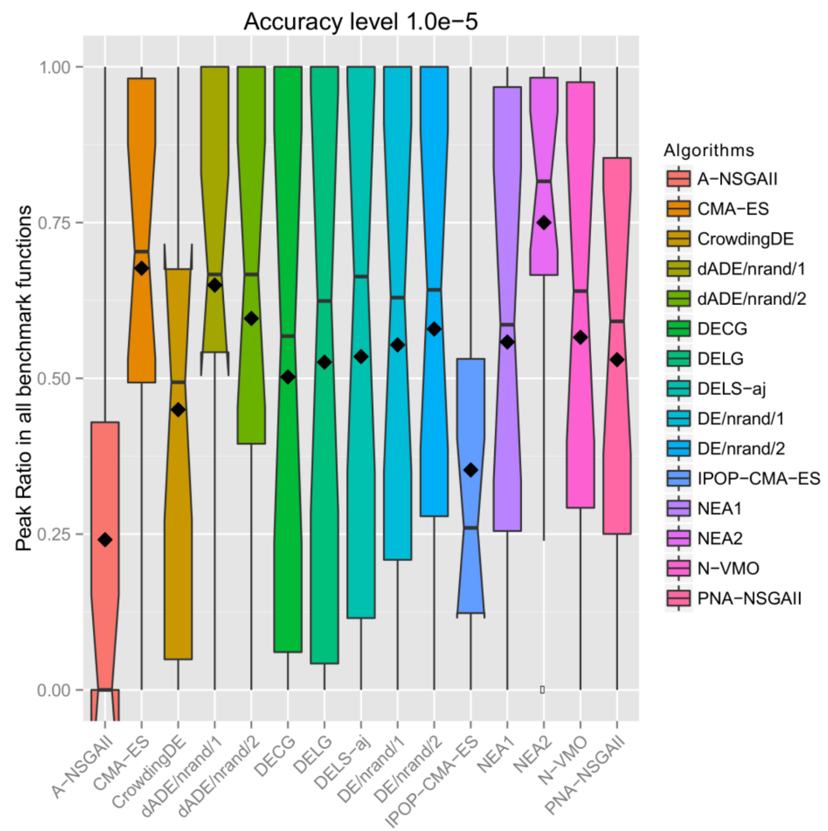
- task: find all global optima (1 to 20D) with given accuracy level





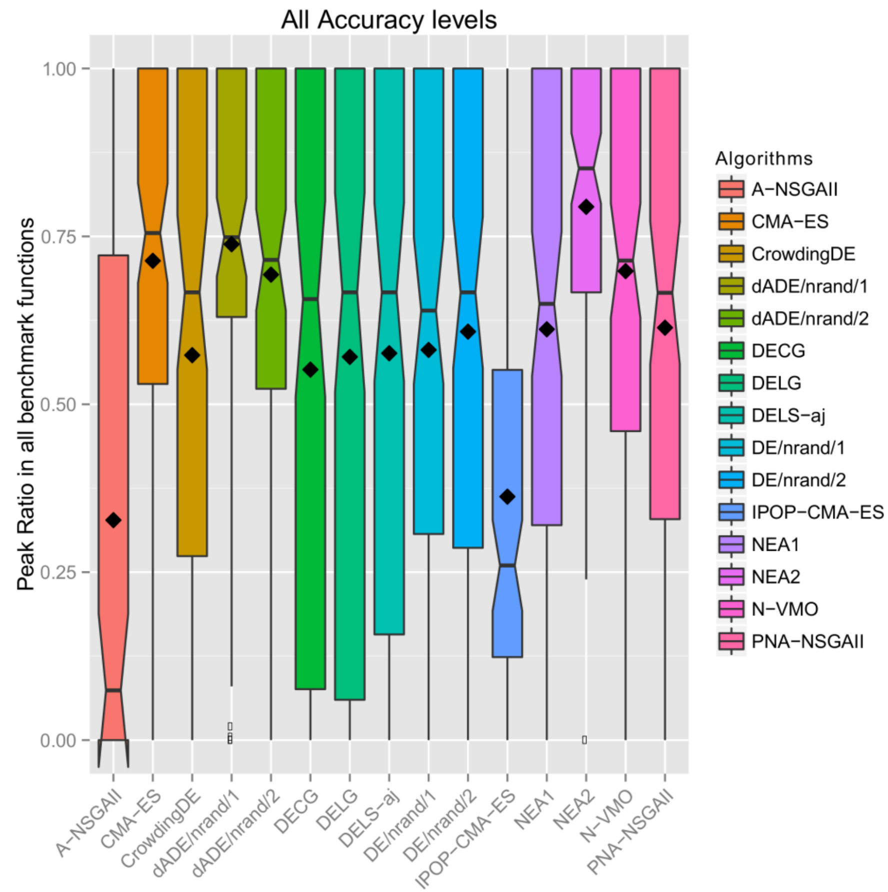
MORE ACCURATE, PLEASE





OVERALL ASSESSMENT

- tight race between NEA2 and dADE/nrand/1
- won by the sequential method (this time)
- result depends very much on experimental setup
- critique towards PR as basic performance measure



many thanks to the CEC 2013 niching competition team: Michael Epitropakis, Xiaodong Li and Andries Engelbrecht

the future

THINGS TO DO

- define MMO, tasks and scenarios
- improve problem libraries
- set up benchmarks for different scenarios
- agree on proper performance measures for these
- real-world motivated benchmarks?
- work on MMO algorithms, recombine components?
- MMO algorithms for non real-valued representations?

WHERE IS THE MATERIAL FROM?

Springer book

“Multimodal Optimization by Means of Evolutionary Algorithms”

(monograph on base of my dissertation)

coming out soon!

MMO STOPPING CRITERIA?

S4.2 Proc. p. 141, Tuesday 11:00

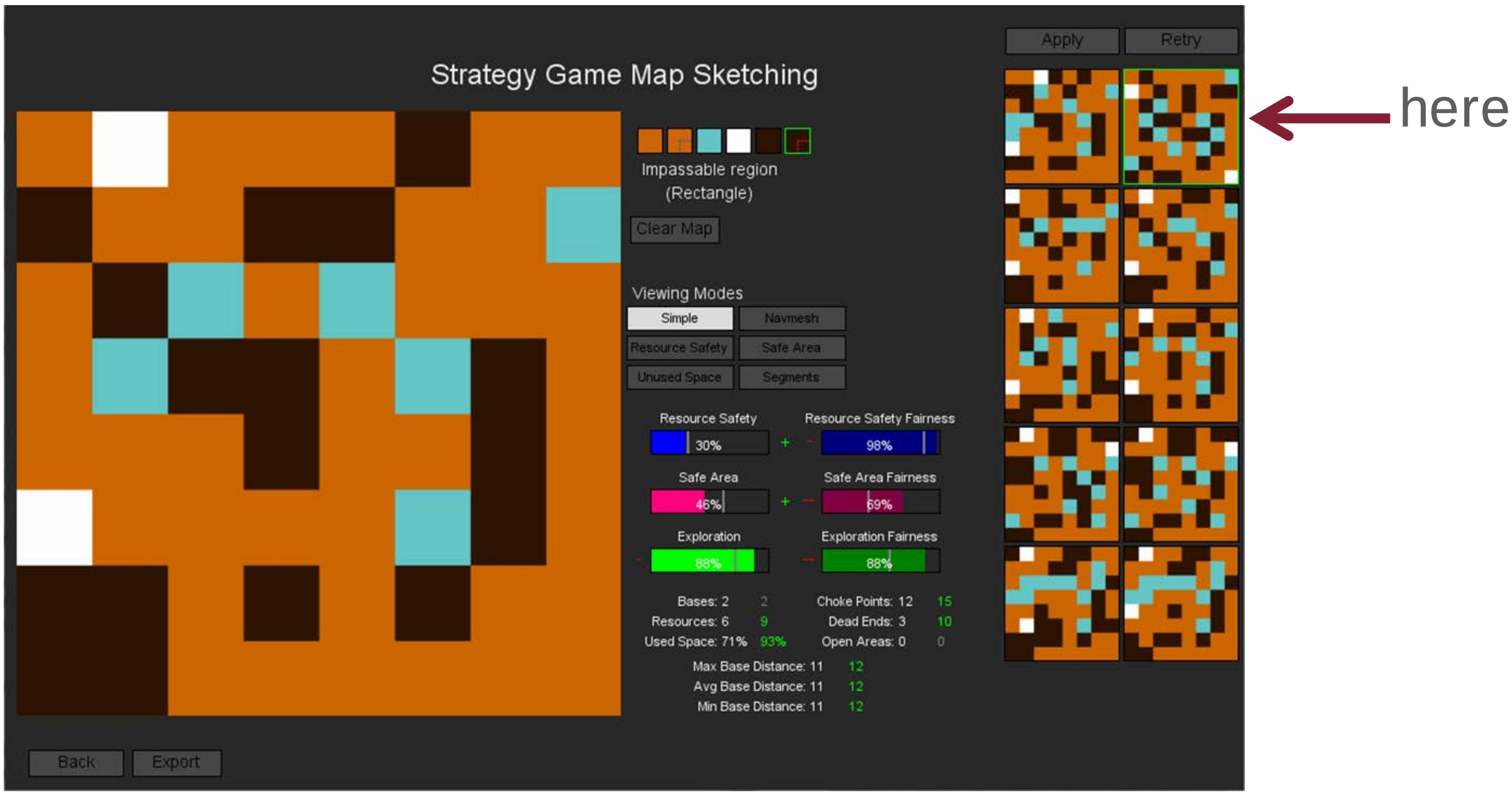
Wessing, Preuss, Trautmann:

Stopping Criteria for Multimodal Optimization

MMO FOR NON REAL-VALUED PROBLEMS

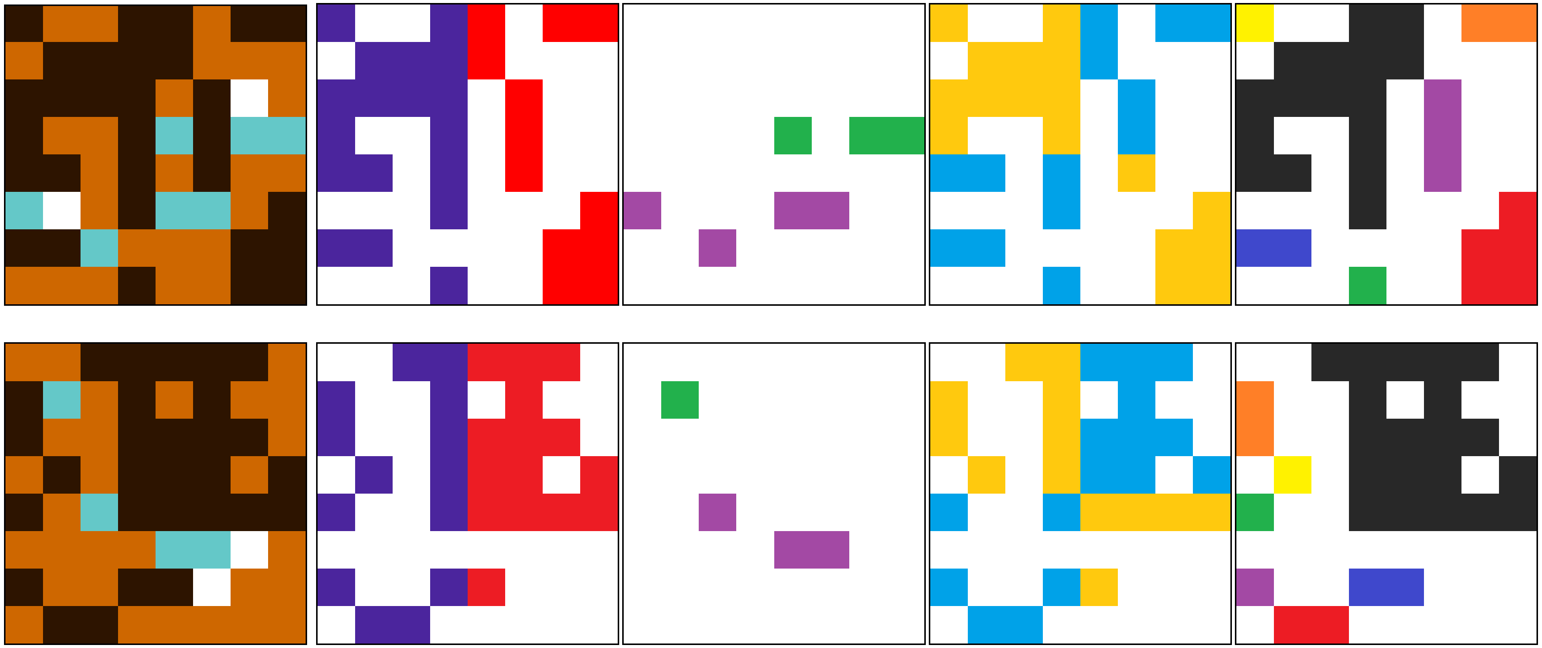
A RECENT EXAMPLE FROM COMPUTATIONAL INTELLIGENCE IN GAMES

- design tool for map sketches: diverse but good set needed



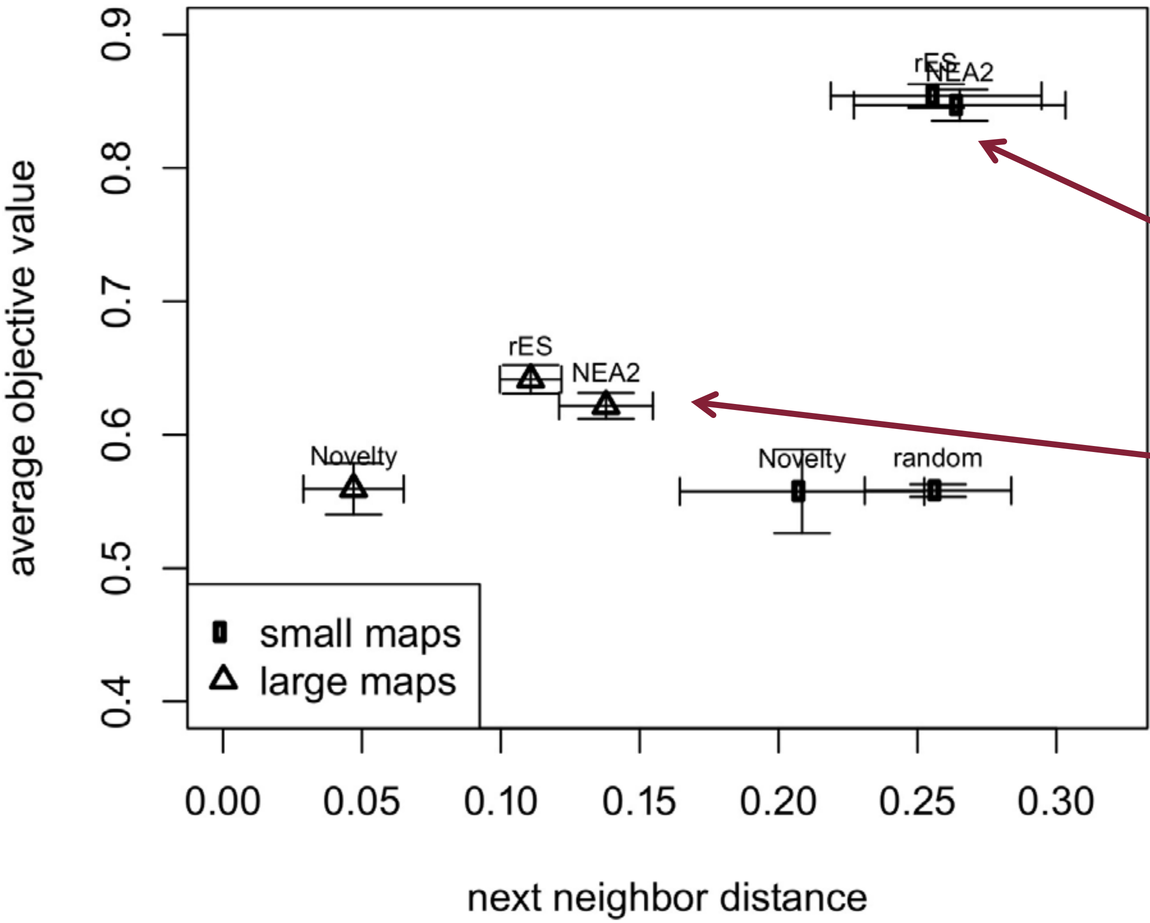
VISUAL IMPRESSION MAP DISTANCE

(original, vertical balance of impassables+left half concentration of impassables, horizontal balance of resources+top half concentration of resources, diagonal concentration of impassables, impassable segments+largest segment)



COMPARISON TO RESTART ES/MC/NOVELTY

AVG. 6 OBJECTIVES AGAINST AVG. MIN. VISUAL IMPRESSION DISTANCES



good for small maps

good for large maps

TAKE HOME

European
Research
Center for
Information
Systems

- FIELD MUST BE DEFINED MUCH BETTER (PROBLEMS, MEASURES)
- LOOK INTO GLOBAL OPTIMIZATION WORK (TOERN, RINNOY KAN, ALI) TO FIND MANY USEFUL CLUES
- MMO METHODS NOT REALLY USEFUL FOR GLOBAL OPTIMIZATION
- BUT USEFUL FOR SET OPTIMIZATION
- UNCOORDINATED RESTARTED LOCAL SEARCH GOOD BASELINE
- NEA2 AND DADE/NRAND/1 GOOD METHODS FOR MMO
- UNEXPLOITED CONNECTIONS TO MULTI-OBJECTIVE OPTIMIZATION
- APPLY MMO TO MORE NON REAL-VALUED REPRESENTATIONS!