Investigating Restricted Tournament Replacement in ECGA for Non-Stationary Environments

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EDAs for Non-Stationary Optimization

Estimation of distribution algorithms (EDAs)

- Last decade has seen the rise and consolidation of EDAs.
  - New algorithms. Many applications. Good results.
  - Its own track at GECCO.
- Broader class of model-based search methods.
  - Others are ant colony optimization, cross-entropy method, stochastic gradient search.
  - In some cases methodologies/results can be transfered.

Dynamic optimization problems (DOPs)

- Fitness function changes over time.
- Fast convergence to the optimum no longer the main goal.
  - Ability to respond to changes in environment.

EDAs for Non-Stationary Optimization (2)

EDAs for DOPs

- More recently, EDAs have been also applied to DOPs.
  - Some work done with univariate EDAs.
  - Not so much for multivariate EDAs.
- The importance of applying multivariate EDAs to DOPs has been recently highlighted (Abbass et al., 2004).
- Learn possible structural decompositions in changing environments.
- Equally important, use model information to improve performance in DOPs.
  - Substructural niching (Sastry et al., 2005).

Extended Compact Genetic Algorithm (ECGA)

ECGA

- EDA which uses marginal product models (MPMs).
  - Model selected solutions to generate new ones.

Example

Population

0101
1111
1010
1110
0001
0000
1111
0001

Marginal Product Model

[1,3]		[2]		[4]	
00	0.5	0	0.5	0	0.375
01	0	1	0.5	1	0.625
10	0				
11	0.5				

ECGA for DOPs

ECGA w/ random restart

- Abbass, Sastry, & Goldberg (2004).
- First application of ECGA to DOPs.
- Demonstrated importance of applying more powerful EDAs to DOPs.
- Change of environment was assumed to be known/detected.
- At each change in the environment the population is randomly restarted.
- Proposed dynamic versions of adversarial problems with bounded difficulty.

ECGA for DOPs

Algorithm

1. Create random population **P** and evaluate.
2. If change of environment detected:
   - Re-initialize population **P** at random and evaluate.
3. Select **P'** individuals from population **P**.
4. Find the MPM which best represent the distribution in **P'**.
5. Sample a new population **O** from the learned MPM and evaluate.
6. Replace all individuals in **P** by those from **O**.
7. Return to step 2.

ECGA for DOPs v2

ECGA w/ random restart and "niching"

- Sastry, Abbass, & Goldberg (2005).
- Same as previous approach but with...
- ... substructural niching (Sastry et al., 2005).
  - Probability of sampling substructures is proportional to their fitness.
  - Requires maintenance of fitness model.
- But the main source of diversity still comes from random restart.
- Change of environment is also assumed to be known.
- Maybe potential not fully exploited...

Restricted Tournament Replacement

- Niching method successful used in EDAs.
  - hBOA to tackle hierarchical problems.
  - ECGA to real-value optimization and classification.
- Reduces population size requirements.

For each individual X in the offspring population:

1. Select a random subset of individuals W with size w from the original population.
2. Let Y be the solution from W that is most similar to X, in terms of genotypic distance.
3. Replace Y with X, if X is better, otherwise discard X.

Substructural RTR

- Same concept as substructural niching.
- Maintain diversity at the substructural level.
- Compare similar substructures rather than single genes.
- Once sampling substructures, maintain them as a whole.
- Simpler than substructural niching.
  - Does not require substructural fitness information.
- Sample complexity for maintaining all optima might be similar to substructural niching $\rightarrow O(2m)$.
  - Need further analysis.
  - But better than standard RTR $\rightarrow O(2^m)$.

Substructural RTR

Example

Consider the MPM [1,2,3,4] [5,6,7,8] [9,10,11,12]:

Offspring	1111 1111 1111		
Parent 1	0111 1011 1110	$d_1 = 3$	$d_2 = 3$
Parent 2	0000 1111 1111	$d_1 = 4$	$d_2 = 1$

- Parent 1 is the most similar using gene-wise distance (d_1).
- Parent 2 is the most similar using substructure-wise distance (d_2).

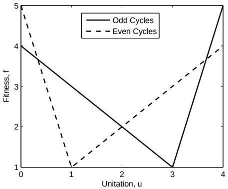
ECGA+RTR for DOPs

Algorithm

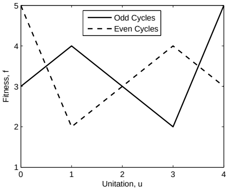
1. Create random population **P** and evaluate.
2. Select **P'** individuals from population **P**.
3. Find the MPM which best represent the distribution in **P'**.
4. Sample a new population **O** from the learned MPM and evaluate.
5. If change of environment detected:
    - Reevaluate population **P**.
6. Insert individuals from **O** into **P** using RTR.
7. Return to step 2.

Experimental Setup

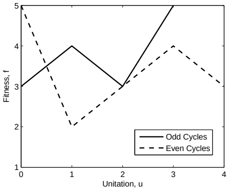
- Same as in Abbass, Sastry, & Goldberg (2004).
- Dynamic approach to adversarial problems of bounded difficulty.
- $m - k$ additively decomposable problems $\rightarrow \ell = m \cdot k$
- Experiments for 3 different subfunctions.



(a) Function 1



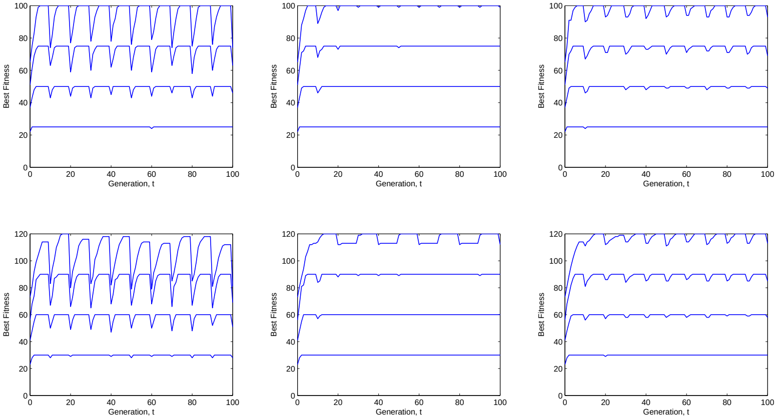
(b) Function 2



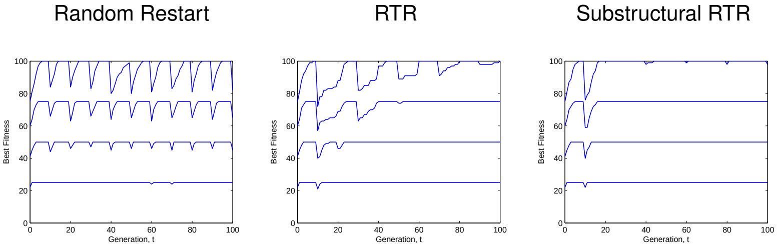
(c) Function 3

Function 1, $m = \{5, 10, 15, 20\}$, $k = \{4, 5\}$

Random Restart | RTR | Substructural RTR

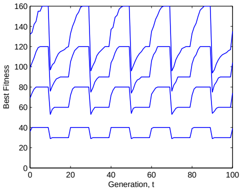


Function 2, $m = \{5, 10, 15, 20\}$, $k = 4$

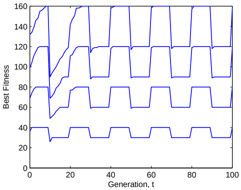


Function 3, $\ell = \{24, 48, 72, 96\}$, $k = 3 \leftrightarrow 4$

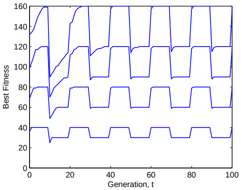
Random Restart



RTR



Substructural RTR



Black-Box Optimization in DOPs

- BBO algorithms need little or no information about the problem.
- NFL theorems are applicable to DOPs, but in practice we are not interested in all possible problems.
  - Particular domain of interest.
  - Problems under a certain bound of difficulty.
- Example: EDAs are adequate for problems where identifying important subsolutions is crucial to succeed.
- Same argument can be made for DOPs. If the
  - number of environments
  - or the period between changes varies unboundedly,
- No method will outperform the random restart of the population.

Black-Box Optimization in DOPs

- Recognize that diversity maintenance approaches are more suitable if changes are bounded in some way.
- On the other hand, using a restart approach requires an efficient method to detect changes.
  - Problem-dependent and non-trivial task.
- Each approach has its own associated costs and in some sense a particular domain of application.

Removing assumption of known changes in ECGA+RTR

- Demonstrate utility of diversity preservation approach.
- Re-evaluate individuals not replaced by RTR.

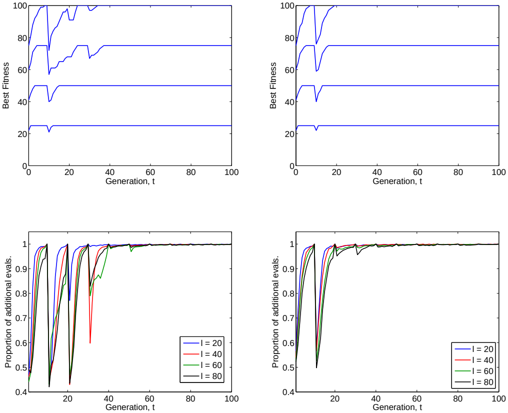
ECGA+RTR for DOPs

Algorithm

1. Create random population **P** and evaluate.
2. Select **P'** individuals from population **P**.
3. Find the MPM which best represent the distribution in **P'**.
4. Sample a new population **O** from the learned MPM and evaluate.
5. Insert individuals from **O** into **P** using RTR.
6. Re-evaluate individuals in **P** which were not replaced in step 5.
7. Return to step 2.

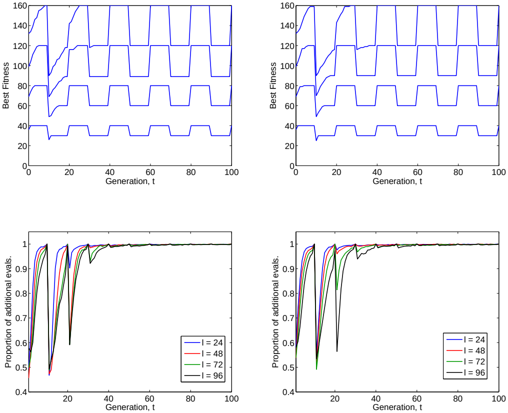
Function 2, $m = \{5, 10, 15, 20\}$, $k = 4$

RTR | Substructural RTR



Function 3, $\ell = \{24, 48, 72, 96\}$, $k = 3 \leftrightarrow 4$

RTR | Substructural RTR



Summary & Conclusions

Summary & Conclusions

- RTR in ECGA has been investigated for DOPs.
- Substructural RTR has been proposed.
- More robust than standard RTR.
- Diversity preservation in ECGA is a valid approach to tackle DOPs.

Future Work

- Scalability analysis of the behavior of ECGA+RTR for increasing number of environments.
- Detection of environment changes based on model information.

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