Incorporating Directional Information within a Differential Evolution Algorithm for Multiobjective Optimization

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GECCO'06 Humies

RMIT UNIVERSITY

Outline

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1. Research Motivation
   - Improving the efficiency of evolutionary multiobjective optimization
2. Improving on Multiobjective DE
   - Adopted techniques and the proposed approach
3. Experiments and Summary
   - Experiments
   - Summary
4. Human Competitive Criteria
   - Why our results satisfy criteria B and F?
   - Why this entry should be considered?

Why use Differential Evolution in Multiobjective Optimization?

- EAs offers a robust and effective optimization approach for solving multiobjective problems.
- Using a population of candidate solutions, an EA is able to maintain useful information about characteristics of the environment.
- Another population-based optimization technique, DE, is characterized by its correlated step sizes, rotational invariance (Salomon, 1996), and ability to self-adapt the step sizes and direction of the search over time.
- DE has been successfully applied to a large number of real world problems, eg., IIR-filter design, aerodynamic shapes, etc.

A Multiobjective DE algorithm

- Built on the NSGA-II framework (Deb, 2002).
- Uses non-dominated sorting, crowding distances, and tournament selection.
- However, as reported by Deb, et. al (2002), NSGA II performs poorly on a rotated multiobjective problem (the SBX operator is not rotation invariant).
- Differential Evolution variant $DE/current-to-rand/1$: $u_{i,G+1} = x_{i,G} + K(x_{r3,G} - x_{i,G}) + F(x_{r1,G} - x_{r2,G})$, where K and F are control parameters; Randomly select parents $r1, r2, r3 \in \{1, 2, \ldots, n | r1 \neq r2 \neq r3 \neq i\}$
- Can deal with parameter interactions, and is rotationally invariant.
- In this work, the basic Multiobjective DE algorithm is enhanced by adopting directional information to guide the search towards better regions of the search space.

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What is this research about?

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- If we know which solutions are better or non-dominated with respect to their ranks, we can direct the search.
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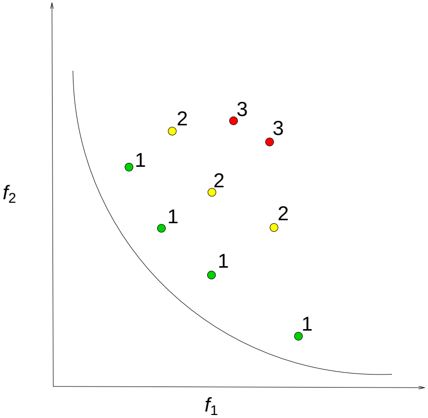
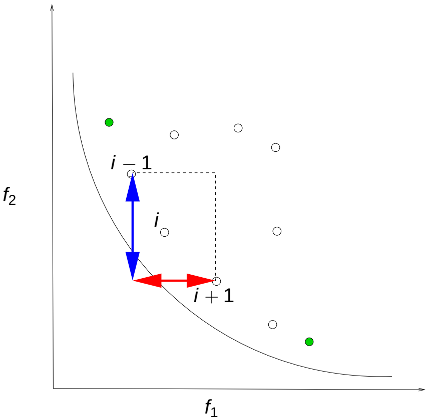
Fitness assignment: Non-dominated sorting



Fitness assignment: Crowding distances



Selection: Tournament selection using ranks and crowding distance

A solution *i* is selected over a solution *j* if ....

- solution *i* has a better rank than solution *j*.
- they have the same rank, but solution *i* has a better crowding distance than solution *j*.

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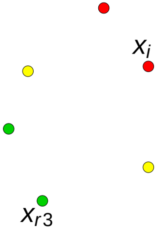
Recombination: Converging towards the Pareto-front



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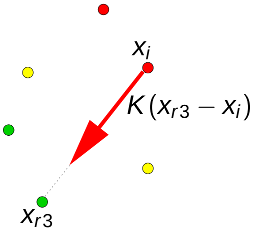

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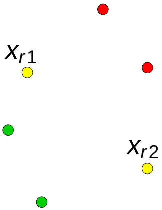
Recombination: Spreading across the Pareto-front



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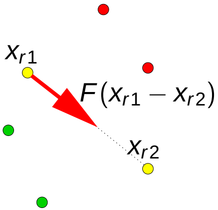

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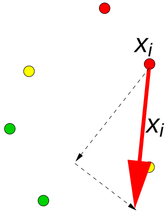
Combining spread and convergence vectors



$$x_i + K(x_{r3} - x_i) + F(x_{r1} - x_{r2})$$

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Experimental settings

- **Rotated problems** - Four rotated problems are employed; unimodal, multimodal, discontinuous, and non-uniformally mapped. Please refer to our GECCO'06 paper on EMO test functions for details.
- **DE settings** - K = 0.8, f = 0.4.
- **Other settings** - Pop. size of 100. Typical settings for NSGA-II.
- **Evaluation metrics** - Generational Distances (from Q to P* and P* to Q)

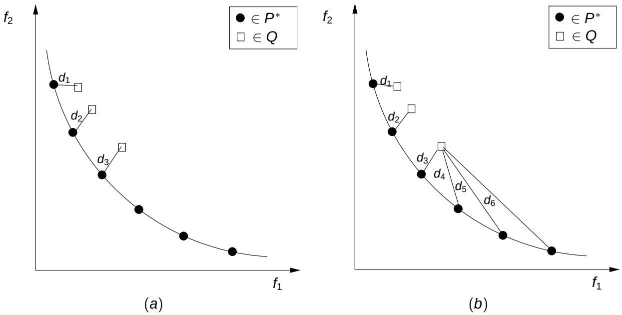

Figure: Evaluation metric

Results

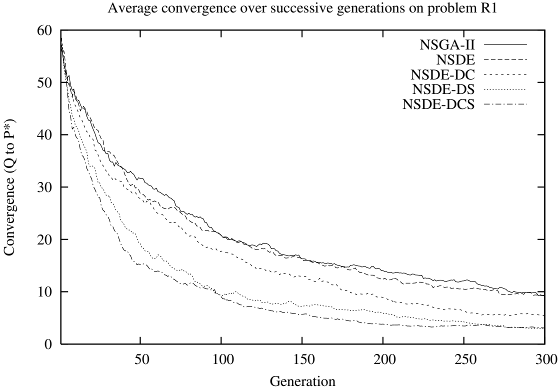

Figure: Average convergence over 50 runs over a period of 300 Generations (30,000 problem evaluations) on Problem R1.

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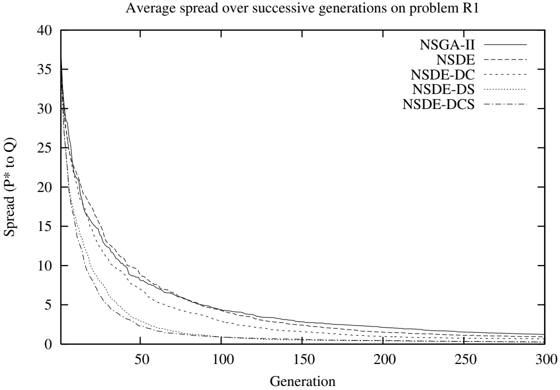

Figure: Average spread over 50 runs over a period of 300 Generations (30,000 problem evaluations) on Problem R1.

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Summary

- We have studied the use of directional information within a multiobjective DE on 4 rotated problems with parameter interactions.
- The use of directional information in DE improves the efficiency of the search, by eliminating areas of the search space from being considered.
- Directional information can improve the speed of convergence and spread.

For detailed information about this work, please refer to our GECCO’06 paper on Multiobjective DE.

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Criteria B and F

- (B) The result is equal to or better than a result that was accepted as a new scientific result at the time when it was published in a peer-reviewed scientific journal.
- (F) The result is equal to or better than a result that was considered an achievement in its field at the time it was first discovered.

Note: A paper published in *IEEE Trans. Evol. Comput., 6(2): 182-197, 2002* by Deb, et. al shows that NSGA II performs better than other EMO algorithms on non-rotated EMO test problems (ZDT series). However, it performs poorly on a rotated EMO problem.

Why our results satisfy criteria B and F?

- EMO algorithms outperform human beings with respect to their ability to find non-dominated solution sets in complex problem domains with many parameters.
- The use of directional information in a Differential EMO algorithm dramatically improves the performance of EMO, with respect to the diversity of the non-dominated solutions, and the convergence speed of the non-dominated solutions.
- Our proposed Non-dominated Sorting Differential EMO algorithm can handle much more effectively the problem of parameter interactions, a difficult issue that is yet to be systematically addressed by EMO research community, including the popular NSGA II, SPEA II, PAES, etc.

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This entry should be considered for the following reasons:

- Most real world problems have parameter interactions, involve multiple possibly conflicting objectives, and have expensive evaluation functions that may take a long time to evaluate. It is impossible for a human being to be competitive with EMO algorithms in general.
- The proposed approach using Differential Evolution and directional information addresses these issues associated with an EMO algorithm.
- This work proposes an EMO algorithm that can handle more effectively multi-objective problems with parameter interactions, and can do so more efficiently by minimizing the number of evaluations required by the algorithm.

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