Oppositional Biogeography-Based Optimization

M. Ergezer, D. Simon, and D. Du

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Outline

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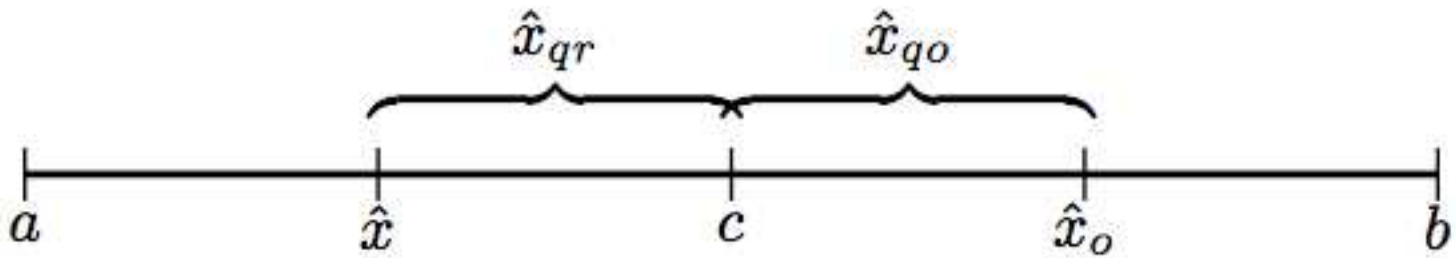
Biogeography-Based Optimization

- Application of biogeography to evolutionary algorithms
- Immigration and emigration of species between islands (solutions) for better habitats
- Can match or outperform other EAs
  - Markov analysis [1]
  - Experimental studies [2]

Opposition-Based Learning

- Designed for reinforcement learning in neural networks [3]
  - Already used in other EAs and demonstrated good convergence properties [4].
- Utilize opposite numbers to converge to the solution
- Hypothesis: “Opposite numbers are more likely to be closer to the solution than random ones”
  - Thus, by comparing a number to its opposite, a smaller search space is needed to converge to the right solution(s).

Definition of Opposite Points



Let $\hat{x}$ be any real number between [*a*,*b*],

*O*pposite point:

$$\hat{x}_o = a + b - \hat{x}$$

*Q*uasi-opposite point:

$$\hat{x}_{qo} = \mathrm{rand}(c, \hat{x}_o)$$

*Q*uasi-reflected point:

$$\hat{x}_{qr} = \mathrm{rand}(c, \hat{x})$$

Probabilistic Comparison of Opposite Points

$$\mathrm{E}\left(\Pr[|\hat{x}_o - x| < |\hat{x} - x|]\right) = \frac{1}{2}$$

$$\mathrm{E}\left(\Pr[|\hat{x}_{qo} - x| < |\hat{x} - x|]\right) = \frac{9}{16}$$

$$\mathrm{E}\left(\Pr[|\hat{x}_{qr} - x| < |\hat{x} - x|]\right) = \frac{11}{16}$$

where x is global minima,

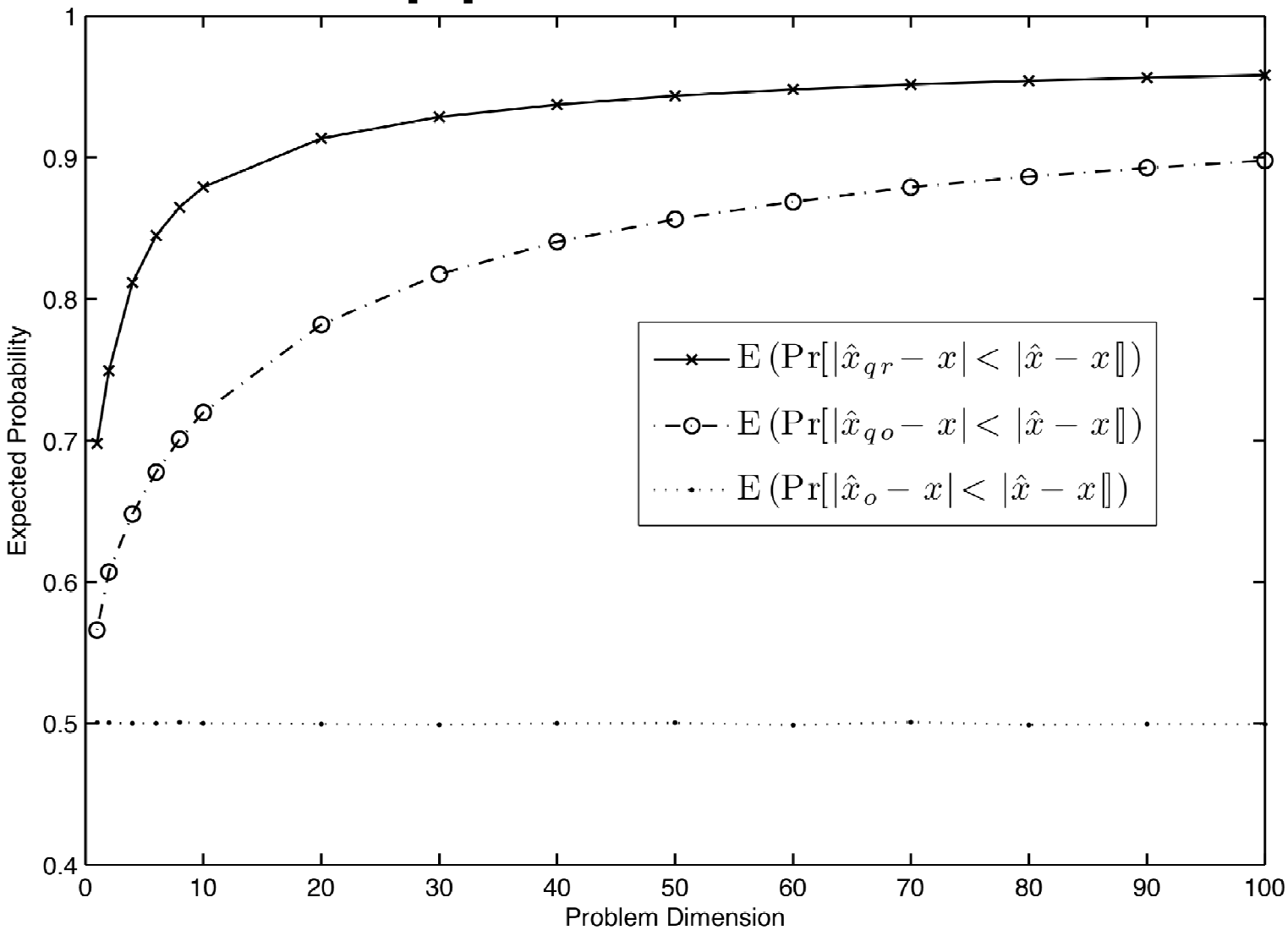
$\hat{x}$ is EA's solution estimate,

$\hat{x}_o$ is opposition of $\hat{x}$

$\hat{x}_{qo}$ is quasi-opposition of $\hat{x}$

$\hat{x}_{qr}$ is quasi-reflection of $\hat{x}$

Effects of Dimension on Opposite Points



Empirical Results

- Simulation Metrics
  - Mean Fc: Average number of function evaluations for successful runs
  - Success rate, SR: Ratio of number of successful runs to the number of trials
- Simulation Settings
  - 16 benchmark functions
  - 20 dimensional
  - Population size of 50
  - 50 Monte Carlo simulations

Empirical Results

Benchmark	BBO		OBBO	
Functions	Mean Fc	SR	Mean Fc	SR
Ackley	23,150	1	2,394	1
Alpine	14,293	1	9,430	1
Fletcher	-	0	-	0
Griewank	372,488	0.24	2,102	1
Penalty1	39,092	1	1,513	1
Penalty2	37,082	1	1,678	1
Quartic	168,375	1	27,050	1
Rastrigin	4,997	1	2,111	1
Rosenbrock	-	0	8,223	1
Schwefel 1.2	2,796,393	0.5	4,893	1
Schwefel 2.21	-	0	8,110	1
Schwefel 2.22	13,841	1	2,977	1
Schwefel 2.26	124,248	1	8,092	1
Sphere	4,902	1	1,240	1
Step	157,187	1	997	1
Zakharov	1,064,367	0.48	6,086	1
Mean	370,801	0.70	5,793	0.94

Conclusion

- Introduced a new Opposition-Based Learning algorithm:
  - Quasi-reflection
- Proved quasi-reflection has the highest probability of yielding an answer closer to the solution than any other OBL method
- Increased BBO's success rate from 70% to 94% while reducing the mean cost function evaluation by 98%
- Find analytical expressions for the higher dimensional probabilities
- Repeat analysis for the case when solution is not uniformly distributed

References

[1] D. Simon, M. Ergezer, and D. Du, “Markov analysis of biogeography-based optimization.” Available online at http://academic.csuohio.edu/simond/bbo/markov

[2] D. Simon, “A probabilistic analysis of a simplified biogeography-based optimization algorithm.” Available online at http://academic.csuohio.edu/simond/bbo/simplified.edu

[3] M. Ventresca and H. Tizhoosh, “Improving the convergence of backpropagation by opposite transfer functions,” in IEEE International Joint Conference on Neural Networks, pp. 9527-9534, 2006.

[4] H. Wang, Y. Liu, S. Zeng, H. Li, and C. Li, “Opposition-based particle swarm algorithm with Cauchy mutation,” in IEEE Congress on Evolutionary Computation, Singapore, pp. 4750-4756, 2007.