Towards a Better Diversity of Evolutionary Multi-Criterion Optimization Algorithms using Local Searches

Haitham Seada
Department of Computer Science and Engineering
Michigan State University
428 South Shaw Lane
East Lansing, MI 48824
seadahai@msu.edu *

Mohamed Abouhawwash
Department of Mathematics
Faculty of Science
Mansoura University
Mansoura 35516, Egypt
saleh1284@mans.edu.eg

Kalyanmoy Deb
Department of Electrical and Computer Engineering
Michigan State University
428 South Shaw Lane
East Lansing, MI 48824
kdeb@egr.msu.edu †

ABSTRACT

In EMO diversity of the obtained solutions is an important factor, particularly for decision makers. NSGA-III is a recently proposed reference direction based algorithm that was shown to be successful up to as many as 15 objectives. In this study, we propose a diversity enhanced version of NSGA-III. Our algorithm augments NSGA-III with two types of local search. The first aims at finding the true extreme points of the Pareto front, while the second targets internal points. The two local search optimizers are carefully weaved into the fabric of NSGA-III niching procedure. The final algorithm maintains the total number of function evaluations to a minimum, enables using small population sizes, and achieves higher diversity without sacrificing convergence on a number of multi and many-objective problems.

Keywords

Multiobjective Evolutionary Optimization; Local Search; Extreme Points

1. INTRODUCTION

Diversity preservation in EMO has evolved over the years. Initially, Several diversity preservation approaches were borrowed from single-objective evolutionary computation literature. Later, other algorithms like SPEA2 [8] and NSGA-II [2] were proposed and dominated the field for years. They were however unable to maintain diversity in more than two objectives [5]. In the last 10 years decomposition has been widely adopted as a means of maintaining diversity in higher dimensions, as in MOEA/D [7] and more recently in NSGA-III [3].

*The first author gratefully acknowledges the partial funding he received from Beacon center towards this study, conducted at COIN lab (www.coin-laboratory.com).

GECCO'16 Companion July 20-24, 2016, Denver, CO, USA

ACM ISBN 978-1-4503-4323-7/16/07.

DOI: http://dx.doi.org/10.1145/2908961.2908991

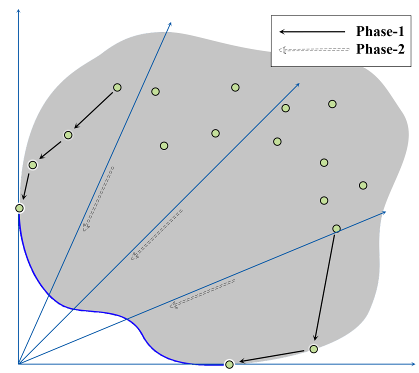

Figure 1: *Phases 1 and 2* of Div-NSGA-III

Ishibuchi's IM-MOGLS [4] is considered the first attempt to use mathematical optimization in the context of EMO. Subsequent researchers followed his steps. The use of Achievement Scalarization Functions (ASF) in EMO has also been explored in a few studies among which are Bosman's [1] and the work of Sindhya et al. [6].

2. DIVERSITY-BASED NSGA-III

Our proposed approach, modifies the niching mechanism of NSGA-III. Instead of continuously emphasising convergence, our approach breaks this pattern every α generations. The modified niching mechanism is outlined in Algorithm 1. Initially, the algorithm seeks extreme points using a biased-weighted-sum (BWS) local search (Equation 1). We call this *phase-1* (lines 1 to 4). We assume a number of extreme points equal to the number of objectives M. If a better extreme point is found, it will be used for later normalizations. Otherwise, the algorithm temporarily assumes that the current extreme points are the true ones, and switches to *phase-2*. *phase-2* the algorithms tries to fill in the gaps found in the front attained so far. And since BWS local search is unable to reach non-convex sections of the front, we use an ASF-based local search (Equation 2) along empty (having no associated points) reference directions.

It is important to note that if a better extreme point is found during evolution, the algorithm switches back to *phase-1*. Consequently, our algorithm keeps alternating between the two phases until the front reaches the maximum possible stretch with the minimum number of gaps.

Unlike the usual niching procedure adopted by NSGA-II

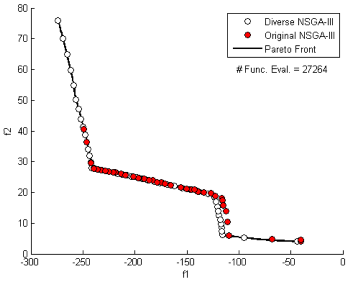

Figure 2: Median fronts of both algorithms (OSY)

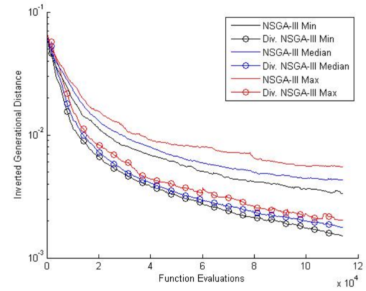

Figure 3: IGD vs. number of func. eval. (DTLZ2(10))

and NSGA-III our algorithm selects the closest individual to each reference direction (niche). Regardless of an individual's rank, if it is the only representative of its niche, it will be selected at the expense of – may-be – better ranked individuals which are already outperformed in their own niche (line 4). See Figure 1.

Algorithm 1 Modified NSGA-III Niching

Input: merged population (G), population size (N), reference directions (D), ideal point (I), intercepts (T), maximum number of function evaluations $(FeMax)$, maximum number of local search operations per iteration β
Output: New Population P'

```
1: F ← getFeasible(P)
2: E ← getExtremePoints(F)
3: E(i) ← BWS_i(FeMax), i = 1,...,M          % phase-1
4: P' ← getBestInNiche(d,G), ∀d ∈ D
5: if stagnant(E) then
6:     for i = 1 to β do                       % phase-2
7:         P' ← ASF(choose(x), I, T, FeMax)
8:     end for
9: end if
10: while |P'| ≤ N do
11:     x ← highestRank(G)
12:     G ← G \ x
13:     P' ← x, s.t. x ∉ P'
14: end while
```

$$\begin{aligned} \underset{\mathbf{x}}{\text{Minimize}} \quad & \mathrm{BWS_i}(\mathbf{x}) = \varepsilon \tilde{f}_i(x) + \sum_{j=1,\ j\neq i}^{M} w_j \tilde{f}_j(x), \\ \text{subject to} \quad & \varepsilon << min_{j=1,j\neq i}^{M} w_j \end{aligned} \tag{1}$$

$$\begin{aligned} \underset{\mathbf{x}}{\text{Minimize}} \quad & \mathrm{ASF}(\mathbf{x}, \mathbf{z}^r, \mathbf{w}) = \max_{i=1}^{M} \left(\frac{\tilde{f}_i(x) - u_i}{w_i} \right), \\ \text{subject to} \quad & g_j(\mathbf{x}) \leq 0, \quad j = 1, 2, \ldots, J. \end{aligned} \tag{2}$$

3. RESULTS

Our test problems include ZDT-(1,2,3,4,6), TNK, BNH, SRN, OSY, 3-obj. DTLZ-(1,2) and 10-obj. DTLZ-(1,2). Only Figures 2 and 3 are shown for brevity. the superiority of our proposed approach over the original NSGA-III is clear. The advantages of using Div-NSGA-III surpass this speedup factor. It also allows using previously prohibitively small population sizes.

4. CONCLUSION

In this study, we propose an enhanced version of the recently proposed NSGA-III. Our proposed approach focuses on diversity without sacrificing convergence, through a carefully designed niching operator, where NSGA-III is augmented with two local search mechanisms. The two mechanisms keep alternating until the desired diversity is attained. Our simulation results clearly show the superiority of our approach compared to the the original NSGA-III over a wide range of problems.

5. REFERENCES

[1] P. A. Bosman. On gradients and hybrid evolutionary algorithms for real-valued multiobjective optimization. *Evolutionary Computation, IEEE Transactions on*, 16(1):51–69, 2012.

[2] K. Deb, S. Agrawal, A. Pratap, and T. Meyarivan. A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: Nsga-ii. *Lecture notes in computer science*, 1917:849–858, 2000.

[3] K. Deb and H. Jain. An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part i: solving problems with box constraints. *Evolutionary Computation, IEEE Transactions on*, 18(4):577–601, 2014.

[4] H. Ishibuchi and T. Murata. A multi-objective genetic local search algorithm and its application to flowshop scheduling. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, 28(3):392–403, 1998.

[5] V. Khare, X. Yao, and K. Deb. Performance scaling of multi-objective evolutionary algorithms. In *Evolutionary Multi-Criterion Optimization*, pages 376–390. Springer, 2003.

[6] K. Sindhya, K. Deb, and K. Miettinen. A local search based evolutionary multi-objective optimization approach for fast and accurate convergence. In *Parallel Problem Solving from Nature–PPSN X*, pages 815–824. Springer, 2008.

[7] Q. Zhang and H. Li. Moea/d: A multiobjective evolutionary algorithm based on decomposition. *Evolutionary Computation, IEEE Transactions on*, 11(6):712–731, 2007.

[8] E. Zitzler, M. Laumanns, L. Thiele, E. Zitzler, E. Zitzler, L. Thiele, and L. Thiele. Spea2: Improving the strength pareto evolutionary algorithm, 2001.