A Niching Framework based on Fitness Proportionate Sharing for Multi-Objective Genetic Algorithm (MOGA-FPS)

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ABSTRACT

In this paper, we propose a new niching framework based on Fitness Proportionate Sharing (FPS) to improve the diversity preservation in multi-objective optimization. The traditional sharing approach in standard Multi-Objective Genetic Algorithm (MOGA) is replaced with the proposed niching framework and the adapted MOGA is named MOGA-FPS. We also propose an algorithm which dynamically finds the most suitable niche radius. Experimental results show that MOGA-FPS significantly improves MOGA performance and maintains a well spread distribution of optimal solution set for bi-objective test functions compared with NSGA-II, MOGAS (Multi-Objective Genetic Algorithm using a new fitness sharing function).

CCS CONCEPTS

• **Theory of computation → Mathematical optimization**; • **Computing methodologies → Genetic algorithms**.

KEYWORDS

Multi-Objective Optimization, Sharing Function, Pareto-Optimal Solution

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1 INTRODUCTION

Diversity preservation is an important issue in EMOAs (Evolutionary Multi-Objective Algorithms). A solution set with well-spread distribution provides decision makers with more information for choosing preferred solutions [4]. Standard sharing function is used in MOGA [2] as a diversity maintenance technique. Despite the fact that the standard sharing function has shown to maintain diversity in MOGA, its challenges also include: (i) struggles to preserve diversity when combined with elite-preserving strategies [3]; (ii) crowded solution removal cannot be guaranteed when the population contains many non-dominated solutions; (iii) the setting of the parameter (niche radius) that adapts well to each test function. To overcome these challenges, we propose a niching framework based on FPS [6] to retain niche masters and completely eliminate other individuals in each niche. We also introduce a dynamic niche radius selection procedure to adjust the niche size depending on the test function and the population.

2 METHODOLOGY

The proposed niching approach is developed based on FPS strategy. FPS strategy performs sharing in niches based on individual fitness and recently, was successfully extended to cluster analysis in [7, 8]. The fitness sharing function is elaborated by equation (4) in [6]. Unlike [6], the proposed niching framework performs FPS in a different manner. During the fitness sharing stage, we maintained the original fitness of individual i as shown in equation (1) and scaled other individuals' fitness using equation (2). Sharing is performed on the objective space. Let Sh be a variable that ensures every individual belongs to a unique niche and N is the population size, we use d_{ij} to denote the normalized distance between two individuals in the same rank and C is the niche count for the subsequent fitness sharing. Algorithm 1 summarizes the proposed niching approach.

$$F_i = F_i, \tag{1}$$

$$\tilde{F_j} = \frac{F_j}{C}. \tag{2}$$

With equation 1 & 2, we have mitigated the challenges (i) & (ii) mentioned in the introduction section. To address challenge (iii), we introduced a dynamic niche radius (δ_{sh}) selection procedure. Specifically, we first compute the maximum pairwise distance in each rank and retain them in a vector. A median value is obtained from the maximum pairwise distances retained in the vector and is scaled with a certain fraction (p) value to obtain the niche radius (δ_{sh}). The value of p is problem dependent and it is set as $0.01 - 0.05$ in this paper.

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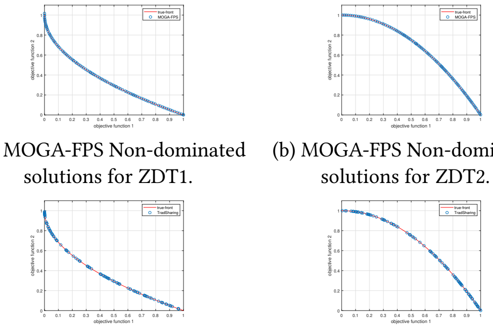
Algorithm 1 The proposed niching framework.

Sh = $\emptyset$
for $i = 1 : N$ **do**
  C = $\emptyset$
  if i $\notin$ Sh **then**
    for $j = 1 : N$ **do**
      if rank i == rank j
      find d_ij
      if d_ij $\leq \delta_{sh}$
      C = C $\cup$ j
    end for
    Maintain the original fitness of the niche master using equation 1
    Scale the fitness of the other members in the niche using equation 2
    Sh = Sh $\cup$ C
  end if
end for



(a) MOGA-FPS Non-dominated solutions for ZDT1.

(b) MOGA-FPS Non-dominated solutions for ZDT2.

(c) MOGA Non-dominated solutions for ZDT1.

(d) MOGA Non-dominated solutions for ZDT2.

Figure 1: Distribution of Non-dominated solutions of the last generation for ZDT1 & ZDT2 using MOGA-FPS and MOGA.

3 RESULTS

We compared the MOGA-FPS with several famous Pareto-based EMOAs (NSGA-II [1], MOGASc (a variant of MOGAS [3]) & MOGA [2]). All seven adopted continuous test functions are summarized in the first column of Table 1. Each algorithm is repeated 30 times and table 1 presents the average spacing [5] values of MOGA-FPS and the other competing algorithms. A smaller spacing indicates an even distribution of the solution set and thus MOGA-FPS outperforms the competing algorithms indicating smaller spacing values for all test suites. Figure 1 shows the non-dominated solution distribution obtained by MOGA-FPS and MOGA for ZDT1 & ZDT2 respectively. As shown in Figure 1, MOGA-FPS obtained an even and well spread non-dominated solution set while MOGA shows non-uniform solution distribution on the Pareto-front.

Table 1: Average spacing metric values comparison between MOGA-FPS, NSGA-II, MOGASc, MOGA on all problems with the best performance highlighted in bold.

Test suite	n_d	MOGA-FPS	NSGA-II	MOGASc	MOGA
FON	3	**1.9798E-03**	6.68946-03	5.0628E-03	7.8314E-03
KUR	3	**9.0986E-02**	1.0567E-01	1.4537E-01	1.8088E-01
ZDT1	30	**4.2318E-03**	7.0212E-03	1.7053E-02	1.0018E-02
ZDT2	30	**2.1995E-03**	7.3835E-03	5.7836E-03	1.0557E-02
ZDT3	30	**2.5187E-03**	7.0591E-03	5.8503E-03	9.5228E-03
ZDT4	10	**3.4103E-03**	6.7298E-03	5.7992E-03	7.1751E-03
ZDT6	10	**3.5728E-03**	6.9174E-03	4.7931E-03	6.4277E-03

4 CONCLUSION & FUTURE DIRECTIONS

In this paper, we presented a new diversity preservation technique and integrated it with the elite-preserving MOGA framework. The adapted MOGA, namely MOGA-FPS, mitigates the drawbacks associated with the original MOGA and minimize the gaps among optimal solution sets. Furthermore, we proposed a dynamic niche radius selection strategy for MOGA-FPS to adapt to the change of the population or benchmark problems. Experimental results and comparison studies demonstrate that MOGA-FPS shows statistically better performance than the state-of-the-art approaches. In the future, we will focus on investigating the efficacy of MOGA-FPS on three and more objective optimization problems.

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