Multi-Objective Diversity Maintenance

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F.0 [**General**]

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1. INTRODUCTION

Diversity maintenance is of central importance to the development and application of evolutionary computation methods and Estimation of Distribution algorithms (Yuan & Gallagher, 2005).

The most common approach to diversity maintenance is to apply a penalty for individuals contributing insufficiently to diversity (Holland, 1975; Goldberg & Richardson, 1987).

This can be viewed as an attempt to combine two distinct objectives into a single scalar value. However, a linear weighting of two objectives is not necessarily appropriate and can be difficult to control (Soule, 1998).

In multi-objective optimization, diversity has been used in combination with *multiple* other objectives (De Jong, Watson, & Pollack, 2001; De Jong & Pollack, 2003; Toffolo & Benini, 2003). Here, we propose to use a diversity objective in combination with a single other objective, namely the normal fitness function. To the best of our knowledge, the use of a diversity objective in combination with a single other objective has so far not been investigated. The results with multiple other objectives suggest that this approach to diversity maintenance is very promising.

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1.1 Diversity Maintenance Methods

1.2 The Sharing method

We describe a variant of fitness sharing (Holland, 1975; Goldberg & Richardson, 1987).

Individual i's fitness f_i is divided by a penalty term $1+\beta\overline{s}_i$, where $\overline{s}_i$ denotes the average similarity of i to the rest of the population:

$$f_i' = \frac{f_i}{1+\beta\overline{s}_i} \quad (1)$$

where the similarity between two individuals i and j, s_{ij} is $s_{ij} = \max(1 - \frac{d_{ij}}{\sigma}, 0)$, and d is the distance between the two individuals i and j. There is a threshold σ from where individuals are considered completely different. This similarity between two individuals is scaled between 0 and 1. The average similarity s of individual i equals $\overline{s}_i = \frac{1}{n-1}\sum_{j=1,j!=i}^{N} s_{ij}$, where n is the number of individuals in the population.

As a comparison method, we employ Fitness uniform selection (2002).

1.3 Multi-Objective Diversity Maintenance

The multi-objective approach to diversity maintenance was first proposed in work on code growth (De Jong et al., 2001), where it outperformed basic genetic programming and found hypothesized minimum size solutions to the 3, 4 and 5-parity problems.

Rather than modifying the fitness function as is being done by the sharing method, the Multi-Objective Diversity Maintenance method views the fitness and diversity (measured as the average distance of an individual to the population) as separate entities. Individuals are selected based on how many individuals they are dominated by, using best of four tournament selection.

2. RESULTS

We use two types of problems: two-dimensional problems (5 De Jong functions (De Jong, 1975) and 10 random landscapes) and NK-landscapes (N=60, K=10). The diversity maintenance methods are tested using a standard genetic algorithm. Each method uses an optimized mutation rate for that method.

The results of testing the algorithm on the two-dimensional landscapes are given in Table 1. The Tukey-Kramer test was used to assess significance (Zar, 1999). For the Rosenbrock

Times global optimum found with landscape	Baseline	FUSS	Sharing	MODM
Rosenbrock	48.68 +/- 0.97	4.88 +/- 0.35	91.20 +/- 0.47	99.92 +/- 0.05
Quartic	100 +/- 0.00	95.64 +/- 0.37	100 +/- 0.00	100 +/- 0.00
Foxholes	36.84 +/- 0.73	87.20 +/- 0.61	78.72 +/- 0.83	81.52 +/- 0.73
Random	3.66 +/- 0.16	20.19 +/- 0.32	47.11 +/- 0.31	72.00 +/- 0.38

Table 1: Results for the two-dimensional landscapes.

	Baseline	FUSS	Sharing	MODM
Optimal mutation μ rate	1.9	2.2	1.2	0.3
Maximal fitness +/- standard error	93.83 +/- 0.08	91.49 +/- 0.10	95.03 +/- 0.09	96.16 +/- 0.06
Average fitness in the population	74.23	64.45	81.45	72.47

Table 2: Results for the NK landscapes.

function for example, we can conclude at a significance level of $\alpha = 0.05$ that all methods perform differently, resulting in the following order:

$$MODM > Sharing > Baseline > FUSS$$

For all 2-dimensional problems, Multi-Objective Diversity Maintenance belonged to the best performing methods. Only in a single case (the Foxholes problem) another method (FUSS) performed better on average, but this difference was not statistically significant.
Results with the NK landscape are shown in Table 2 and Figure 1.

3. CONCLUSIONS

From the results we can conclude that the Multi-Objective Diversity Maintenance method is most effective to maintain diversity and to find the best solution. It outperforms the other frequency-dependent selection methods and the control algorithm. We conclude that Multi-objective Diversity Maintenance is an efficient and effective diversity maintenance method that may find general application in genetic algorithms.

The multi-objective diversity maintenance method not only searches around the local fitness peaks it has found, but also maintains individuals that are as different from the rest of the population as possible. As a result, genetic diversity is high, and a relatively large part of the search space is covered.

In future research, we would like to apply the MODM method to more practical test problems and in coevolutionary settings.

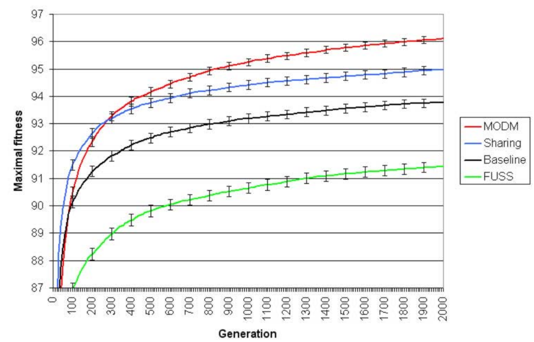

Figure 1: The maximal fitness in the population as a function of generations for the various algorithms on the NK landscape.

References

De Jong, E. D., & Pollack, J. B. (2003). Multi-objective methods for tree size control. *Genetic Programming and Evolvable Machines*, *4*(3), 211–233.

De Jong, E. D., Watson, R. A., & Pollack, J. B. (2001). Reducing bloat and promoting diversity using multi-objective methods. In L. Spector et al. (Ed.), *Proceedings of the Genetic and Evolutionary Computation Conference, GECCO-01*, pp. 11–18, San Francisco, CA. Morgan Kaufmann.

De Jong, K. A. (1975). *An Analysis of the Behavior of a Class of Genetic Adaptive Systems*. Ph.D. thesis, University of Michigan.

Goldberg, D. E., & Richardson, J. (1987). Genetic algorithms with sharing for multimodal function optimization. In Grefenstette, J. J. (Ed.), *Genetic algorithms and their applications : Proc. of the second Int. Conf. on Genetic Algorithms*, pp. 41–49, Hillsdale, NJ. Lawrence Erlbaum Associates.

Holland, J. H. (1975). *Adaptation in Natural and Artifical Systems*. University of Michigan Press, Ann Arbor, MI.

Hutter, M. (2002). Fitness uniform selection to preserve genetic diversity. In *Proceedings of the 2002 Congress on Evolutionary Computation (CEC-2002)*, pp. 783–788.

Soule, T. (1998). *Code Growth in Genetic Programming*. Ph.D. thesis, University of Idaho.

Toffolo, A., & Benini, E. (2003). Genetic diversity as an objective in multi-objective evolutionary algorithms. *Evolutionary Computation*, *11*(2).

Yuan, B., & Gallagher, M. (2005). On the importance of diversity maintenance in estimation of distribution algorithms. In *Proceedings of the 2005 conference on Genetic and evolutionary computation*, pp. 719–726.

Zar, J. (1999). *Biostatistical Analysis* (4 edition). Prentice Hall, New Jersey.