Assessing the Performance of the Pareto Archived Evolution Strategy

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Abstract

Proper comparison of the performance of two or more multiobjective optimisers is a complex problem of prime importance to the multiobjective evolutionary field. In this workshop paper we report on the use of sound statistical techniques and new test functions to assess the performance of a novel evolutionary optimiser, the Pareto Archived Evolutionary Strategy, and to compare its performance with two well known MOGAs. The test functions and statistical tools described here, and our results, have all been made available for use by other researchers.

1 Introduction

In order for good statistical assessments and comparisons of multiobjective optimisers to be made, two requirements must be fulfilled. The first is that sound statistical techniques are employed and the second is that testing is carried out on a diverse set of standard test problems. To test the performance of a new mulitobjective algorithm, the Pareto Archived Evolution Stategy (PAES), we employed statistical techniques put forward by Fonseca and Fleming and used six different test problems. Four of these problems have been used elsewhere [1, 2, 8] but two are new to the multiobjective evolutionary field. Since it is our aim to encourage use of both the techniques and test functions reported here we have made these problems and our statistical analysis tools freely available[1]. At the same location we also provide full results sets for these problems so that direct comparisons with our results can be made.

[1] www.cs.rdg.ac.uk/research/ssr97jdk/multiobjective

2 The PAES Algorithm

The PAES algorithm has been introduced in [5] and is described more fully in [6]. It was developed initially for solving a three-objective telecommunications routing problem which had been found to yield best to local search methods, when the three objectives were combined in a weighted sum. The original PAES algorithm, PAES(1+1), is thus a strictly local search optimiser but is nonetheless capable of finding a diverse set of solutions in the Pareto optimal set. This is accomplished through the maintenance of an archive which stores all non-dominated solutions found. The archive serves two distinct purposes: to return the best solutions found from the run and to act as a comparison set to aid in the evaluation of all new solutions generated.

3 The Test Problems

The performance of PAES was compared with the Niched Pareto GA [4] and a nondominated sorting GA [9] on a suite of standard test functions. The first four of these are the same as used by Bentley [1] i.e. Schaffer's functions F1, F2, and F3, and Fonseca's f1, renamed F4 here. Functions F1–F4 contain, respectively, a single objective and one optima, a single range of optima, two ranges of optima, and a single range of optima spread across two dimensions. Their use in testing multiobjective optimisers is in their implicit setting of two challenges: first, the set of nondominated solutions delivered by the optimiser should contain all of the function's Pareto optima. Second, it is generally felt best if there is no strong bias favouring one Pareto optimum over others. In other words, in a MOGA, for example, the number of copies of each Pareto optimum in the final population should be similar. If not, this would seem to reveal a bias which may be undesirable in practical applications.

We designed F5 (described below) to provide stronger challenges in these respects; it is easily defined, but is a non-trivial problem. Each Pareto optimum is intrinsically difficult to find, and there are n distinct Pareto optima for chromosomes of length n, each of which has a different frequency i.e. some are far easier to find than others. This makes both challenges (as described above) stringent tests for any multiobjective optimiser.

The function F5 uses an n-ary chromosome of n genes. There are two objectives defined by the following two functions (in which G_i is the ith gene).

$$F_{51} = n - 1 - \sum_{i=0}^{n-2} \begin{cases} 1 & \text{if } G_{i+1} - G_i = 1 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

$$F_{52} = n - 1 - \sum_{i=0}^{n-2} \begin{cases} 1 & \text{if } G_i - G_{i+1} = 1 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

Our final test problem, The Adaptive Distributed Database Management Problem (ADDMP) is a load-balancing problem from the telecommunications field. A detailed description of it can be found in [7]. By providing the full evaluation function and a set of parameters which define a particular scenario, the ADDMP can be used as a valid test function for use by other researchers. These can be found via the ECTELNET[2] website[3].

4 Statistical Comparison of Multiobjective Optimisers

Proper comparison of the results of two multiobjective optimisers is a complex issue. A discussion of the issues faced, and a powerful solution, is described by Fonseca and Fleming [3]. We have implemented their methods so that statistical comparison of the performance of optimisers searching for solutions in any number number of objectives can be performed. Extensive results from our comparisons between the PAES, NPGA and NDSGA are given in [6], and our implementation of the statistical methods are freely available from the WWW site given earlier.

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[2]The Telecomms subgroup of EvoNet: The European Network of Excellence in Evolutionary Computation

[3]www.dcs.napier.ac.uk/evonet/

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