Evolutionary Multimodal Optimization Revisited*

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Abstract. We revisit a class of multimodal function optimizations using evolutionary algorithms reformulated into a multiobjective framework where previous implementations have needed niching/sharing to ensure diversity. In this paper, we use a steady-state multiobjective algorithm which preserves diversity *without* niching to produce diverse sampling of the Pareto-front with significantly lower computational effort.

Multimodal optimization (MMO) and multiobjective optimization (MOO) are two classes of optimizations requiring multiple (near-)optimal solutions: having found a solution set, a user makes a selection from the (hopefully) diverse options. In this context, niching/sharing techniques have been commonly employed to ensure a diverse solution set although such techniques work the best when one has *a priori* knowledge of the problem. In most real-problems, the analytical form is unknown and so picking good niche parameters is problematic. Consequently, most of the work related to MMO using EAs has been done to *test* the efficacy of the EAs in solving *known* problems rather than *solving* the problem *per se*. Watson [1] concluded that sharing-based GAs often perform *worse* than random search and questioned whether niching is really useful for identifying multiple fitness peaks in MMOs.

We have revisited solving MMO using EAs without any problem-dependent parameters using the same reformulation of MMO into a MOO framework as [2], to obtain good diversity in objective space without any *explicit diversity-preserving* operator.

Deb [2] has recast of a number of single-objective MMO problems into dual-objective MOO problems and empirically investigated the effects of sharing. Many have studied the promotion of diversity using sharing for MOO problems – see [3] for a review. We have used a MOO algorithm [3] which, to the best of our knowledge, is the only implementation which does not need *any* explicit sharing mechanism; we demonstrate its efficacy in achieving diversity for two sample MMO problems, *F1* (Sect. 4.1 of [2]) and *F2* (Sect. 5.3 of [2]) which were considered by earlier researchers using multiobjective methods. We have used the same formulation, as far as is

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known, for fair comparison. We repeated the experiments many hundreds of times, each with a different initial population to check the consistency of the results. Typical results selected on the basis of their *average* performance are presented below.

The multi-modal *F2* function can be recast as a multiobjective problem requiring the simultaneous minimization of $f_{21}(x_1)$ and f_{22}; see Sect. 5.3 of reference [2] for more details. Figure 1a shows the initial population (size = 100) where we obtain individuals near the optima by random chance. Figure 1b shows the population after 100 epochs which can be compared with the results for 500 generations in [2] and are superior to those in [2] both in terms of proximity to the Pareto-optimal front and diversity. Significantly this has been achieved at reduced computational cost. We have also studied the *F1* function (Sect. 4.1 of [2]) and find a result entirely consistent with that we have observed with function *F2* – see [3].

Explicit diversity preserving methods need prior knowledge and their efficacy depends on parameter fine-tuning; without proper values they cannot be beneficial. Claims of the superiority of variable- *vs.* objective space sharing are unfounded, problem dependent and nothing general can be said on the selection of proper values for niching/sharing.

In conclusion, we have shown that we can solve multimodal problems by recasting them as multiobjective ones *without an explicit niching/sharing*. Comparing our results with previous work [2], the algorithm employed here provided superior diversity and proximity to the true Pareto-front at reduced computational cost.

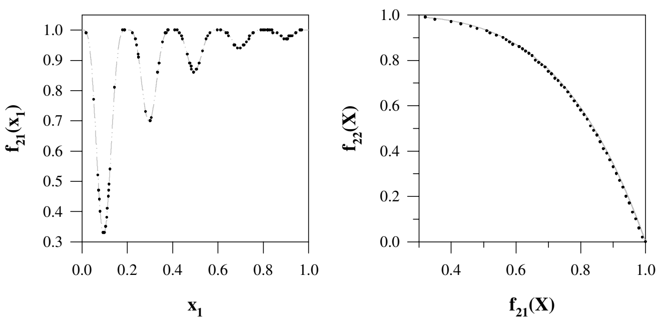

Fig. 1. Function *F2* – Initial population shown in (a) x_1 *vs.* f_{21} and (b) f_{21} *vs.* f_{22} plots.

References

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