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Bounding the Archive Size in Multiobjective Optimization

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ABSTRACT

The archive of most multiobjective optimization methods should contain a certain number of solutions while keeping a good diversity. Having a set of solutions with a good diversity is optimal from a decision maker's point of view. On the other hand, presenting a huge set of non-dominated solutions is useless because it can be hard for the decision makers to select the most appropriate. As reported by S. Mostaghim in [4], the multiobjective evolutionary algorithms that do not restrict the archives tend to increase the selection pressure. Therefore, most of the multiobjective evolutinary algorithms (MOEAs) restrict the archives using several different bounding methods. These methods are used by MOEAs as eliminating filters. The aim is to prune a non-dominated set generating a representative subset which maintains the main characteristics of the original set.

In this paper we compare bounding methods for archives based on well-established methods such as clustering and other more modern approaches such as Self Organizing Maps (SOMs). SOMs [2] are unsupervised neural networks that project high-dimensional data onto two-dimensional maps. The projections preserve the topology so that similar data items are mapped to nearby locations. These maps comprehensively visualize natural groupings and relationships in the data and have been successfully applied in a broad spectrum of research areas ranging from speech recognition to financial analysis. This methodology has never been used as a eliminating filter in MOEAs so this is the most innovative part of our studies. Most of the tests are made on the set of functions suggested by Deb [2] and within the multiobjective particle swarm optimization (MOPSO) algorithm [4]. This method is motivated by the simulation of social behavior of bird flocking, the potential solutions fly through the problem space by following the current optimum. Each single solution is a *bird* in the search space. Birds fly through the problem space by following the current optimum *guide*. Even if most of the results refers to MOPSO, these bounding methods can be generalized to many other MOEAs.

The objective of this study is dedicated to the investigation of these techniques with their impact on the convergence and diversity of solutions. The obtained results are very satisfactory both for the hypervolume metric and the diversity performance metric computed directly for the median attainment

surface [5]. Fig.1 are a median attainment surfaces plot summarizing some results. These results prove that SOM can be used as a good bounding method and that can improve the diversity of non-dominated solutions while maintaining a good convergence to the correct Pareto frontier.

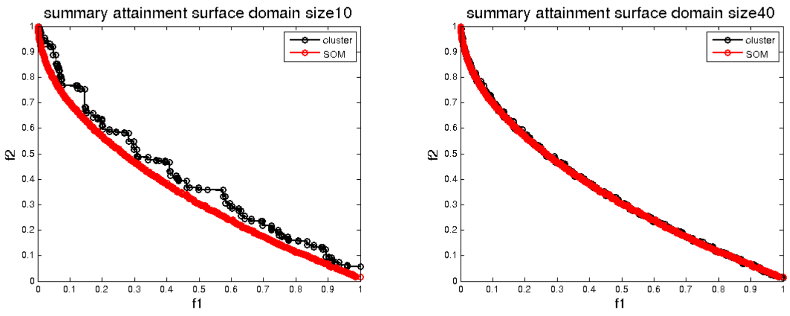

Figure 1: Median attainment surfaces on ZDT1 with an archive size of 10 (left) and 40 (right) points.

Fig.1 and 2 summarize results of 10 runs on function ZDT1 with an initial population of 100 points and 200 iterations. Generational distance (GD) computes the average distance from the obtained non-dominated set and the Pareto-optimal set. Lower values of GD represent better convergence of solutions. SOM method demonstrate to be better than cluster method especially for smaller archives.

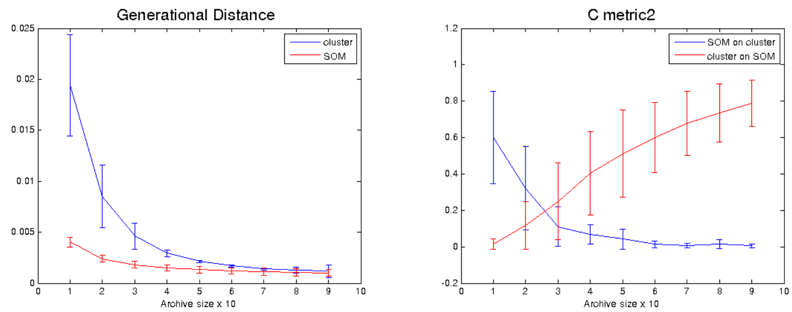

Figure 2: Generational distance and C-metric on ZDT1 for cluster and SOM bounding methods.

The effects of archive bounding have also been tested on a real-world problem, a protein-ligand docking. First results shows that different methodology drives the convergence of MOPSO towards solutions of different chemical interest.

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