Visualising the Search Process for Multi-objective Optimisation*

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ABSTRACT

This paper proposes different visualisation techniques to understand the behaviour of an algorithm's entities during the search process when solving multi-objective optimisation problems. A scatter plot is used to highlight the Pareto-ranking of the entities during the search. Different fronts of the entities are indicated through the ball sizes of the scatter plot. Using a parallel coordinate plot for visualising the effect of control parameter values on the performance of an algorithm is also proposed. Possible extensions for dynamic multi-objective optimisation are also discussed.

CCS CONCEPTS

• **Human-centered computing** → **Visualization techniques**;
• **Theory of computation** → *Evolutionary algorithms*;

KEYWORDS

Visualisation, multi-objective optimisation, scatter plot, parallel coordinates

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1 INTRODUCTION

Many optimisation problems have multiple objectives, with at least two of these objectives in conflict with one another. Therefore, a single solution does not exist and the goal of an algorithm is to find a set of optimal trade-off solutions. In the decision variable space the set of optimal trade-off solutions is referred to as the Pareto-optimal set (POS) and the corresponding vectors in the objective space is referred to as the Pareto-optimal front (POF). This kind of optimisation problems is referred to as multi-objective optimisation problems (MOOPs).

Much research has been conducted on the development of algorithms to solve MOPs. However, the field is evolving and starting to focus on dynamic multi-objective optimisation problems (DMOOPs) and optimisation problems with more than three objectives, referred to as many-objective optimisation problems (MaOOPs). Therefore, visualisation techniques that can enhance the understanding of the behaviour of an algorithm's entities during the search process, as well as the effect of parameter values on the performance of the algorithm, will become important when trying to solve these new types of optimisation problems.

This paper introduces a specialised scatter plot to indicate the quality of an entity's solution. The use of parallel coordinate plots to understand the effect of parameter values on an algorithm's performance is also discussed.

The rest of the paper's layout is as follows: Section 2 provides background information required for the rest of the paper. The visualisation techniques proposed in this paper are discussed in Section 3. Finally, conclusions are drawn in Section 4.

2 BACKGROUND

This section presents background information on aspects that are relevant for this study.

2.1 Visualisation Techniques

Approaches to visualise the search process and the results of an algorithm's search have been proposed to aid domain experts in decision making [7]. The ability to visualize the optimization process can lead to an increase in the effectiveness of decision making for system designers [6, 7].

Over the years visualisation techniques to visualize the optimization process and the set of found solutions (trade-off solutions) have been developed and refined [8], such as the scatter plot [1] and the parallel coordinate plots [5].

2.2 Multi-objective Optimisation

When solving MOOPs, two solutions' quality can be compared with vector domination. Solution A dominates solution B if they are both at least equal in quality for all objectives and A is better than B for at least one objective. The term Pareto-optimal is used to refer to the best decision vectors and the POS contains all Pareto-optimal decision vectors. Their corresponding decision vectors are also Pareto-optimal and build the POF.

3 VISUALISATION APPROACHES

This section discusses the proposed visualisation approaches.

3.1 Scatter Plot for Front Visualisation

A scatter plot is used to identify the front (Pareto-rank) of each entity of the algorithm during the search process. Each entity is

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represented by a ball. Different sized balls are used to indicate the front that the entity belongs to. A larger size indicates a worse (higher) rank. A video that illustrates how the entities move between different fronts is included in the additional material. This Non-dominated sorting genetic algorithm II (NSGA-II) [2] with 100 individuals was tested on DTLZ3 with a dimension of 30. The code was written using DEAP [3], Python and MatPlotLib [4].

The video illustrates how each entity moves between different fronts during the search process. Figure 1 illustrates the produced fronts for a generation 3 and is a screen grab from the video.

This visualisation approach will highlight for example when some or the majority of the entities suddenly perform worse and keep ending up in a higher front (rank). When working with DMOOPs, this will enable the visualisation of the effect of the environment change on the ranking of the entities and how long it takes for them to recover and to obtain better ranks. It can also indicate whether entities get stuck on a local POF or when entities get stuck in a previous environment after a change and cannot explore the search space properly anymore. This approach can also be combined with colours to indicate the value of a performance measure during the search process. For example, if the hypervolume is used to measure the accuracy of the found solutions, a different colour can be used to indicate whether the hypervolume value is improving or not. This will enable the visualisation of two measures at the same time, namely how both the ranking of each entity and the performance measure changes over time.

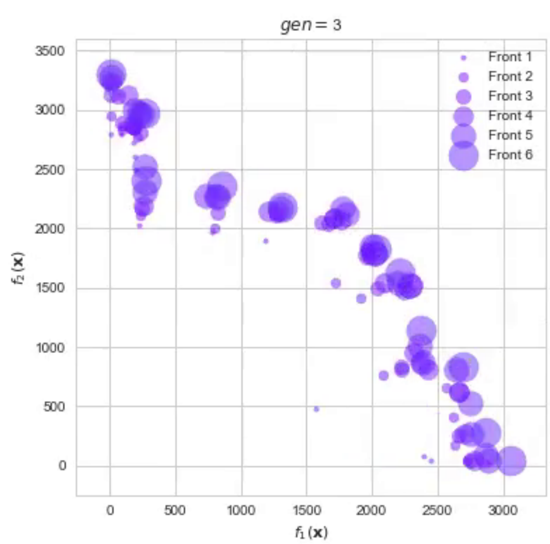

Figure 1: Scatter plot indicating different fronts using different sized balls at generation 3

3.2 Parallel Coordinate Plots

When solving MaOOPs the results are typically represented using a parallel coordinate plot, plotting the values obtained by the set of entities for each of the objectives. Each axis represents a different objective and indicates the spread of values that were obtained for each of the objective. A similar approach can be used for multi-objective optimisation (MOO). Analysing the parallel coordinate plot can indicate whether the algorithm is struggling to find good values for a specific objective.

For visualisation purposes for MOO, the plot can be used as follows: each axis of the plot represents a specific control parameter that is investigated and the last axes represent performance measures. Therefore, the plot will indicate which values for each of the control parameters lead to good performance. This approach can be used to understand the effect of parameter values on the performance of the algorithm with regards to specific performance measures, which can assist with the tuning of parameter values.

4 CONCLUSION

This paper proposed a visualisation approach using a specialised scatter plot. Different sizes of balls in the scatter plot indicate the front that the entity belongs to. This approach can be combined with a colour representing a specific measure, such as accuracy. Then over time it can be seen how the entities' rank change and how these changes also influence the performance measure value.

Parallel coordinate plots can be used to visualise the effect of control parameter values on the performance of an algorithm. By placing the control parameter values on the axis, and the performance measure value on the last axis, control parameter value ranges that result in good performance of the algorithm can be identified.

Future work will include extending these approaches for dynamic multi-objective optimisation and many-objective optimisation.

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