Visualization for Analyzing Trajectory-Based Metaheuristic Search Algorithms

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1 INTRODUCTION

Most combinatorial (optimization) problems are computationally intractable. We often have to be satisfied with *good* solutions and typically metaheuristic algorithms (such as various forms of local search, tabu search, etc) are used. Given the heuristic nature of such search algorithms, there are two important considerations in designing a metaheuristic algorithm:

- Choice of metaheuristics to employ, which may include problem specific tweaks;
- Selecting the appropriate parameters to drive the heuristics.

We call this problem of designing the appropriate metaheuristic problem for a combinatorial (optimization) problem, the *metaheuristic tuning problem* [1, 3, 7]. Anecdotal evidence suggests that tuning takes a major effort, i.e. [1] states that 90% of the design and testing time can be spent fine-tuning the algorithm.

Although it can be easy to come up with a variety of metaheuristics, tuning the metaheuristic implementation is not straightforward. Firstly, the metaheuristics may not be well understood. It might also be applied to problems which may not have been studied. Thus, it may not be clear how to perform tuning. Secondly, the space in which the tuning can operate on is very rich — there are many ways of combining different kinds of metaheuristics each with their own choice of strategies and variations. Furthermore, they each have their own parameters. In this paper, we take a broad view of the metaheuristic tuning problem and understand it to also encompass algorithm design and debugging.

Traditionally, the approach for to the tuning problem is either manual experimentation or more automated approaches such as finding the best parameter values [1], best configuration [3], or self-tuning algorithms [2]. In this paper, we take a different approach which takes a human/programmer perspective — how to aid human in solving the tuning problem. Like human-guided search [6], we believe that a cooperative paradigm with the human in the loop can be productive. The difference with human-guided search is that it is concerned with using the human to produce better solutions, while we want to use the human to produce better metaheuristic algorithms.

Ultimately, we would like a man-machine cooperation which can help the human to debug, analyze and improve a metaheuristic algorithm for particular problems. Some of the questions which we would like to help answer are:

1. Does the actual search behavior match how we think the algorithm should behave?
2. Are there signs of cycling behavior?
3. How does the metaheuristic algorithm make progress?
4. How effective the metaheuristic in conducting intensification and/or diversification?
5. How wide is the search coverage?
6. How far is the (greedy) initial solution to the best found solution?
7. Does the search quickly identify the region where the best solutions found reside or does it wander elsewhere?
8. How do the trajectories of two different metaheuristics compare?
9. What is the effect of modifying certain parameters, components or strategies with respect to the search behavior?

In this paper, we focus on the tuning problem for metaheuristic algorithms which are search trajectory based, such as iterated local search, simulated annealing, tabu search, etc. We believe that a good approach to get man-machine cooperation is with an interactive visualisation of the search trajectory. One way of understanding how a program works is with a debugger. We have built the analog of a debugger, the visualizer VIZ, for understanding search trajectories of metaheuristic algorithms. VIZ provides visualization and animation (forwards and backwards) in time. It has multiple visualizations: (i) problem independent visualization which allows it to be used on a broad range of metaheuristic algorithms in a generic way; and (ii) it can also make use of problem specific visualizations. Although VIZ is still in prototype stage, we believe that it is the first serious attempt at an interactive tool with emphasis on the human computer interaction aspects to help humans understand the dynamic behavior of metaheuristic algorithms and guide the tuning process.

2 SEARCH TRAJECTORY VISUALIZATION

Visualizing the search trajectory, i.e. local movement of the current solution along the search space is difficult because the problem is usually in very high dimensions and the search space is also extremely large. We are only aware of (very) few proposals for search trajectory visualization.

N-to-2 space mapping [4] gives a mapping from a higher dimensional problem space to 2-D for visualizing, e.g. coverage of search space. However, the proposed visualization is crowded and static.

In our earlier work, V-MDF [7], we proposed a visualization called the *distance radar*. A current set of elite solutions is chosen, called *anchor points*. The distance radar displays two graphs: the distance between the current solution in the search trajectory w.r.t the set of anchor points (one sorted by fitness and the other by recency). While V-MDF can help answering *some* of the questions about how the search trajectory is behaving, e.g. questions 1/2/4/7, the visualization is not very intuitive for answering questions 3/5/6/8/9. Another drawback is that the graphs can change simply because the elite set

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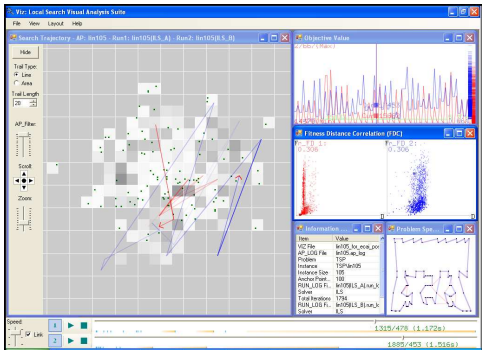

Figure 1. Screen shot of VIZ with multiple visualizations

changes with time. The visualization is less effective because the visualization is essentially one dimensional, graphs which show distance information.

With VIZ, we want to ensure that the visualization can be intuitive and exploit the fact that humans are good at recognizing visual patterns, in particular, not just in a static image but also how things change which exploits movement and temporal features. We make use of an abstract 2-D visualization where instead of trying to map the anchor points and points along the search trajectory from a high dimension to 2-D, we consider abstract points which are differentiated from each other using a distance metric. We do not have the space to discuss the visualization in detail — an example of a possible metric is the Hamming distance. These points can then be laid out in 2-D to approximate a visualization of the abstract points, we have used a spring model for the layout [5]. The search trajectory is then drawn interactively as a trail as shown in Fig. 1 and 2. The strength of this approach is that we now have a problem independent visualization which can be used with a suitably defined metric to demonstrate search trajectories.

3 THE VISUALIZER: VIZ

Fig. 1 shows VIZ's GUI. VIZ functions in interactive fashion as a kind of video player to play back an animation of the search trajectory drawn as a trail. The trail fades with time so that the animation does not clutter up the screen. Colors are used to compare two metaheuristic algorithms. Anchor points[3] are landmarks to indicate the progress of the search trajectory in the abstract search space. Auxiliary visualizations are used to complement search trajectory visualization, e.g. time series of objective values, problem specific, etc. The animation of the geometric pattern of the trail, its relation to the anchor points, and auxiliary visualizations can be used to answer *all* the questions posed in Sec. 1.

Space doesn't permit more details, rather we use the following example which demonstrates how one can visualize the differences between two variants of Iterated Local Search (ILS) on TSP [9]. In TSP, it is conjectured that a heuristic algorithm should exploit the "Big Valley" property, a region in the TSP search space where most local optima (including the global optima) lie [8].

In this example, we want to know whether our algorithms make use of this property. We created two variants of the ILS algorithm which are run on the same TSP instance: ILS_A and ILS_B. The visualization of the search trajectories from ILS_A and ILS_B is shown in Fig. 1 (as a trail) and Fig. 2 (as region coverage). At a glance,

[3] These are slightly different from V-MDF, as anchor points in VIZ are now static: carefully chosen from the log files to achieve diversity and quality. The fitness of the anchor points is indicated via the contour map.

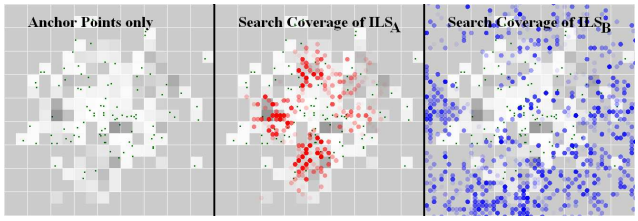

Figure 2. Search trajectory of ILS_A vs ILS_B on the same TSP instance

one can check the existence of the search intensification indicative of searching in a "Big Valley" by checking whether the search trajectory covers region with a cluster of many good anchor points (TSP local optima). Fig. 2 shows that the search trajectory for ILS_A is concentrated in the middle of the screen (indicative of a "Big Valley" region). On the other hand, after similar number of iterations, the coverage of ILS_B seems to be more diverse. ILS_B seems to spend most of it's time exploring areas far from the cluster of good anchor points.

This gives a possible explanation of the algorithm behavior and suggests directions for tuning our algorithms. If our solution behaves like ILS_A, we know that we are on the right track, perhaps only few minor adjustments are needed. On the other hand, if it behaves like ILS_B, we may want to modify our ILS algorithm such that it is more focused.

4 CONCLUSION

We have presented a new approach for visualizing search trajectory and introduced the visualizer tool VIZ. This is not intended to replace the existing analysis tools, but rather it is meant to augment the existing tools to help the algorithm designer better understand the behavior of a trajectory based metaheuristic search algorithm and to debug and to tune the algorithm. A prototype of VIZ which is under continuous development is at: `http://www.comp.nus.edu.sg/~stevenha/viz`

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