A Dynamic Restart Strategy for Randomized BT Search

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Local search (LS) and multi-agent-based search (ERA [1]) are stochastic and incomplete procedures for solving a Constraint Satisfaction Problem (CSP). Their performance is seriously undermined by local optima and deadlocks, respectively. Although complete, backtrack (BT) search suffers from thrashing and a high degree of unpredictability in its run-time even within the same problem domain. Further, when the problem is large, the completeness of BT cannot be guaranteed in practice. Gomes et al. [2] proposed to use randomization and rapid restarts (RRR) to overcome the heavy tail behavior of BT. RRR requires the specification of a cutoff value determined from an overall profile of the cost of search for solving the problem. When no such profile is known, the cutoff value is chosen by trial-and-error. Walsh [3] proposed the strategy Randomization and Geometric Restart (RGR), which does not rely on a cost profile but determines the cutoff value as a function of a constant parameter and the number of variables in the problem. Neither RRR nor RGR takes into account the intermediate results of search (i.e., across restarts). We propose an improved restart strategy, Randomization and *Dynamic* Geometric Restarts (RDGR), which dynamically adapts the value of the cutoff parameter to the results of the search process. This is done by geometrically increasing the cutoff value for the following restart only when the quality of the current best solution is improved upon. We empirically evaluate the performance of RDGR by comparing it against a deterministic BT with various ordering heuristics, local search, ERA, and RGR in the context of a real-world resource allocation problem [4]. Our experiments show that, for the same execution time, RDGR always outperforms RGR in terms of percentage of test runs and yields more stable results. Our results can be summarized as follows (where $\succ$ denotes algorithm dominance): On tight but solvable instances, ERA $\succ$ RDGR $\succ$ RGR $\succ$ BT $\succ$ LS; and on over-constrained instances, RDGR $\succ$ RGR $\succ$ BT $\succ$ LS $\succ$ ERA. We are currently validating our findings on randomly generated problems. We will also use the insight gained from the distinction between tight (but solvable) and over-constrained problem instances uncovered in our case-study to build new hybrid search strategies. This work is supported by NSF grants #EPS-0091900 and CAREER #0133568. The experiments were conducted utilizing the Research Computing Facility of UNL.

References

1. Liu, J., Jing, H., Tang, Y.: Multi-agent oriented constraint satisfaction. Artificial Intelligence **136** (2002) 101–144
2. Gomes, C.P., Selman, B., Kautz, H.: Boosting combinatorial search through randomization. In: AAAI 98. (1998) 431–437
3. Walsh, T.: Search in a small world. In: IJCAI 99. (1999) 1172–1177
4. Lim, R., Guddeti, P., Choueiry, B.: An Interactive System for Hiring and Managing Graduate Teaching Assistants. In: Prestigious Applications of Intelligent Systems (ECAI 04). (2004)