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Deadline Groovy Search

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Abstract-- A new approach for the contract search problem, the called Deadline Aware Search (DAS). DAS reacts to the approaching deadline during search. A method of measuring heuristic error on-line and using those errors in a model to construct corrected heuristic estimates is proposed and used in DAS.

Keywords--Gridworld navigation,15-puzzle, Dynamicrobot navigation.

I. INTRODUCTION

A new approach for the contract search problem, the called Deadline Aware Search (DAS). Unlike anytime search algorithms that do not alter their search strategy in reaction to the approaching deadline, DAS reacts to the approaching deadline during search. We begin by presenting a general overview of the algorithm and its behavior. We then discuss the estimation of two quantities needed by the algorithm: the maximum achievable search depth d_{max} and distance to the cheapest solution beneath a node $\hat{d}_{cheapest}(s)$. Finally, we discuss DAS's techni- que for recoveringfrom situations in which it estima- tes that no goal isreachable given the current search behavior.

II. NEW APPROACH

DAS is a simple approach, derived directly from the objectiveof contract search. It expands, among all the statesleading to solutions deemed reachable within the time remaining,the one with the minimum f(s) value. Pseudo-codeof the algorithm is presented in Figure 1.

```
Deadline Aware Search (starting state, deadline)
open ← {starting state}
pruned ← {}
incumbent ← NULL
while (time) < (deadline) and open is non-empty
    d bound ← calculate_d_bound()
    s ← remove state from open with minimal f(s)
    if s is a goal and is better than incumbent
    incumbent ← s
    else if d̂(s) < d bound
    for each child s' of state s
        add s' to open̂
    else
    add s to pruned
    if open is empty
    recover_ pruned_ states(open, pruned)
return incumbent
Recover Pruned States (open, pruned)
exp ← estimated expansions remaining
while exp> 0 and pruned is non-empty loop
    s ← remove state from pruned with minimal f(s)
    add s to open
    exp =exp –d̂(s)
```

Figure 1: Pseudo-Code Sketch of Deadline Aware Search

The open listis first initialized with the starting state and then the searchproceeds to expand nodes from the open list until either thesearch time expires or the open list is empty (indicating thatthere is no solution deemed reachable). At eachiterationof the algorithm, the state with minimal f(s) is selectedfor expansion and the current maximum reachable distance,dmax, is calculated. If the distance to this state's best goal$\hat{d}_{cheapest}(s)$ is less than d_{max}, it is expanded and its childrenare added to the open list. Otherwise, it is added tothe pruned list and the search will select the next best nodefor expansion.

Reachability, as estimated by DAS, is a function of astate's distance from its best possible solution, $\hat{d}_{cheapest}(s)$.When there is not enough time to explore all interestingpaths in the search

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space, it makes sense to favor those pathsthat are closer to solutions. One result of using an admissibleheuristic h(s) is that often the best f value of the states undera particular state swill be higher than the value of f(s).Assuming this heuristic error is distributed across a searchspace, the states that are farther from solutions have the potentialof experiencing this increase in f value more oftenbefore reaching their respective solutions than states that arecloser. For this reason, when selecting states for expansionties on f(s) are broken in favor of smaller h(s).

III. EMPIRICAL ANALYSIS

We performed an empirical analysis over several benchmarkdomains in order to evaluate the performance of DeadlineAware Search in comparison to Anytime Repairing A*,Restarting Weighted A*, and Contract Search. In each domain
we tested over a range of deadlines covering around
four orders of magnitude.In an attempt to judge algorithms fairly in the case thatno solution is found within the deadline, all algorithms arerequired to run an initial search algorithm we call “Speedier”.Speedier search is a greedy search on dcheapest(s) inwhich duplicate states are detected and, if already expanded,are ignored. This search completes very quickly, returningwhat is typically a highly suboptimal solution that all algorithmsuse as an incumbent. Therefore any algorithm thatfails to find an improved solution within the deadline willreturn this sub-optimal Speedier solution. This both simplifiesour analysis by assigning a meaningful cost to the nullsolution and is a realistic implementation in the case of aany setting in which returning no solution is absolutely unacceptable.

For ARA* and RWA* we evaluated the following rangeof initial weight settings: 1.2, 1.5, 3.0, 6.0, 10.0 and a weightdecrement of 0.2. The optimal initial weight setting foundfor the 15-Puzzle, Weighted 15-Puzzle, Unit-Cost Grid-World, Life-Cost Grid-World, and Dynamic Robot Navigationwere 3.0, 3.0, 3.0, 6.0, and 1.5, respectively. In eachplot the results for the top two weight settings are illustrated,as there were settings which did not produce the best resultsoverall but performed better for a specific range of deadlines.
Thedeadline is still measured in seconds and when it arrives thealgorithm returns the best solution found thus far.

1) 15-Puzzle

Experiments were performed on the 100 instances of the 15-Puzzle using therohini distance heuristic(korf 100 tiles). We evaluted both a uniform cost model as well as a model in which the cost of moving each tile was the inverse of the numeric value of the tile (1-15). Results are shown in Figure 2. The X-axis of the plots representsthe deadline in seconds and is displayed on a logarithmicscale. The Y-axis of the plot represents solution quality, being defined as cost of the best solution found by any algorithm for the particular instance over the achieved solution cost. Solution quality is used rather than raw solution cost to reduce because we have many domains in which individual instances may have very different optimal solution costs. It is a standard metric used in the satisficing track of the International Planning Competition. In both cost models of the 15-Puzzle domain Deadline Aware Search is a clear improvement over both ARA* andContract Search for the full range of deadlines.

Figure 2 shows that with the short deadline of only around 0.5 seconds, DAS was able to find, on average, the same quality of solutions that took ARA* with an optimal weight setting would find with more than twice that much time. For the standard tiles domain, contract search is competitive with deadline aware search for large deadlines, where both algorithms solve the problem optimally, and for small deadlines, where both algorithms return the Speedier solution.

2) Dynamic Robot Navigation

The objective in these problems is to find the fastest path from the starting location of the robot to some goal location and heading, taking motion dynamics such as momentum into account. The instances used in our experiments were 500 by 500 cells in size. We scatter 75 lines, up to 70 cells in length, with random orientations across the domain and present results averaged over 100 instances. Results are shown in Figure 2. Results in this domain show Deadline Aware Search as a clear improvement over ARA*, RWA*, and Contract Search for the full range of deadlines. Contract Search performed particularly weakly in this domain. We believe this is in part attributed to the fact that the domain has a fairly accurate, albeit inadmissible, dcheapest(s) heuristic. Taking advantage of this heuristic allows Deadline Aware Search to more accurately decide the reachability of states and may have contributed to its success.

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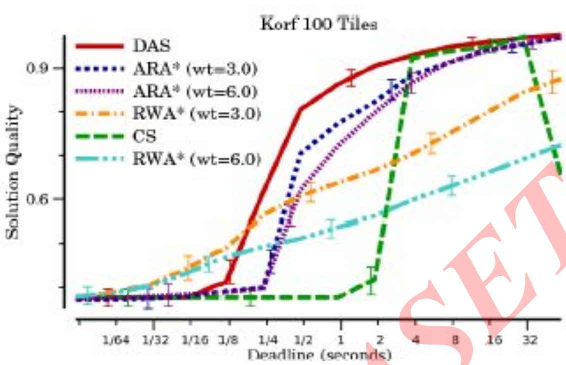
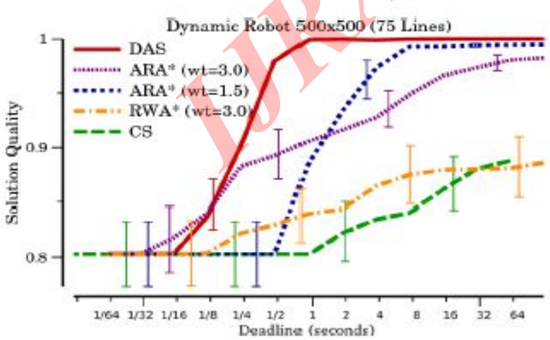
Outside of tie breaking, it is not obvious how the other algorithms could make use of distance estimates.

3) Grid-World Navigation

Experiments were performed on two sets of four-way movement grid-world navigation problems; unit-cost and lifecost. In both domains the starting state is in the lower-left corner of a 2000x1200 map with the goal state in the lowerright corner. Obstacles are distributed randomly and uniformly with a probability of 0.35. The life-cost grid-world, first proposed by Ruml and Do (2007), varies the cost of movement in different layers within the grid creating a clear distinction between shortest path and cheapest path. The cost of traversing each square in the map is equal to the Y coordinate of that location, with (0,0) being the bottom left corner. This implies that the cheapest path through the map would be to traverse to the top of the map, across, then back down to the solution. Results are shown in Figure 2. In the case of life-cost grid-world Deadline Aware Search was competitive with the best of the anytime methods at the optimal parameter settings for shorter deadlines and provided improved results for larger deadlines.





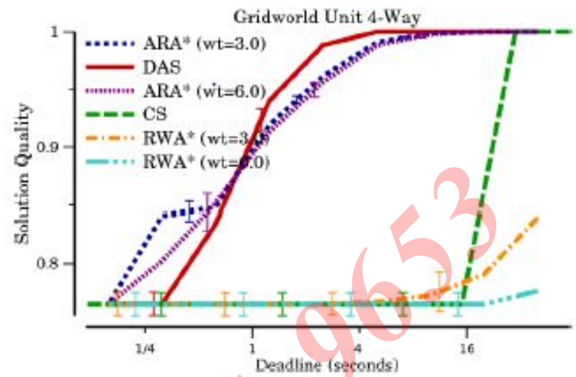


Figure2 Solution quality for a given solving time deadline

IV. DAS BEHAVIOR

The purpose of dmax in DAS is to act as a decreasing upperbound on the distance between any state expanded and its respective best solution. This bound is intended to force the search to progress forwards to meet a particular deadline when it would normally have spent more time exploring different partial solutions sorting out the increasing f(s) values. Depending on the given deadline, the value should typically fall somewhere within the range of current b d(s) values such that some pruning will occur when

necessary and not all states will be pruned unnecessarily. In order to evaluate the behavior of dmax relative to the b d(s) of states expanded during a Deadline Aware Search, implemented a version which uses a limit on the number of state expansions as a deadline and records relevant information during the search. This way the overhead of recording could be factored out of the analysis.

V. CONCLUSION

The choice to include a Speedier search first in our empiricalanalysis for all algorithms could lead to biasing results suchthat algorithms which do not return any solution before thedeadline are rated closer to those which return sub-optimalsolutions which are only marginally better than the Speediersolution. This is not a significant issue in our results, asmost solutions found after the Speedier solution are substantiallyimproved. We recorded the number of times each

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algorithmsucceeded in improving on the Speedier solution. One can see that in some domainssuch as the sliding tiles puzzle, the average solution quality for DAS wasgenerally higher than the anytime approaches. One can alsosee that part of the success of DAS on Dynamic Robots andthe Life-Cost Grid-world Navigation problems comes fromthe fact that it returns significantly more improved solutionsfor shorter deadlines than the other approaches.Overall, the experimental results indicate that DeadlineAware Search can lead to a significant improvement overARA* and RWA* in some domains while remaining competitivein others.

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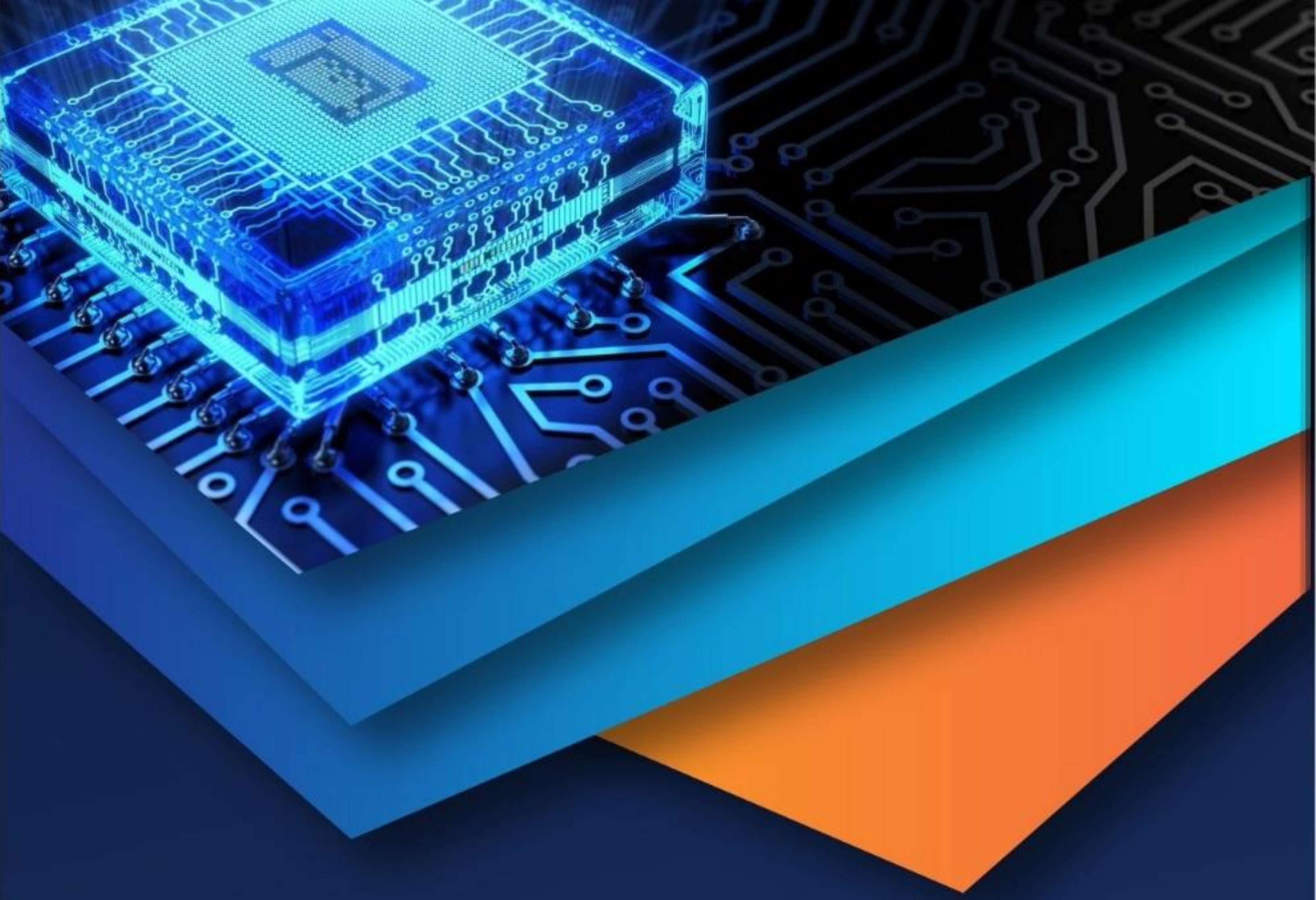
REFERENCES

[1] Aine, S.; Chakrabarti, P.; and Kumar, R. 2010. Heuristic searchundercontract.*Computational Intelligence* 26(4):386–419.
[2] Aine, S. 2011. Personal communication.
[3] Dechter, R., and Pearl, J. 1988. The optimality of A*. In Kanal,L.,and Kumar, V., eds., *Search in Artificial Intelligence*.
Springer-Verlag.166–199.
[4] Hart, P. E.; Nilsson, N. J.; and Raphael, B. 1968. A formal basisforthe heuristic determination of minimum cost paths.*IEEETransactionsof Systems Science and Cybernetics* SSC-4(2):100–107.
[5] Hiraishi, H.; Ohwada, H.; and Mizoguchi, F. 1998.Timeconstrainedheuristic search for practical route finding. In
PacificRim International Conferences on Artificial Intelligence.
[6] Korf, R. E. 1990. Real-time heuristic search.*ArtificialIntelligence*42:189–211.
[7] Likhachev, M.; Gordon, G.; and Thrun, S. 2003. ARA*: AnytimeA*with provable bounds on sub-optimality. In *Proceedings oftheSeventeenth Annual Conference on Neural InformationPorcessingSystems (NIPS-03)*.
[8] Pohl, I. 1973. The avoidance of (relative) catastrophe, heuristiccompetence, genuine dynamic weighting and computationissuesin heuristic problem solving. In *Proceedings of IJCAI-73*,12–17.
[9] Richter, S.; Thayer, J. T.; and Ruml, W. 2009. The joy of forgetting:Faster anytime search via restarting. In *Symposium onCombinatorial Search*.
[10] Ruml, W., and Do, M. B. 2007. Best-first utility-guided search.In*Proceedings of IJCAI-07*, 2378–2384.
[11] Thayer, J. T., and Ruml, W. 2010. Anytime heuristic search:Frameworks and algorithms. In *SoCS 2010*.
[12] Thayer, J. T.; Dionne, A.; and Ruml, W. 2011. Learning inadmissibleheuristics during search. In *Proceedings of the Twenty-FirstInternational Conference on Automated Planning andScheduling(ICAPS-11)*.



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