Cost-Optimal Algorithms for Planning with Procedural Control Knowledge

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1 Motivation and Background

Formalisms for automated planning (to represent and solve planning problems) broadly fall into either domain-independent planning or domain-configurable planning. Domain-independent planning formalisms, such as classical planning, require that the users only provide models of the base actions executable in the domain. In contrast, domain-configurable planning formalisms (e.g., Hierarchical Task Network (HTN) planning [1]) allow users to supplement action models with additional domain-specific knowledge structures that increases the expressivity and scalability of planning systems.

An impressive body of work exploring search heuristics has been developed for classical planning that has helped speed up generation of high-quality solutions. More specifically, search heuristics such as the relaxed planning graph heuristic [2], landmark generation algorithms [3, 5], and landmark-based heuristics [5, 4] dramatically improved optimal and anytime planning algorithms by guiding search towards (near-) optimal solutions to planning problems.

Yet relatively little effort has been devoted to develop analogous techniques to guide search towards high-quality solutions in domain-configurable planning systems. In lieu of such search heuristics, domain-configurable planners often require additional domain-specific knowledge to provide the necessary search guidance. This requirement not only imposes a significant burden on the user, but also sometimes leads to brittle or error-prone domain models.

In this paper, we address this gap by developing the Hierarchically-Optimal Goal Decomposition Planner (HOpGDP), a hierarchical planning algorithm that uses admissible heuristic estimates to generate hierarchically-optimal plans (i.e., plans that are valid and optimal with respect to the given hierarchical knowledge). HOpGDP leverages recent work on a new hierarchical planning formalism called Hierarchical Goal Network (HGN) Planning [8, 6], which combines the hierarchical structure of HTN planning with the goal-based nature of classical planning.

In particular, our contributions are as follows:

- **Admissible Heuristic:** We present $h_{HL}$ (HGN Landmark heuristic), a planning heuristic that extends landmark-based admissible classical planning heuristics to derive admissible cost estimates for HGN planning problems. To the best of our knowledge, $h_{HL}$ is the first non-trivial admissible hierarchical planning heuristic.

- **Optimal Planning Algorithm:** We introduce HOpGDP, an $A^*$ search algorithm that uses $h_{HL}$ to generate hierarchically-optimal plans.

- **Experimental Evaluation:** We describe an empirical study on three benchmark planning domains in which HOpGDP outperforms optimal classical planners due to its ability to exploit hierarchical knowledge. We also found that $h_{HL}$ provides useful search guidance; despite substantial computational overhead, it compares favorably in terms of runtime and nodes explored to HOpGDPblind, using the trivial heuristic $h = 0$.

For the full paper, the readers are referred to the online e-Print [7].

2 Preliminaries

An HGN planning problem is a triple $P = (D, s_0, g_0)$, where $D$ is an HGN domain, $s_0$ is the initial state, and $g_0 = (T, -)$ is the initial goal network. An HGN domain is a pair $D = (D_c, M)$ where $D_c$ is a classical planning domain and $M$ is a set of HGN methods. $D_c$ describes the models of the base actions, while the HGN methods $M$ specifies hierarchical control knowledge the planner needs to respect when generating plans. Finally, a goal network is a partially ordered multiset of goals; this is analogous to the central data structure in HTN planning, the task network [1].

**HGN Methods.** An HGN method encodes knowledge on how to decompose goals. Each method $m$ consists of a goal goal$(m)$ that $m$ decomposes, the conditions precondition(m) under which it is applicable, and the goal network network$(m)$ that $m$ decomposes into.

**Solutions to HGN Planning Problems.** The set of solutions for $P = (D, s_0, g_0)$ is inductively defined as follows: (1) if $g_0$ is empty, the empty plan is a solution. If not, assuming $g \in g_0$ is a goal without predecessors, (2) if $g$ is true in $s_0$, we can remove $g$ from $g_0$, or (3) if there is an action/method applicable in $s_0$ and relevant to $g$, we can apply it; actions progress the state while methods progress the goal network.

Let us denote $S(P)$ as the set of solutions to an HGN planning problem $P$ as allowed by the previous definition. Then we can define what it means for a solution $\pi$ to be hierarchically optimal with respect to $P$ as follows:

**Definition 1** (Hierarchically Optimal Solutions). A solution $\pi^{h,*}$ is hierarchically optimal with respect to $P$ if $\pi^{h,*} = \text{argmin}_{\pi \in S(P)} \text{cost}(\pi)$.

3 The HOpGDP Algorithm and the $h_{HL}$ Heuristic

HOpGDP takes as input an HGN planning problem $P = (D, s_0, g_0)$. It does a standard $A^*$ search using the admissible HGN

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heuristic $h_{\text{HL}}$ (described later in this section) to compute a hierarchically optimal solution to the problem; it either returns a plan if it finds one, or failure if the problem is unsolvable. In particular, starting from the search node $(s_0, gn_0)$, HOpGDP (1) generates successors according to the solution definition in Section 2, and (2) evaluates them using $h_{\text{HL}}$; it repeats this cycle until it either (a) finds a search node with an empty goal network, at which point it can terminate and return the corresponding plan, or (b) exhausts the entire search space, in which case it returns failure. HOpGDP thus explores an identical search space as previous HGN planners like GDP [8], but unlike them, it explores the space in a best-first manner, allowing it to explicitly optimize for total plan cost.

The $h_{\text{HL}}$ Heuristic. As mentioned previously, HOpGDP uses $h_{\text{HL}}$ to compute the $h$-values (and thus, the $f$-values) of search nodes. The main insight behind the construction of $h_{\text{HL}}$ is as follows: given a problem $P = (D, s, gn)$, every goal in $gn$ must be achieved, and in the order specified in $gn$. In other words, the elements of $gn$ can be thought of as landmarks enforced by the hierarchical knowledge, with the partial order serving as landmark orderings. So, one way to develop admissible HGN heuristics is to use goals in $gn$ as starting points for generating an expanded set of landmarks, and then invoke off-the-shelf landmark-based classical planning heuristics on these landmarks to compute admissible estimates.

Concretely, we construct $h_{\text{HL}}$ as follows (details in [7]):

1. We define a relaxation of HGN planning that ignores the provided methods and allows unrestricted action chaining as in classical planning, which expands the set of allowed solutions.
2. We extend landmark generation algorithms for classical planning problems to compute sound landmark graphs for the relaxed HGN planning problems, which in turn are sound with respect to the original HGN planning problems as well, and finally
3. We use admissible classical planning heuristics like $h_L$ [4] on these landmark graphs to compute admissible cost estimates for HGN planning problems.

Based on the admissibility of $h_L$ we can prove that $h_{\text{HL}}$ generates admissible cost estimates for HGN planning problems:

**Theorem 2 (Admissibility of $h_{\text{HL}}$).** Given an HGN planning domain $D$, a search node $(s, gn, \pi)$ and its cost-optimal solution $\pi_{s, gn, \pi}^{\ast, \text{HGN}}$, $h_{\text{HL}}(s, gn, \pi) \leq \pi_{s, gn, \pi}^{\ast, \text{HGN}}$.

4 Experimental Study

We implemented HOpGDP within the Fast-Downward codebase, and extended LAMA’s landmark generation code to develop $h_{\text{HL}}$, our HGN planning heuristic. We tested two hypotheses in our study:

**H1.** HOpGDP’s ability to exploit hierarchical planning knowledge enables it to outperform state-of-the-art optimal classical planners. To test this, we compared the performances of HOpGDP with $A^* - h_L$ [4], the optimal classical planner whose heuristic we extended to develop $h_{\text{HL}}$.

**H2.** The heuristic used by HOpGDP, $h_{\text{HL}}$, provides useful search guidance. To test this, we compared the performances of HOpGDP with HOpGDP$_{\text{blind}}$, which is identical to HOpGDP except that it uses the trivial heuristic estimate of $h = 0$.

We evaluated HOpGDP, HOpGDP$_{\text{blind}}$, and $A^* - h_L$ on three well-known planning benchmarks, Logistics, Blocks World and Depots. Due to space constraints, we show results only for Blocks-World; the reader can find the full experimental study in [7].

Figure 1, which shows the results for Blocks-World, shows that $A^* - h_L$ could only solve problems up to size 10, while HOpGDP$_{\text{blind}}$ and HOpGDP could solve problems up to sizes 16 and 18 respectively within the 30 minute timelimit, thus supporting Hypothesis H1. In terms of node expansions, Figure 1a indicates that the guidance provided by $h_{\text{HL}}$ helped substantially; HOpGDP on average expanded 76% fewer nodes than HOpGDP$_{\text{blind}}$. This savings far outweighed the heuristic computation overhead (on average about 48% of the total running time), resulting in smaller overall planning times for HOpGDP as shown in Figure 1b, supporting Hypothesis H2.

To conclude, our experimental results demonstrate that HOpGDP outperforms optimal classical planners (due to its ability to exploit domain-specific planning knowledge) as well as optimal blind search HGN planners (due to the search guidance provided by $h_{\text{HL}}$).

In the future, we plan to explore extensions of HOpGDP to support anytime-optimal planning as well as temporal planning.

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REFERENCES