Conformant Planning Heuristics Based on Plan Reuse in Belief States

Dunbo Cai, Jigui Sun and Minghao Yin
College of Computer Science and Technology, Jilin University, Changchun, China, 130012
dunbocai@gmail.com

Introduction

Conformant planning involves generating plans under the condition that the initial situation and action effects are undeterministic and sensing is unavailable during plan execution. (Bonet & Geffner 2000) has shown that conformant planning can be transformed into a search problem in the space of belief states. Since then, heuristic based conformant planning has become a promising approach. Following the direction, some effective heuristics, such as those introduced in MBP (Bertoli & Cimatti 2002), Conformant-FF (Brafman & Hoffmann 2004) and POND (Bryce, Kambhampati, & Smith 2006), were proposed. An additive heuristic that obtains the heuristic value of a given belief state by summing the heuristic value of each world state is sensitive to the progress of the search procedure and often guides a search algorithm efficiently. However, it suffers from the problem of overestimating the distances-to-goal of belief states and therefore leads to overlong plans generally. One of the reasons is that the additive heuristic does not take into account relationships between different world states in a belief state. For example, an action sequence for one world state may have progressive effects on others. In this work, we use plan reuse information to make the additive heuristic more reasonable. The information is discovered with the aid of a classical planning heuristic function and in a real time learning style (Barto, Bradtke, & Singh 1995). The resulted heuristic is tested on a conformant planning system that is implemented as an extension of the classical planner Fast Downward (Helmert 2006) to the conformant setting. Preliminary results show that our heuristic is promising in getting better plans on tasks where plan reuse possibilities exist.

An Example

A conformant planning problem is a quadruple \( P = < F, O, bs_0, G > \) where \( F \) is a set of relevant fluents, \( O \) is a set of grounded actions, \( bs_0 \) is the initial situation and \( G \) is a set of goal conditions. We focus on deterministic actions and represents a belief state as \( bs = \{s_0, s_1, \ldots, s_n\} \) where \( s_i \) is a world state that the agent deemed in. In the conformant planning as search in the belief space framework, heuristic functions are key elements.

On belief state, the additive heuristic is defined as:
\[
h_{\text{add}}(bs) = \sum_{s \in bs} h(s), \quad \text{where} \quad h(s) \text{ is the estimation of } s\] computed by any classical planning heuristic function \( h \). It often overestimates the distance of a belief state due to that it assumes a plan for a world state doesn’t affect other ones in the same belief state. To show the aggressive effects among world states, we take a planning instance in the Blocks world domain from the conformant track of IPC5 (International Planning Competition). In the problem, two blocks A and B are involved and the goal is to place B on A. The initial situation is completely uncertain (see Figure 1). It is easy to get that the optimal costs to goal of \( s_0, s_1, s_2, s_3 \) and \( s_4 \) are 4, 3, 2, 1 and 0 respectively. If we use the additive heuristic, the overall estimate of the belief state is 10, which is excessive.

![Figure 1: A conformant problem in Blocks world.](image-url)

However, we may consider these world states according to their costs in an ascendant order. It is easy to see that the classical plan for \( s_3 \) is \( \pi_3 = <\text{stack}(B, A)> \), and the one for \( s_2 \) is \( \pi_2 = <\text{pickup}(B), \text{stack}(B, A)> \). We may find out that if \( \text{pickup}(B) \) is executed in \( s_2 \) then the agent will be in \( s_3 \) and may follow the plans for \( s_3 \). Similarly, agent may execute unstack(A, B) in \( s_0 \) to get into \( s_1 \), and then execute putdown(A) to get into \( s_2 \). As an observation, we may reuse plans of easier world states (with lower goal distances) in harder states (with higher goal distances). Following this strategy, we get the optimal cost of the belief state: \( 1 + 1 + 1 + 1 = 4 \), which is optimal. However, the strategy is not always applicable as there are belief states where one world state is unreachable from any other one. As a result, we pursue plan reuse heuristically and incorporate the information into the additive heuristic.

Heuristic Function

To predicate the chance and cost of reusing plans between two possible states in a belief state and form the overall estimation, we exploit a classical heuristic function \( h_{CG} \). \( h_{CG} \) takes two arguments: the first one represents the initial situation and the second one represents the goal conditions. \( h_{CG} \) is used for estimating both the cost between two world states and the goal-distance of a world state.
A model for computing heuristics

With $h_{CS}$ and a belief state $bs = \{s_0, s_1, \ldots, s_n\}$, a directed graph $\mathcal{G} = (V, E)$ can be constructed, where $V = \{n_i | s_i \in bs\} \cup \{n'_2\}$, $E = \{s_i, n_i\} \cup \{n'_i, n_i\}$. In such a graph, $n_i$ represents a state $s_i$ in $bs$, and $n'_i$ denotes the set of states that satisfies the goal condition. Each edge is associated with a weight that is calculated by $h_{CS}$: $w(n_i, n_j) = h_{CS}(s_i, s_j)$ is the estimated distance between $s_i$ and $s_j$ and $w(n_i, n_j) = h_{CS}(s_i, G)$ is the heuristic distance of state $s_i$. $w(n_i, n_j) = \infty$ indicates unreachability. Given a graph $\mathcal{G}$, the additive heuristic can be redefined as $h_{add}(bs) = \Sigma_{n_i \in V} w(n_i, n_j)$, where $V = V - \{n_i\}$.

To discover plan reuse information, for each node $n_i$ we would like to find the shortest path from $n_i$ to $n_g$. If $n_i$, $n_j$, $n_g$ is such a path for $n_i$, then it is estimated that in state $s_i$ reusing the plan of $s_j$ will lead to a shorter plan for $s_i$. In this sense, after computing the shortest path for each node in $V$, we may define a heuristic function

$$h_{CF}(bs) = \Sigma_{n \in V} w(n, suc(n))$$

(1)

where $suc(n)$ is the successor on the shortest path of $n$. However, the computation of $h_{CF}$ is costly, as $|V| = |bs| - 1$ is always exponential in the initial situation. To reduce the computation effort, we computed (1) approximately.

**Algorithm LRT**(belief state bs)

\begin{verbatim}
SNU(bs) = \{s \in bs | h_{CS}(s, G) = max_{s \in bs} h_{CS}(s, G)\} //initialize
foreach s \in bs
    lrh(s) ← h_{CS}(s, G)
foreach s \in SNU(bs) //look one-step ahead
    best_suc(s) ← NULL
    foreach s' \in SNU(bs) - SNU(bs)
        new_cost ← h_{CS}(s, s') + h_{CS}(s', G)
        if (new_cost ≤ h_{CS}(s, G)) then
            if ((new_cost == h_{CS}(s, G))
                && (best_suc(s) = NULL)
                && (h_{CS}(s, s') ≥ h_{CS}(s, best_suc(s)))) then
                continue
            h_{CS}(s, G) ← new_cost
            best_suc(s) ← s'
    //update helpful actions for s
    HA(s) ← helpful_actions(s, s')
    lrh(s) ← h_{CS}(s, best_suc(s))
return \Sigma_{s \in bs} lrh(s)
\end{verbatim}

Figure 2: The pseudo code to compute $h_{lr}$.

**Look ahead one-step**

We follow a greedy policy to discover plan reuse possibilities. Specifically, only states in $SNU(bs) = \{s \in bs | h_{CS}(s, G) = max_{s \in bs} h_{CS}(s, G)\}$ are considered. For each $s \in SNU(bs)$, we search for a better successor $s'$ with $h_{CS}(s, s') + h_{CS}(s', G) ≤ h_{CS}(s, G)$ if one exists. The resulted heuristic is called $h_{lr}$, which is computed by the algorithm shown in Figure 2.

**Preliminary results and Conclusions**

We extended the Fast Downward planning system for conformant planning, and used the casual graph heuristic $h_{CG}$ as an instance of $h_{CS}$. Both $h_{add}$ and $h_{lr}$ were implemented and compared with the conformant planner Conformant-FF (CFF). The test was done on a wide range of benchmark problems on a PC with a Pentium 4 2.6 GHz processor and 512M memory. Here, we only show some results on the Blocks world and Coins domain from the conformant track of IPC5 (Table 1). The cut-off time is 300 seconds.

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Table 1: Experimental Results: time (s)/plan length, dashes indicate time-outs or out of memory.

In this work, we designed a conformant planning heuristic function based on a classical one in a way that pursues plan reuse between world states in the same belief state. $h_{lr}$ shows a marked improvement to $h_{add}$ yet our system does not scale well due to the explicit representation of belief states. We are currently working on ways to handle such problems. This work is mostly related to FragPlan (Kurien, Nayak, & Smith 2002), but is more flexible than that method.

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**References**


