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On the Effectiveness of Belief State Representation in Contingent Planning

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Abstract

This work proposes new approaches to contingent planning using alternative belief state representations extended from those in conformant planning and a new AND/OR forward search algorithm, called PrAO, for contingent solutions. Each representation was implemented in a new contingent planner. The important role of belief state representation has been confirmed by the fact that our planners all outperform other state-of-the-art planners on most benchmarks and the comparison of their performances varies across all the benchmarks even using the same search algorithm PrAO and same unsophisticated heuristic scheme. The work identifies the properties of each representation method that affect the performance.

Contingent Planning and Previous Approaches

Contingent Planning is the task of generating conditional plans in the presence of incomplete information, uncertain action effects, and sensing actions (Peot and Smith 1992). It is known as one of the most general and hardest problems considered in planning (Haslum and Jonsson 1999).

Significant progress has been made as various contingent planner can solve problems at different level of hardness, e.g., contingent-FF (Hoffmann and Brafman 2005), POND (Bryce *et al.* 2006), and CLG (Albore et al. 2009).

One of the most efficient approaches to contingent planning is to encode the problem into an AND/OR search problem in the belief state space. To deal with incomplete information about the world, the notion of *belief state* has been introduced—defined as a set of possible states. This notion is convenient for capturing the semantic of incomplete information and uncertain action effects and for defining a transition function between belief states. The use of belief states themselves in the implementation of a planner, however, is inefficient and impractical due to their exponential size. The question is then how to represent belief states and, given a representation, how to define a transition function for computing successor belief states under conditional action effects in presence of incomplete information. To address this, (Bertoli et al. 2001) proposed the use of *binary decision diagrams* (BDDs) (Bryant 1992) to represent belief states in a model checking based planner MBP. Later, (Bryce *et al.* 2006) used BDDs to represent literals and actions in the planning graph for computation of heuristics used to search for solutions in their planner POND. The use of the BDD is advantageous since it is more compact than the belief state itself and it allows to check whether a literal holds in a world state easily. Nonetheless, the size of a BDD representation is still very large and sensitive to the order of the variables. Moreover, computing successor belief states in BDDs form during the search is very expensive, requiring intermediate BDDs formulae of exponential size. This explains why MBP and POND do not scale well as shown in (Hoffmann and Brafman 2005; Albore et al. 2009).

At the other extreme of belief state representation, the proposal in (Brafman and Hoffmann 2004; Hoffmann and Brafman 2005) represents belief states indirectly through the action sequences that lead to them from the initial belief state, and uses forward search in the belief space for solutions. The advantage of this method is easily seen as it requires very little memory, scaling up pretty well on a number of problems. The trade-off is that it incurs an excessive amount of repeated computation. Moreover, checking whether a proposition holds after the execution of an action sequence is co-NP-hard. This is, as we believe, one of the main reasons for their planners using this method to hardly find a solution for even small instances of harder problems, e.g., many instances are given in (Albore et al. 2009; To *et al.* 2010a).

(Son and Baral 2001) brought a different perspective to deal with incomplete information that approximates a belief state by the intersection of the states it contains. The advantage of this approach lies in the low-complexity: the successor (approximated) belief state can be computed in polynomial time. The approximation is, however, incomplete. To address this, (Son and Tu 2006) identifies a complete condition for the approximation and develops the technique in their conformant planner, called CPA. The advantage of this approach is that the computation of the successor belief state is still very simple. However, the approximated formula, as shown in the experiments, explodes in many problems.

Our Approaches and Up-to-date Results

To address the issues of the aforementioned approaches, we firstly proposed a novel approach to dealing with incomplete information by using a compact DNF formula, called *minimal DNF*, to represent belief states and defining a direct complete transition function for computing the successor belief states encoded in this representation in the presence of incomplete information efficiently, i.e., polynomial under reasonable assumptions (To *et al.* 2009). The advantage of this method is confirmed by the fact that our conformant planner DNF can solve much larger instances of a majority of domains, including the most challenging ones in the literature. However, the performance of DNF is not as good on the problems where the size of disjunctive formulae encoding the belief states is too large even in a very compact (disjunctive) form. To address this, we proposed a compact CNF formula, called minimal-CNF, (To *et al.* 2010a) and prime implicates as other representations (To *et al.* 2010b).

Recently, in (To *et al.* 2011a), we proposed a new approach to contingent planning using the minimal-DNF and a novel AND/OR forward search algorithm PrAO, which allows to prune the search space significantly in many cases. We extended the function defined in (To *et al.* 2009) for computing successor belief states to handle uncertain action effects and sensing actions required in contingent planning. We deployed the ideas in a planner, called DNF_{ct}, and compared DNF_{ct} with other state-of-the-art contingent planners. The superior performance of DNF_{ct} in most benchmarks available in the literature validates the effectiveness of our representation method and the usefulness of PrAO.

Following this direction, we continued to investigate the effectiveness of minimal-CNF in contingent planning. To this end, we again extended the function developed in (To *et al.* 2010a) for non-deterministic and sensing actions in a new planner, called CNF_{ct}, using the AND/OR forward search algorithm PrAO and a same heuristic function, that based on the number of satisfied sub-goals and the number of known literals in the belief state. For a better understanding of the effectiveness of representation in contingent planning, we modified DNF_{ct} to use the same heuristic function as for $\text{CNF}_{ct}$and compared CNF_{ct} with DNF_{ct} and other state-of-the-art contingent planners. The importance of representation is again confirmed by the fact that CNF_{ct} also offers very competitive performance in a wide range of benchmarks, like DNF_{ct}, and the comparison of their performances varies across all the benchmarks even using the same search algorithm and same unsophisticated heuristic scheme. We identified the properties of these representations that affect the performance of the planner, investigated the advantages and disadvantages of each representation, and identified the classes of problems that promote or degrade each representation (To *et al.* 2011b).

The investigation in (To *et al.* 2011b) shows that DNF_{ct} is fastest, able to solve most problems within the shortest time, but poor in the problems where the size of disjunctive formulae encoding the belief states explodes. In contrast, CNF_{ct} is able to solve more instances in most benchmarks in the literature but with a longer time, in general, due to the higher complexity of the transition function defined for minimal-CNF compared with that for minimal-DNF. This motivated us to consider a compromise of the two approaches which extended the use of prime implicates in (To *et al.* 2010b) to be used for contingent planning in a new planner PI_{ct} in the same search framework as for CNF_{ct} and DNF_{ct}. Again, PI_{ct} is very competitive, faster than CNF_{ct} and more scalable than DNF_{ct}in a large pool of benchmarks. An in-depth investigation on the effectiveness of prime implicates in comparison with minimal-CNF have been introduced in (To *et al.* 2011c)

It is worth noting that the study of different representations is useful and beneficial as each representation is strong or weak in certain classes of problems. Moreover, the results obtained from this study can also be applied in other areas, since logical formulae are also widely used in various areas.

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