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PREVIEW

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PREVIEW

INTERVAL COMPUTATION METHODS AND PROBABILISTIC METHODS
FOR PLANNING AND PLAN CHECKING UNDER UNCERTAINTY
AND INCOMPLETE INFORMATION

by

RAÚL A. TREJO, M.S.C.S.

DISSERTATION

Presented to the Faculty of the Graduate School of

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for the Degree of

DOCTOR OF PHILOSOPHY

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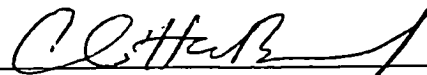
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RAÚL A. TREJO

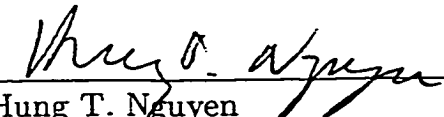
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*To my wife, Claudia.
To my mother, Agripina.
To Grandma, In Memoriam.*

PREVIEW

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R. Trejo. May 2001.

Abstract

The main problem of *planning* is to find a sequence of actions that an agent must perform to achieve a given objective. An important part of planning is checking whether a given plan achieves the desired objective. Historically, in AI, the planning and plan checking problems were mainly formulated and solved in a *deterministic* environment, when the initial state is known precisely and when the results of each action in each state is known (and uniquely determined). In this deterministic case, planning is difficult, but plan checking is straightforward.

In many real-life situations, however, the agent does not have complete information about the initial state of the system. In the best case, the agent may know the probabilities of the different fluents that describe the state of the system; sometimes even such probabilities are unknown and the agent has no information whatsoever about the initial state of some fluents.

Recently, there has been proposal to use ‘sensing’ actions to plan in presence of incompleteness. In this work we use the action description language \mathcal{A} proposed in 1993 by M. Gelfond and V. Lifschitz, and its extensions, that allow for sensing actions. In real-life planning, we often also use the knowledge about the system’s *past* behavior. To describe such more realistic planning situations, a special language \mathcal{L} was developed in 1997 by C. Baral, M. Gelfond and A. Proveti.

In this work we expand the known results about computational complexity of

planning to this more general class of planning problems. The language \mathcal{A} allows planning in the situations with complete information. It is known that, if we consider only plans of feasible (polynomial) length, the planning problem for such situations is **NP**-complete: even checking whether a given objective is attainable from a given initial state is **NP**-complete. In this work, we show that the planning problem in presence of incompleteness is indeed harder: it belongs to the next level of complexity hierarchy (in precise terms, it is $\Sigma_2\mathbf{P}$ -complete). To overcome the complexity of this problem, C. Baral and T. Son have proposed several approximations. We show that under certain conditions, one of these approximations – 0-approximation – makes the problem **NP**-complete (thus indeed reducing its complexity). We also show results about the complexity of planning when the past states are considered.

Then we address the planning problem when initial probabilities of fluents are known. We describe how methods of interval computations can be used to get a feasible approximation to plan checking under probabilistic uncertainty. The resulting method is a natural generalization of 0-approximation. It turns out that some of the resulting probabilistic techniques coincides with heuristically proposed “fuzzy” methods. Thus, we justify these fuzzy heuristics as a reasonable feasible approximation to the (NP-hard) probabilistic problem.

In view of the usefulness of interval computation techniques in planning, we overview these techniques and propose improvements which lead to optimal and sub-optimal interval methods.

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PREVIEW

Chapter 1

Introduction

1.1 The Planning and Plan Checking Problems

The main problem of *planning* is to find a sequence of actions that an agent must perform to achieve a given objective. An important part of planning is *plan checking* (also called *projection*): the case when we already have a plan and we need to check that this plan achieves the desired objective.

1.1.1 Traditional Planning

Historically, in AI, the planning and plan checking problems were formulated and solved in a *deterministic* environment, when the initial state is known precisely and when the results of each action in each state is known (and uniquely determined) [3].

To formulate the deterministic planning problem precisely we must be able to describe states of the world and actions. States are usually characterized by their properties; in planning, the properties of states are called *fluents*. Traditionally, the set of all possible fluents is denoted by F . The set of all possible actions is usually denoted by A . We also need rules which describe how an action $a \in A$

changes a state s . The set of such rules is referred to as the *domain description* of the system being modeled. We denote by $res(a, s)$ the state reached by executing action a in state s . For a plan $\alpha = [a_1, \dots, a_n]$ we use $res(\alpha, s)$ as an abbreviation of $res(a_n, res(a_{n-1}, \dots, res(a_1, s) \dots))$.

In principle, we can have different types of objectives that we want to achieve by a plan. Traditional planning starts with the case in which the objective is simple: to satisfy a certain property; for example, a typical objective of an assembling manufacture robot is to reach the state of the world in which the manufactured item is fully assembled. It is known that more complicated objectives can be reduced to such simpler ones (see, e.g. [3]); in view of this possibility, we will consider only objectives of this type, i.e., objectives of the type f or $\neg f$ where $f \in F$.

In these terms, the *planning* problem can be formulated as follows:

- given a set of fluents F , a goal f or $\neg f$ ($f \in F$), a set of actions A and a set of rules describing how these actions affect the state of the world,
- find a sequence of actions $\alpha = [a_1, \dots, a_k]$ that, when executed from the initial state of the world s_0 , makes f true.

The problem of *plan checking* is:

- given F , A , f and a sequence of actions α ,
- to check whether the goal becomes true after execution of α in the initial state or not.

The problems of planning and plan checking have been extensively studied for the case when the initial state of the world is completely known, and the state reached after executing an action is uniquely determined [3].

The language \mathcal{A} proposed in 1993 by M. Gelfond and V. Lifschitz allows planning in the situations with complete information.

1.1.2 Planning with Past Information

The planning problem, as formulated in the language \mathcal{A} , is based on the assumption that the only information we have is the information about the current state. In real life, in addition to the information about the current state, we often have some information about the previous behavior of the system.

To describe such more realistic planning problems, in [6, 7], the language \mathcal{A} was extended to a new language \mathcal{L} . In this new language, to describe the history of the system, first of all, the current state s_N is separated from the initial state s_0 , so we may have statements about what is true at s_0 (“ F at s_0 ”) and statements about what is true at s_N (“ F at s_N ”). In addition, we may have information about other states in the past; to describe this information, language \mathcal{L} allows to use several constants s_i to describe past moments of time, and allow:

- statements of the type “ s_1 precedes s_2 ” which order past moments of time;
- statements of the type “ F at s_i ” which describe the properties of the system at the past moments of time, and
- statements which describe past actions:
 - “ α between s_1, s_2 ” means that a sequence of actions α was performed at some point between the moments s_1 and s_2 , and
 - “ α occurs_at s ” means that the sequence of actions α was implemented at moment s .