Exploiting Procedural Domain Control Knowledge in State-of-the-Art Planners

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Abstract

Domain control knowledge (DCK) has proven effective in improving the efficiency of plan generation by reducing the search space for a plan. *Procedural* DCK is a compelling type of DCK that supports a natural specification of the skeleton of a plan. Unfortunately, most state-of-the-art planners do not have the machinery necessary to exploit procedural DCK. To resolve this deficiency, we propose to compile procedural DCK directly into PDDL2.1, thus enabling any PDDL2.1-compatible planner to exploit it. The contribution of this paper is threefold. First, we propose a PDDL-based semantics for an Algol-like, procedural language that can be used to specify DCK in planning. Second, we provide a polynomial algorithm that translates an ADL planning instance and a DCK program, into an equivalent, program-free PDDL2.1 instance whose plans are only those that adhere to the program. Third, we argue that the resulting planning instance is well-suited to being solved by domain-independent heuristic planners. To this end, we propose three approaches to computing domain-independent heuristics for our translated instances, sometimes leveraging properties of our translation to guide search. In our experiments on familiar PDDL planning benchmarks we show that the proposed compilation of procedural DCK can significantly speed up the performance of a heuristic search planner. Our translators are implemented and available on the web.

Introduction

Domain control knowledge (DCK) imposes domain-specific constraints on the definition of a valid plan. As such, it can be used to impose restrictions on the course of action that achieves the goal. While DCK sometimes reflects a user's desire to achieve the goal a particular way, it is most often constructed to aid in plan generation by reducing the plan search space. Moreover, if well-crafted, DCK can eliminate those parts of the search space that necessitate backtracking. In such cases, DCK together with blind search can yield valid plans significantly faster than state-of-the-art (SOA) planners that do not exploit DCK. Indeed most planners that exploit DCK, such as TLPLAN (Bacchus & Kabanza 1998) or TALPLANNER (Kvarnström & Doherty 2000), do little more than blind depth-first search with cycle checking in a DCK-pruned search space. Since most DCK

reduces the search space but still requires a planner to backtrack to find a valid plan, it should prove beneficial to exploit better search techniques. In this paper we explore ways in which SOA planning techniques and existing SOA planners can be used in conjunction with DCK, with particular focus on *procedural* DCK.

As a simple example of DCK, consider the `trucks` domain of the 5th International Planning Competition, where the goal is to deliver packages between certain locations using a limited capacity truck. When a package reaches its destination it must be delivered to the customer. We can write simple and natural procedural DCK that significantly improves the efficiency of plan generation for instance: *Repeat the following until all packages have been delivered: Unload everything from the truck, and, if there is any package in the current location whose destination is the current location, deliver it. After that, if any of the local packages have destinations elsewhere, load them on the truck while there is space. Drive to the destination of any of the loaded packages. If there are no packages loaded on the truck, but there remain packages at locations other than their destinations, drive to one of these locations.*

Procedural DCK (as used in HTN (Nau *et al.* 1999) or Golog (Levesque *et al.* 1997)) is action-centric. It is much like a programming language, and often times like a plan skeleton or template. It can (conditionally) constrain the order in which domain actions should appear in a plan. In order to exploit it for planning, we require a procedural DCK specification language. To this end, we propose a language based on GOLOG that includes typical programming languages constructs such as conditionals and iteration as well as nondeterministic choice of actions in places where control is not germane. We argue that these action-centric constructs provide a natural language for specifying DCK for planning. We contrast them with DCK specifications based on linear temporal logic (LTL) which are state-centric and though still of tremendous value, arguably provide a less natural way to specify DCK. We specify the syntax for our language as well as a PDDL-based semantics following Fox & Long (2003).

With a well-defined procedural DCK language in hand, we examine how to use SOA planning techniques together with DCK. Of course, most SOA planners are unable to exploit DCK. As such, we present an algorithm that translates a PDDL2.1-specified ADL planning instance and as-

sociated procedural DCK into an equivalent, program-free PDDL2.1 instance whose plans provably adhere to the DCK. Any PDDL2.1-compliant planner can take such a planning instance as input to their planner, generating a plan that adheres to the DCK.

Since they were not designed for this purpose, existing SOA planners may not exploit techniques that optimally leverage the DCK embedded in the planning instance. As such, we investigate how SOA planning techniques, rather than planners, can be used in conjunction with our compiled DCK planning instances. In particular, we propose domain-independent search heuristics for planning with our newly-generated planning instances. We examine three different approaches to generating heuristics, and evaluate them on three domains of the 5th International Planning Competition. Our results show that procedural DCK improves the performance of SOA planners, and that our heuristics are sometimes key to achieving good performance.

Background

A Subset of PDDL 2.1

A *planning instance* is a pair $I = (D, P)$, where D is a domain definition and P is a problem. To simplify notation, we assume that D and P are described in an ADL subset of PDDL. The difference between this ADL subset and PDDL 2.1 is that no concurrent or durative actions are allowed.

Following convention, domains are tuples of finite sets $(PF, Ops, Objs_D, T, \tau_D)$, where PF defines domain predicates and functions, Ops defines operators, $Objs_D$ contains domain objects, T is a set of types, and $\tau_D \subseteq Objs_D \times T$ is a type relation associating objects to types. An operator (or action schema) is also a tuple $\langle O(\vec{x}), \vec{t}, Prec(\vec{x}), \mathit{Eff}(\vec{x}) \rangle$, where $O(\vec{x})$ is the unique operator name and $\vec{x} = (x_1, \ldots, x_n)$ is a vector of variables. Furthermore, $\vec{t} = (t_1, \ldots, t_n)$ is a vector of types. Each variable x_i ranges over objects associated with type t_i. Moreover, $Prec(\vec{x})$ is a boolean formula with quantifiers (BQF) that specifies the operator's preconditions. BFQs are defined inductively as follows. Atomic BFQs are either of the form $t_1 = t_2$ or $R(t_1, \ldots, t_n)$, where t_i ($i \in \{1, \ldots, n\}$) is a term (i.e. either a variable, a function literal, or an object), and R is a predicate symbol. If φ is a BFQ, then so is $Qx\text{-}t\, \varphi$, for a variable x, a type symbol t, and $Q \in \{\exists, \forall\}$. BFQs are also formed by applying standard boolean operators over other BFQs. Finally $\mathit{Eff}(\vec{x})$ is a list of conditional effects, each of which can be in one of the following forms:

$$\forall y_1\text{-}t_1 \cdots \forall y_n\text{-}t_n . \varphi(\vec{x}, \vec{y}) \Rightarrow R(\vec{x}, \vec{y}), \tag{1}$$

$$\forall y_1\text{-}t_1 \cdots \forall y_n\text{-}t_n . \varphi(\vec{x}, \vec{y}) \Rightarrow \neg R(\vec{x}, \vec{y}), \tag{2}$$

$$\forall y_1\text{-}t_1 \cdots \forall y_n\text{-}t_n . \varphi(\vec{x}, \vec{y}) \Rightarrow f(\vec{x}, \vec{y}) = obj, \tag{3}$$

where φ is a BFQ whose only free variables are among $\vec{x}$ and $\vec{y}$, R is a predicate, f is a function, and obj is an object After performing a ground operator – or *action* – $O(\vec{c})$ in a certain state s, for all tuples of objects that may instantiate $\vec{y}$ such that $\varphi(\vec{c}, \vec{y})$ holds in s, effect (1) (resp. (2)) expresses that $R(\vec{c}, \vec{y})$ becomes true (resp. false), and effect (3) expresses that $f(\vec{c}, \vec{y})$ takes the value obj. As usual, states are represented as finite sets of atoms (ground formulae of the form $R(\vec{c})$ or of the form $f(\vec{c}) = obj$).

Planning problems are tuples $(Init, Goal, Objs_P, \tau_P)$, where $Init$ is the initial state, $Goal$ is a sentence with quantifiers for the goal, and $Objs_P$ and τ_P are defined analogously as for domains.

Semantics: Fox & Long (2003) have given a formal semantics for PDDL 2.1. In particular, they define when a sentence is *true* in a state and what *state trace* is the result of performing a set of *timed actions*. A state trace intuitively corresponds to an execution trace, and the sets of timed actions are ultimately used to refer to plans. In the ADL subset of PDDL2.1, since there are no concurrent or durative actions, time does not play any role. Hence, state traces reduce to sequences of states and sets of timed actions reduce to sequences of actions.

Building on Fox and Long's semantics, we assume that $\models$ is defined such that $s \models \varphi$ holds when sentence φ is true in state s. Moreover, for a planning instance I, we assume there exists a relation $Succ$ such that $Succ(s, a, s')$ iff s' results from performing an executable action a in s. Finally, a sequence of actions $a_1 \cdots a_n$ is a plan for I if there exists a sequence of states $s_0 \cdots s_n$ such that $s_0 = Init$, $Succ(s_i, a_{i+1}, s_{i+1})$ for $i \in \{0, \ldots, n-1\}$, and $s_n \models Goal$.

Domain-Independent Heuristics for Planning

In sections to follow, we investigate how procedural DCK integrates into SOA domain-independent planners. Domain-independent heuristics are key to the performance of these planners. Among the best known heuristic-search planners are those that compute their heuristic by solving a relaxed STRIPS planning instance (e.g., as done in HSP (Bonet & Geffner 2001) and FF (Hoffmann & Nebel 2001) planners). Such a relaxation corresponds to solving the same planning problem but on an instance that ignores deletes (i.e. ignores negative effects of actions).

For example, the FF heuristics for a state s is computed by expanding a *relaxed planning graph* (Hoffmann & Nebel 2001) from s. We can view this graph as composed of *relaxed states*. A relaxed state at depth $n + 1$ is generated by *adding* all the effects of actions that can be performed in the relaxed state of depth n, and then by copying all facts that appear in layer n. The graph is expanded until the goal or a fixed point is reached. The heuristic value for s corresponds to the number of actions in a *relaxed plan* for the goal, which can be extracted in polynomial time.

Both FF-like heuristics and HSP-like heuristics can be computed for (more expressive) ADL planning problems.

A Language for Procedural Control

In contrast to state-centric languages, that often use LTL-like logical formulae to specify properties of the states traversed during plan execution, procedural DCK specification languages are predominantly action-centric, defining a plan template or skeleton that dictates *actions* to be used at various stages of the plan.

Procedural control is specified via *programs* rather than logical expressions. The specification language for these programs incorporates desirable elements from imperative programming languages such as iteration and conditional

constructs. However, to make the language more suitable to planning applications, it also incorporates nondeterministic constructs. These elements are key to writing flexible control since they allow programs to contain missing or open program segments, which are filled in by a planner at the time of plan generation. Finally, our language also incorporates property testing, achieved through so-called *test actions*. These actions are not real actions, in the sense that they do not change the state of the world, rather they can be used to specify properties of the states traversed while executing the plan. By using test actions, our programs can also specify properties of executions similarly to state-centric specification languages.

The rest of this section describes the syntax and semantics of the procedural DCK specification language we propose to use. We conclude this section by formally defining what it means to plan under the control of such programs.

Syntax

The language we propose is based on GOLOG (Levesque *et al.* 1997), a robot programming language developed by the cognitive robotics community. In contrast to GOLOG, our language supports specification of types for program variables, but does not support procedures.

Programs are constructed using the implicit language for actions and boolean formulae defined by a particular planning instance I. Additionally, a program may refer to variables drawn from a set of program variables V. This set V will contain variables that are used for nondeterministic choices of arguments. In what follows, we assume $\mathcal{O}$ denotes the set of operator names from Ops, fully instantiated with objects defined in I or elements of V.

The set of programs over a planning instance I and a set of program variables V can be defined by induction. In what follows, assume ϕ is a boolean formula with quantifiers on the language of I, possibly including terms in the set of program variables V. Atomic programs are as follows.

1. nil: Represents the empty program.
2. o: Is a single operator instance, where $o \in \mathcal{O}$.
3. **any**: A keyword denoting "any action".
4. $\phi?$: A *test action*.

If σ_1, σ_2 and σ are programs, so are the following:

1. $(\sigma_1; \sigma_2)$: A sequence of programs.
2. **if** ϕ **then** σ_1 **else** σ_2: A conditional sentence.
3. **while** ϕ **do** σ: A while-loop.
4. σ^*: A nondeterministic iteration.
5. $(\sigma_1 | \sigma_2)$: Nondeterministic choice between two programs.
6. $\pi(x\text{-}t)\,\sigma$: Nondeterministic choice of variable $x \in V$ of type $t \in T$.

Before we formally define the semantics of the language, we show some examples that give a sense of the language's expressiveness and semantics.

- **while** $\neg clear(B)$ **do** $\pi(b\text{-}block)\,putOnTable(b)$: while B is not clear choose any b of type block and put it on the table.
- **any***; $loaded(A, Truck)?$: Perform any sequence of actions until A is loaded in $Truck$. Plans under this control are such that $loaded(A, Truck)$ holds in the final state.

- ($load(C, P); fly(P, LA) \,|\, load(C, T); drive(T, LA)$): Either load C on the plane P or on the truck T, and perform the right action to move the vehicle to LA.

Semantics

The problem of planning for an instance I under the control of program σ corresponds to finding a plan for I that is also an execution of σ from the initial state. In the rest of this section we define what those legal executions are. Intuitively, we define a formal device to check whether a sequence of actions $\vec{a}$ corresponds to the execution of a program σ. The device we use is a nondeterministic finite state automaton with ε-transitions (ε-NFA).

For the sake of readability, we remind the reader that ε-NFAs are like standard nondeterministic automata except that they can transition without reading any input symbol, through the so-called ε-transitions. ε-transitions are usually defined over a state of the automaton and a special symbol ε, denoting the empty symbol.

An ε-NFA $A_{\sigma, I}$ is defined for each program σ and each planning instance I. Its alphabet is the set of operator names, instantiated by objects of I. Its states are *program configurations* which have the form $[\sigma, s]$, where σ is a program and s is a planning state. Intuitively, as it reads a word of actions, it keeps track, within its state $[\sigma, s]$, of the part of the program that remains to be executed, σ, as well as the current planning state after performing the actions it has read already, s.

Formally, $A_{\sigma, I} = (Q, \mathcal{A}, \delta, q_o, F)$, where Q is the set of program configurations, the alphabet $\mathcal{A}$ is a set of domain actions, the transition function is $\delta : Q \times (\mathcal{A} \cup \{\varepsilon\}) \to 2^Q$, $q_0 = [\sigma, Init]$, and F is the set of final states. The transition function δ is defined as follows for atomic programs.

$$\delta([a, s], a) = \{[nil, s']\} \text{ iff } Succ(s, a, s'), \text{ s.t. } a \in \mathcal{A}, \quad (4)$$

$$\delta([\mathbf{any}, s], a) = \{[nil, s']\} \text{ iff } Succ(s, a, s'), \text{ s.t. } a \in \mathcal{A}, \quad (5)$$

$$\delta([\phi?, s], \varepsilon) = \{[nil, s]\} \text{ iff } s \models \phi. \quad (6)$$

Equations 4 and 5 dictate that actions in programs change the state according to the $Succ$ relation. Finally, Eq. 6 defines transitions for $\phi?$ when ϕ is a sentence (i.e., a formula with no program variables). It expresses that a transition can only be carried out if the plan state so far satisfies ϕ.

Now we define δ for non-atomic programs. In the definitions below, assume that $a \in \mathcal{A} \cup \{\varepsilon\}$, and that σ_1 and σ_2 are subprograms of σ, where occurring elements in V may have been instantiated by any object in the planning instance I.

$$\delta([(\sigma_1; \sigma_2), s], a) = \bigcup_{[\sigma_1', s'] \in \delta([\sigma_1, s], a)} \{[(\sigma_1'; \sigma_2), s']\} \text{ if } \sigma_1 \neq nil, \quad (7)$$

$$\delta([(nil; \sigma_2), s], a) = \delta([\sigma_2, s], a), \quad (8)$$

$$\delta([\mathbf{if}\ \phi\ \mathbf{then}\ \sigma_1\ \mathbf{else}\ \sigma_2, s], a) = \begin{cases} \delta([\sigma_1, s], a) & \text{if } s \models \phi, \\ \delta([\sigma_2, s], a) & \text{if } s \not\models \phi, \end{cases}$$

$$\delta([(\sigma_1 | \sigma_2), s], a) = \delta([\sigma_1, s], a) \cup \delta([\sigma_2, s], a),$$

$$\delta([\mathbf{while}\ \phi\ \mathbf{do}\ \sigma_1, s], a) = \begin{cases} \{[nil, s]\} & \text{if } s \not\models \phi \text{ and } a = \varepsilon, \\ \delta([\sigma_1; \mathbf{while}\ \phi\ \mathbf{do}\ \sigma_1, s], a) & \text{if } s \models \phi, \end{cases}$$

$$\delta([\sigma_1^*, s], a) = \delta([(\sigma_1; \sigma_1^*), s], a) \text{ if } a \neq \varepsilon \quad (9)$$

$$\delta([\sigma_1^*, s], \varepsilon) = \delta([(\sigma_1; \sigma_1^*), s], \varepsilon) \cup \{[nil, s]\}, \qquad (10)$$

$$\delta([\pi(x\text{-}t)\,\sigma_1, s], a) = \bigcup_{(o,t) \in \tau_D \cup \tau_P} \delta([\sigma_1|_{x/o}, s], a). \qquad (11)$$

where $\sigma_1|_{x/o}$ denotes the program resulting from replacing any occurrence of x in σ_1 by o. For space reasons we only explain two of them. First, a transition on a sequence corresponds to transitioning on its first component first (Eq. 7), unless the first component is already the empty program, in which case we transition on the second component (Eq. 8). On the other hand, a transition of σ_1^* represents two alternatives: executing σ_1 at least once, or stopping the execution of σ_1^*, with the remaining program nil (Eq. 9, 10).

To end the definition of $A_{\sigma, I}$, Q corresponds precisely to the program configurations $[\sigma', s]$ where σ' is either nil or a subprogram of σ such that program variables may have been replaced by objects in I, and s is any possible planning state. Moreover, δ is assumed empty for elements of its domain not explicitly mentioned above. Finally, the set of accepting states is $F = \{[nil, s] \mid s \text{ is any state over } I\}$, i.e., those where no program remains in execution. We can now formally define an execution of a program.

Definition 1 (Execution of a program). A sequence of actions $a_1 \cdots a_n$ is an execution of σ in I if $a_1 \cdots a_n$ is accepted by $A_{\sigma, I}$.

The following remark illustrates how the automaton transitions in order to accept executions of a program.

Remark 1. Let $\sigma = (\textbf{if } \varphi \textbf{ then } a \textbf{ else } b; c)$, and suppose that $Init$ is the initial state of planning instance I. Assume furthermore that a, b, and c are always possible. Then $A_{\sigma, I}$ accepts ac if $Init \models \varphi$.
Proof. Suppose $q \vdash_a q'$ denotes that $A_{\sigma, I}$ can transition from q to q' by reading symbol a. Then if $Init \models \varphi$ observe that $[\sigma, Init] \vdash_a [nil; c, s_2] \vdash_c [nil, s_3]$, for some planning states s_2 and s_3.

Now that we have defined those sequences of actions corresponding to the execution of our program, we are ready to define the notion of planning under procedural control.

Definition 2 (Planning under procedural control). A sequence of action $\vec{a}$ is a *plan for instance I under the control of program σ* if $\vec{a}$ is a plan in I and is an execution of σ in I.

Compiling Control into the Action Theory

This section describes a translation function that, given a program σ in the DCK language defined above together with a PDDL2.1 domain specification D, outputs a new PDDL2.1 domain specification D_σ and problem specification P_σ. The two resulting specifications can then be combined with any problem P defined over D, creating a new planning instance that embeds the control given by σ, i.e. that is such that only action sequences that are executions of σ are possible. This enables any PDDL2.1-compliant planner to exploit search control specified by any program.

To account for the state of execution of program σ and to describe legal transitions in that program, we introduce a few bookkeeping predicates and a few additional actions. Figure 1 graphically illustrates the translation of an exam-
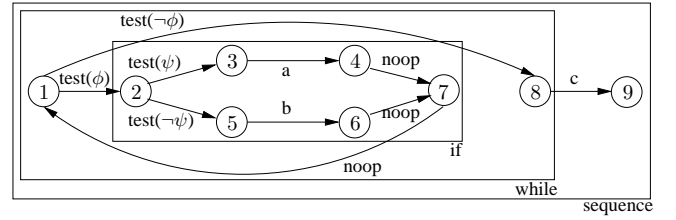

Figure 1: Automaton for **while** ϕ **do** (**if** ψ **then** a **else** b); c.

ple program shown as a *finite state automaton*. Intuitively, the operators we generate in the compilation define the transitions of this automaton. Their preconditions and effects condition on and change the automaton's state.

The translation is defined inductively by a function $C(\sigma, n, E)$ which takes as input a program σ, an integer n, and a list of program variables with types $E = [e_1\text{-}t_1, \ldots, e_k\text{-}t_k]$, and outputs a tuple (L, L', n') with L a list of domain-independent operator definitions, L' a list of domain-dependent operator definitions, and n' another integer. Intuitively, E contains the program variables whose scope includes (sub-)program σ. Moreover, L' contains restrictions on the applicability of operators defined in D, and L contains additional control operators needed to enforce the search control defined in σ. Integers n and n' abstractly denote the program state before and after execution of σ.

We use two auxiliary functions. $Cnoop(n_1, n_2)$ produces an operator definition that allows a transition from state n_1 to n_2. Similarly $Ctest(\phi, n_1, n_2, E)$ defines the same transition, but conditioned on ϕ. They are defined as:[1]

$$Cnoop(n_1, n_2) = \langle noop\_n_1\_n_2(), [\,], state = s_{n_1}, [state = s_{n_2}] \rangle$$

$$Ctest(\phi, n_1, n_2, E) = \langle test\_n_1\_n_2(\vec{x}), \vec{t}, Prec(\vec{x}), Eff(\vec{x}) \rangle \text{ with}$$
$$(\vec{e\text{-}t}, \vec{x}) = mentions(\phi, E), \ \vec{e\text{-}t} = e_1\text{-}t_1, \ldots, e_m\text{-}t_m,$$
$$Prec(\vec{x}) = \big(state = s_{n_1} \wedge \phi[e_i/x_i]_{i=1}^m \wedge$$
$$\textstyle\bigwedge_{i=1}^m bound(e_i) \to map(e_i, x_i)\big),$$
$$Eff(\vec{x}) = [state = s_{n_2}] \cdot [bound(e_i), map(e_i, x_i)]_{i=1}^m.$$

Function $mentions(\phi, E)$ returns a vector $\vec{e\text{-}t}$ of program variables and types that occur in ϕ, and a vector $\vec{x}$ of new variables of the same length. Bookkeeping predicates serve the following purposes: *state* denotes the state of the automaton; $bound(e)$ expresses that the program variable e has been bound to an object of the domain; $map(e, o)$ states that this object is o. Thus, the implication $bound(e_i) \to map(e_i, x_i)$ forces parameter x_i to take the value to which e_i is bound, but has no effect if e_i is not bound.

Consider the inner box of Figure 1, depicting the compilation of the if statement. It is defined as:

$$C(\textbf{if } \phi \textbf{ then } \sigma_1 \textbf{ else } \sigma_2, n, E) = (L_1 \cdot L_2 \cdot X, L_1' \cdot L_2', n_3)$$
$$\text{with } (L_1, L_1', n_1) = C(\sigma_1, n+1, E),$$
$$(L_2, L_2', n_2) = C(\sigma_2, n+1, E), \ n_3 = n_2 + 1,$$
$$X = [\ Ctest(\phi, n, n+1, E), \ Ctest(\neg\phi, n, n_1+1, E),$$
$$Cnoop(n_1, n_3), \ Cnoop(n_2, n_3)\ ]$$

and in the example we have $\phi = \psi, n = 2, n_1 = 4, n_2 = 6, n_3 = 7, \sigma_1 = a$, and $\sigma_2 = b$.

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[1] We use $A \cdot B$ to denote the concatenation of lists A and B.

The inductive definitions for other programs σ are:

$C(nil, n, E) = ([\,], [\,], n)$

$C(O(\vec{r}), n, E) = ([\,], [\langle O(\vec{x}), \vec{t}, Prec'(\vec{x}), Eff'(\vec{x})\rangle], n+1)$ with

$\quad \langle O(\vec{x}), \vec{t}, Prec(\vec{x}), Eff(\vec{x})\rangle \in Ops, \;\; \vec{r} = r_1, \ldots, r_m,$

$\quad Prec'(\vec{x}) = (state = s_n \wedge$

$$\bigwedge_{i \text{ s.t. } r_i \in E} bound(r_i) \rightarrow map(r_i, x_i) \wedge \bigwedge_{i \text{ s.t. } r_i \notin E} x_i = r_i),$$

$\quad Eff'(\vec{x}) = [\, state = s_n \Rightarrow state = s_{n+1}] \cdot$

$\qquad [state = s_n \Rightarrow bound(r_i) \wedge map(r_i, x_i)]_{i \text{ s.t. } r_i \in E}$

$C(\phi?, n, E) = (\,[Ctest(\phi, n, n+1, E)], [\,], \; n+1)$

$C((\sigma_1; \sigma_2), n, E) = (L_1 \cdot L_2, \; L_1' \cdot L_2', \; n_2)$ with

$\quad (L_1, L_1', n_1) = C(\sigma_1, n, E), (L_2, L_2', n_2) = C(\sigma_2, n_1, E)$

$C((\sigma_1 | \sigma_2), n, E) = (L_1 \cdot L_2 \cdot X, L_1' \cdot L_2', n_2 + 1)$ with

$\quad (L_1, L_1', n_1) = C(\sigma_1, n+1, E),$

$\quad (L_2, L_2', n_2) = C(\sigma_2, n_1 + 1, E),$

$\quad X = [\, Cnoop(n, n+1), \; Cnoop(n, n_1 + 1),$

$\qquad Cnoop(n_1, n_2 + 1), \; Cnoop(n_2, n_2 + 1)\,]$

$C(\mathbf{while}\, \phi \,\mathbf{do}\, \sigma, n, E) = (L \cdot X, L', n_1 + 1)$ with

$\quad (L, L', n_1) = C(\sigma, n+1, E), \; X = [Ctest(\phi, n, n+1, E),$

$\quad Ctest(\neg\phi, n, n_1 + 1, E), Cnoop(n_1, n)]$

$C(\sigma^*, n, E) = (L \cdot [Cnoop(n, n_2), Cnoop(n_1, n)], L', n_2)$

$\quad$ with $(L, L', n_1) = C(\sigma, n, E), n_2 = n_1 + 1$

$C(\pi(x\text{-}t, \sigma), n, E) = (L \cdot X, L', n_1 + 1)$ with

$\quad (L, L', n_1) = C(\sigma, n, E \cdot [x\text{-}t]),$

$\quad X = [\langle free\_n_1(x), t, \; state = s_{n_1},$

$\qquad [state = s_{n_1 + 1}, \neg bound(x), \forall y. \neg map(x, y)]\rangle\,]$

The atomic program **any** is handled by macro expansion to above defined constructs.

As mentioned above, given program σ, the return value $(L, L', n_{\text{final}})$ of $C(\sigma, 0, [\,])$ is such that L contains new operators for encoding transitions in the automaton, whereas L' contains restrictions on the applicability of the original operators of the domain. Now we are ready to integrate these new operators and restrictions with the original domain specification D to produce the new domain specification D_σ.

D_σ contains a constrained version of each operator $O(\vec{x})$ of the original domain D. Let $[\langle O(\vec{x}), \vec{t}, Prec_i(\vec{x}), Eff_i(\vec{x})\rangle]_{i=1}^n$ be the sublist of L' that contains additional conditions for operator $O(\vec{x})$. The operator replacing $O(\vec{x})$ in D_σ is defined as:

$$\langle O'(\vec{x}), \vec{t}, \; Prec(\vec{x}) \wedge \bigvee_{i=1}^n Prec_i(\vec{x}), \; Eff(\vec{x}) \cup \bigcup_{i=1}^n Eff_i(\vec{x})\rangle$$

Additionally, D_σ contains all operator definitions in L. Objects in D_σ are the same as those in D, plus a few new ones to represent the program variables and the automaton's states s_i ($0 \le i \le n_{\text{final}}$). Finally D_σ inherits all predicates in D plus $bound(x)$, $map(x, y)$, and function $state$.

The translation, up to this point, is problem-independent; the problem specification P_σ is defined as follows. Given any predefined problem P over D, P_σ is like P except that its initial state contains condition $state = s_0$, and its goal contains $state = s_{n_{\text{final}}}$. Those conditions ensure that the program must be executed to completion.

As is shown below, planning in the generated instance $I_\sigma = (D_\sigma, P_\sigma)$ is equivalent to planning for the original instance $I = (D, P)$ under the control of program σ, except that plans on I_σ contain actions that were not part of the original domain definition (*test*, *noop*, and *free*).

Theorem 1 (Correctness)**.** Let $Filter(\vec{a}, D)$ denote the sequence that remains when removing from $\vec{a}$ any action not defined in D. If $\vec{a}$ is a plan for instance $I_\sigma = (D_\sigma, P_\sigma)$ then $Filter(\vec{a}, D)$ is a plan for $I = (D, P)$ under the control of σ. Conversely, if $\vec{a}$ is a plan for I under the control of σ, there exists a plan $\vec{a}'$ for I_σ, such that $\vec{a} = Filter(\vec{a}', D)$.
Proof. See (Baier, Fritz, & McIlraith 2007).

Now we turn our attention to analyzing the succinctness of the output planning instance relative to the original instance and control program. Assume we define the size of a program as the number of programming constructs and actions it contains. Then we obtain the following result.

Theorem 2 (Succinctness)**.** If σ is a program of size m, and k is the maximal nesting depth of $\pi(x\text{-}t)$ statements in σ, then $|I_\sigma|$ (the overall size of I_σ) is $O(km)$.
Proof. See (Baier, Fritz, & McIlraith 2007).

The encoding of programs in PDDL2.1 is, hence, in worst case $O(k)$ times bigger than the program itself. It is also easy to show that the translation is done in time linear in the size of the program, since, by definition, every occurrence of a program construct is only dealt with once.

Exploiting DCK in SOA Heuristic Planners

Our objective in translating procedural DCK to PDDL2.1 was to enable *any* PDDL2.1-compliant SOA planner to seamlessly exploit our DCK. In this section, we investigate ways to best leverage our translated domains using domain-independent heuristic search planners.

There are several compelling reasons for wanting to apply domain-independent heuristic search to these problems. Procedural DCK can take many forms. Often, it will provide explicit actions for some parts of a sequential plan, but not for others. In such cases, it will contain unconstrained fragments (i.e., fragments with nondeterministic choices of actions) where the designer expects the planner to figure out the best choice of actions to realize a sub-task. In the absence of domain-specific guidance for these unconstrained fragments, it is natural to consider using a domain-independent heuristic to guide the search.

In other cases, it is the choice of action arguments that must be optimized. In particular, fragments of DCK may collectively impose global constraints on action argument choices that need to be enforced by the planner. As such, the planner needs to be *aware* of the procedural control in order to avoid backtracking. By way of illustration, consider a travel planning domain comprising two tasks "buy air ticket" followed by "book hotel". Each DCK fragment restricts the actions that can be used, but leaves the choice of arguments to the planner. Further suppose that budget is limited. We would like our planner to realize that actions used to complete the first part should save enough money to complete the second task. The ability to do such lookahead can be achieved via domain-independent heuristic search.

In the rest of the section we propose three ways in which one can leverage our translated domains using a domain-independent heuristic planner. These three techniques differ predominantly in the operands they consider in computing heuristics.

Direct Use of Translation (*Simple*) As the name suggests, a simple way to provide heuristic guidance while enforcing program awareness is to use our translated domain directly with a domain-independent heuristic planner. In short, take the original domain instance I and control σ, and use the resulting instance I_σ with any heuristic planner.

Unfortunately, when exploiting a relaxed graph to compute heuristics, two issues arise. First, since both the map and $bound$ predicates are relaxed, whatever value is already assigned to a variable, will remain assigned to that variable. This can cause a problem with iterative control. For example, assume program $\sigma_L \stackrel{\text{def}}{=}$ **while** ϕ **do** $\pi(c\text{-}crate)\, unload(c, T)$, is intended for a domain where crates can be only unloaded sequentially from a truck. While expanding the relaxed plan, as soon as variable c is bound to some value, action $unload$ can only take that value as argument. This leads the heuristic to regard most instances as unsolvable, returning misleading estimates.

The second issue is one of efficiency. Since fluent $state$ is also relaxed, the benefits of the reduced branching factor induced by the programs is lost. This could slow down the computation of the heuristic significantly.

Modified Program Structure (*H-ops*) The *H-ops* approach addresses the two issues potentially affecting the computation of the *Simple* heuristic. It is designed to be used with planners that employ relaxed planning graphs for heuristic computation. The input to the planner in this case is a pair $(I_\sigma, HOps)$, where $I_\sigma = (D_\sigma, P_\sigma)$ is the translated instance, and $HOps$ is an additional set of planning operators. The planner uses the operators in D_σ to generate successor states while searching. However, when computing the heuristic for a state s it uses the operators in $HOps$.

Additionally, function *state* and predicates *bound* and *map* are *not* relaxed. This means that when computing the relaxed graph we actually delete their instances from the relaxed states. As usual, *deletes* are processed before *adds*. The expansion of the graph is stopped if the goal or a fixed point is reached. Finally, a relaxed plan is extracted in the usual way, and its length is reported as the heuristic value.

The un-relaxing of $state$, $bound$ and map addresses the problem of reflecting the reduced branching factor provided by the control program while computing the heuristics. However, it introduces other problems. Returning to the σ_L program defined above, since $state$ is now un-relaxed, the relaxed graph expansion cannot escape from the loop, because under the relaxed planning semantics, as soon as ϕ is true, it remains true forever. A similar issue occurs with the nondeterministic iteration.

This issue is addressed by the $HOps$ operators. Due to lack of space we only explain how these operators work in the case of the while loop. To avoid staying in the loop forever, the loop will be exited when actions in it are no longer adding effects. Figure 2 provides a graphical repre-
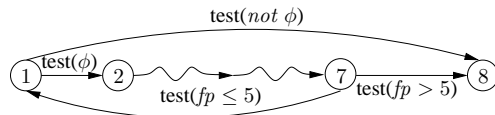

Figure 2: *H-ops* translation of **while** loops. While computing the heuristics, pseudo-fluent fp is increased each time no new effect is added into the relaxed state, and it is set to 0 otherwise. The loop can be exited if the last five (7-2) actions performed didn't add any new effect.

sentation. An important detail to note is that the loop is not entered when ϕ is not found true in the relaxed state. (The expression $not\ \phi$ should be understood as negation as failure.) Moreover, the pseudo-fluent fp is an internal variable of the planner that acts as a real fluent for the $HOps$.

Since loops are guaranteed to be exited, the computation of *H-ops* is guaranteed to finish because at some relaxed state the final state of the automaton will be reached. At this point, if the goal is not true, no operators will be possible and a fixed point will be produced immediately.

A Program-Unaware Approach (*Basic*) Our program-unaware approach (*Basic*) completely ignores the program when computing heuristics. Here, the input to the planner is a pair (I_σ, Ops), where I_σ is the translated instance, and Ops are the *original* domain operators. The Ops operators are used exclusively to compute the heuristic. Hence, *Basic*'s output is not at all influenced by the control program.

Although *Basic* is program unaware, it can sometimes provide good estimates, as we see in the following section. This is especially true when the DCK characterizes a solution that would be naturally found by the planner if no control were used. It is also relatively fast to compute.

Implementation and Experiments

Our implementation[2] takes a PDDL planning instance and a DCK program and generates a new PDDL planning instance. It will also generate appropriate output for the *Basic* and *H-ops* heuristics, which require a different set of operators. Thus, the resulting PDDL instance may contain definitions for operators that are used only for heuristic computation using the `:h-action` keyword, whose syntax is analogous to the PDDL keyword `:action`.

Our planner is a modified version of TLPLAN, which does a best-first search using an FF-style heuristic. It is capable of reading the PDDL with extended operators.

We performed our experiments on the *trucks*, *storage* and *rovers* domains (30 instances each). We wrote DCK for these domains. For lack of space, we do not show the DCK in detail, however for trucks we used the control shown as an example in the Introduction. We ran our three heuristic approaches (*Basic*, *H-ops*, and *Simple*) and cycle-free, depth-first search on the translated instance (*blind*). Additionally, we ran the original instance of the program (DCK-free) using the domain-independent heuristics provided by the planner (*original*). Table 1 shows various statistics on the performance of the approaches. Furthermore, Fig. 3 shows times for the different heuristic approaches.

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[2]Available at www.cs.toronto.edu/kr/systems

		original	*Simple*	*Basic*	*H-ops*	*blind*
Trucks	#n	1	0.31	0.41	0.26	19.85
	#s	9	9	15	14	3
	ℓ_{min}	1	1	1	1	1
	ℓ_{avg}	1.1	1.03	1.02	1.04	1.04
	ℓ_{max}	1.2	1.2	1.07	1.2	1.07
Rovers	#n	1	0.74	1.06	1.06	1.62
	#s	10	19	28	22	30
	ℓ_{min}	1	1	1	1	1
	ℓ_{avg}	2.13	1.03	1.05	1.21	1.53
	ℓ_{max}	4.59	1.2	1.3	1.7	2.14
Storage	#n	1	1.2	1.13	0.76	1.45
	#s	18	18	20	21	20
	ℓ_{min}	1	1	1	1	1
	ℓ_{avg}	4.4	1.05	1.01	1.07	1.62
	ℓ_{max}	21.11	1.29	1.16	1.48	2.11

Table 1: Comparison between different approaches to planning (with DCK). #n is the average factor of expanded nodes to the number of nodes expanded by *original* (i.e., #n=0.26 means the approach expanded 0.26 times the number of nodes expanded by original). #s is the number of problems solved by each approach. ℓ_{avg} denotes the average ratio of the plan length to the shortest plan found by any of the approaches (i.e., ℓ_{avg}=1.50 means that on average, on each instance, plans where 50% longer than the shortest plan found for that instance). ℓ_{min} and ℓ_{max} are defined analogously.

Not surprisingly, our data confirms that DCK helps to improve the performance of the planner, solving more instances across all domains. In some domains (i.e. storage and rovers) blind depth-first cycle-free search is sufficient for solving most of the instances. However, quality of solutions (plan length) is poor compared to the heuristic approaches. In trucks, DCK is only effective in conjunction with heuristics; blind search can solve very few instances.

We observe that *H-ops* is the most informative (expands fewer nodes). This fact does not pay off in time in the experiments shown in the table. Nevertheless, it is easy to construct instances where the *H-ops* performs better than *Basic*. This happens when the DCK control restricts the space of valid plans (i.e., prunes out valid plans). We have experimented with various instances of the storage domain, where we restrict the plan to use only one hoist. In some of these cases *H-ops* outperforms *Basic* by orders of magnitude.

Summary and Related Work

DCK can be used to constrain the set of valid plans and has proven an effective tool in reducing the time required to generate a plan. Nevertheless, many of the planners that exploit it use arguably less natural state-centric DCK specification languages, and their planners use blind search. In this paper we examined the problem of exploiting procedural DCK with SOA planners. Our goal was to specify rich DCK naturally in the form of a program template and to exploit SOA planning techniques to actively plan towards the achievement of this DCK. To this end we made three contributions: provision of a procedural DCK language syntax and semantics; a polynomial-time algorithm to compile DCK and a planning instance into a PDDL2.1 planning instance that could be input to any PDDL2.1-compliant planner; and finally a set of techniques for exploiting domain-independent heuristic search with our translated DCK plan-

ning instances. Each contribution is of value in and of itself. The language can be used without the compilation, and the compiled PDDL2.1 instance can be input to any PDDL2.1-compliant SOA planner, not just the domain-independent heuristic search planner that we propose. Our experiments show that procedural DCK improves the performance of SOA planners, and that our heuristics are sometimes key to achieving good performance.

Much of the previous work on DCK in planning has exploited state-centric specification languages. In particular, TLPLAN (Bacchus & Kabanza 1998) and TALPLANNER (Kvarnström & Doherty 2000) employ declarative, state-centric, temporal languages based on LTL to specify DCK. Such languages define necessary properties of states over fragments of a valid plan. We argue that they could be less natural than our procedural specification language.

Though not described as DCK specification languages there are a number of languages from the agent programming and/or model-based programming communities that are related to procedural control. Among these are EAGLE, a goal language designed to also express intentionality (dal Lago, Pistore, & Traverso 2002). Moreover, GOLOG is a procedural language proposed as an alternative to planning by the cognitive robotics community. It essentially constrains the possible space of actions that could be performed by the programmed agent allowing non-determinism. Our DCK language can be viewed as a version of GOLOG. Further, languages such as the Reactive Model-Based Programming Language (RMPL) (Kim, Williams, & Abramson 2001) – a procedural language that combines ideas from constraint-based modeling with reactive programming constructs – also share expressive power and goals with procedural DCK. Finally, Hierarchical Task Network (HTN) specification languages such as those used in SHOP (Nau *et al.* 1999) provide domain-dependent hierarchical task decompositions together with partial order constraints, not easily describable in our language.

A focus of our work was to exploit SOA planners and planning techniques with our procedural DCK. In contrast, well-known DCK-enabled planners such as TLPLAN and TALPLANNER use DCK to prune the search space at each step of the plan and then employ blind depth-first cycle-free search to try to reach the goal. Unfortunately, pruning is only possible for maintenance-style DCK and there is no way to plan towards achieving other types of DCK as there is with the heuristic search techniques proposed here.

Similarly, GOLOG interpreters, while exploiting procedural DCK, have traditionally employed blind search to instantiate nondeterministic fragments of a GOLOG program. Most recently, Claßen *et al.* (2007) have proposed to integrate an incremental GOLOG interpreter with a SOA planner. Their motivation is similar to ours, but there is a subtle difference: they are interested in combining *agent programming* and efficient planning. The integration works by allowing a GOLOG program to make explicit calls to a SOA planner to achieve particular conditions identified by the user. The actual planning, however, is not controlled in any way. Also, since the GOLOG interpreter executes the returned plan immediately without further lookahead, back-
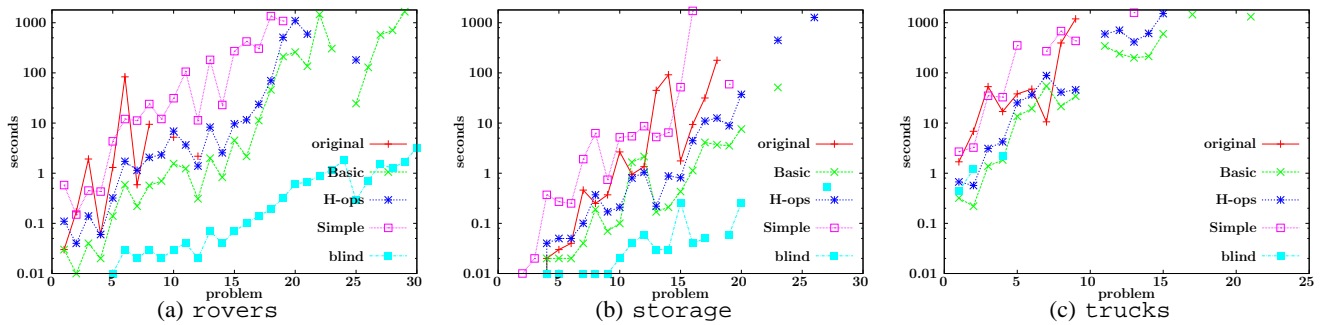
Figure 3: Running times of the three heuristics and the original instance; logarithmic scale; run on an Intel Xeon, 3.6GHz, 2GB RAM

tracking does not extend over the boundary between GOLOG and the planner. As such, each fragment of nondeterminism within a program is treated independently, so that actions selected locally are not informed by the constraints of later fragments as they are with the approach that we propose. Their work, which focuses on the semantics of ADL in the situation calculus, is hence orthogonal to ours.

Finally, there is related work that compiles DCK into standard planning domains. Baier & McIlraith (2006), Cresswell & Coddington (2004), Edelkamp (2006), and Rintanen (2000), propose to compile different versions of LTL-based DCK into PDDL/ADL planning domains. The main drawback of these approaches is that translating full LTL into ADL/PDDL is worst-case exponential in the size of the control formula whereas our compilation produces an addition to the original PDDL instance that is linear in the size of the DCK program. Son *et al.* (2006) further show how HTN, LTL, and GOLOG-like DCK can be encoded into planning instances that can be solved using answer set solvers. Nevertheless, they do not provide translations that can be integrated with PDDL-compliant SOA planners, nor do they propose any heuristic approaches to planning with them.

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