Continual Planning in Golog

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Abstract

To solve ever more complex and longer tasks, mobile robots need to generate more elaborate plans and must handle dynamic environments and incomplete knowledge. We address this challenge by integrating two seemingly different approaches – PDDL-based planning for efficient plan generation and GOLOG for highly expressive behavior specification – in a coherent framework that supports continual planning. The latter allows to interleave plan generation and execution through assertions, which are placeholder actions that are dynamically expanded into conditional sub-plans (using classical planners) once a replanning condition is satisfied. We formalize and implement continual planning in GOLOG which was so far only supported in PDDL-based systems. This enables combining the execution of generated plans with regular GOLOG programs and execution monitoring. Experiments on autonomous mobile robots show that the approach supports expressive behavior specification combined with efficient sub-plan generation to handle dynamic environments and incomplete knowledge in a unified way.

Introduction

Imagine a domestic service robot with the task to clean up the dining table by fetching cups, putting clean ones back on the shelf and dirty ones into the dishwasher. This task can be solved using a GOLOG (Levesque et al. 1997) program stating that while cups are left on the table fetch one, sense whether it is clean, and put it at the appropriate place. A different approach is taken in planning where a planner such as FAST DOWNWARD (Helmert 2006) determines a sequence of actions to clean the table. GOLOG supports incomplete knowledge and sensing (e.g. whether cups are dirty), but current implementations are very inefficient when it comes to pure planning, whereas planning is efficient but needs complete knowledge. Real-world execution furthermore requires a control loop for maintaining a world model, incorporating sensing results, and monitoring action execution, which planning-based systems typically implement in an ad-hoc fashion. To alleviate some of these issues, GOLOG and PDDL planning have been integrated such that a GOLOG program could call an embedded PDDL planner for sub-tasks (Claßen et al. 2012). However, this earlier approach could cope with incomplete knowledge only in a limited fashion. While sensing could be used in other parts of the GOLOG program, planning subtasks required the agent to possess complete information about (the necessary part of) the world state. This excludes a large class of problems where it is possible to come up with a major part of a plan beforehand, but that may contain smaller parts to be filled later through sensing. In our example, the agent may generate an overall plan for cleaning the table, but the decision on where to put an individual cup depends on whether it is dirty, which is subject to sensing. Continual planning (Brenner and Nebel 2009) addresses this issue by interleaving planning and plan execution, allowing the agent to handle incomplete knowledge even within a planning problem.

In this paper, we extend GOLOG with continual planning, which so far is only supported in some PDDL-based systems. We define a new GOLOG action type assertion, which is a placeholder for conditional sub-plans that depend on yet missing information. We define Know-If fluents for representing incomplete knowledge, where a Know-If fluent $F_{KIF}$ is true iff the value of the fluent $F$ is known. The evaluation shows competitive and even better performance than PDDL-based continual planning alone. A particular benefit of our approach is that we can combine GOLOG control structures with efficient planning to support incomplete knowledge in both parts. Moreover, we obtain a framework that integrates all parts of a robot task in GOLOG, including the top-most execution loop that queries the planner and then executes and monitors such plans. Using an extended GOLOG execution monitoring makes the system more robust and allows to deal with dynamic environments.

In the following section, we introduce GOLOG, PDDL and continual planning. Next, we define our approach to continual planning by means of assertions and describe our representation of incomplete knowledge. Finally, we evaluate the approach for domestic and logistics service robots.

Related Work

The Situation Calculus and GOLOG

The Situation Calculus (McCarthy 1963; Reiter 2001) is a first-order logic which allows to represent world states as first-order terms called situations. Relations (functions)
which may change from situation to situation are called relational (functional) fluents. Situations are results of actions, the situation after doing action \(a\) in situation \(s\) is denoted as \(\text{do}(a, s)\). The initial situation \(S_0\) and the action preconditions and effects are defined in a basic action theory (BAT). Precondition axioms are of the form \(\text{Poss}(\alpha(\vec{x}), s) \equiv \Pi_\alpha(\vec{x}, s)\) where \(\Pi_\alpha(\vec{x}, s)\) is a first-order formula. Successor state axioms (SSA) for relational fluents \(F\) are of the form \(F(\vec{x}, \text{do}(a, s)) \equiv \gamma_F^+(\vec{x}, a, s) \vee F(\vec{x}, s) \wedge \neg \gamma_F^-(\vec{x}, a, s)\) where \(\gamma_F^+(\vec{x}, a, s)\) is a first-order formula describing whether action \(a\) causes fluent \(F\) to be true (false). As an example, \(\text{Poss}(\text{goto}(l), s) \equiv \neg \text{robot} \_ \text{at}(l, s)\) states that the action \(\text{goto}(l)\) is executable in situation \(s\) iff the robot is not currently at \(l\); \(\text{robot} \_ \text{at}(l, \text{do}(a, s)) \equiv a = \text{goto}(l) \vee \text{robot} \_ \text{at}(l, s) \wedge \neg \exists l' a = \text{goto}(l')\) states that after executing action \(a\), the robot is at location \(l\) if \(a\) is the action \(\text{goto}(l)\) or if the robot is at \(l\) in situation \(s\) and is not going anywhere else. A BAT includes foundational axioms for situations and defines a relation < on situations, where \(s_1 < s_2\) means \(s_2\) results from \(s_1\) by executing an action sequence.

GOLOG (Levesque et al. 1997) is a high-level programming language based on the Situation Calculus. It offers imperative programming constructs such as sequences of actions and iteration as well as nondeterministic branching. The semantics of GOLOG can be specified in terms of transitions (De Giacomo et al. 2009), which describe single steps of computation between configurations of the program. In GOLOG, configurations are of the form \((\delta, s)\) where \(\delta\) is the remaining program and \(s\) is the current situation. \(\text{Trans}(\delta, s, \delta', s')\) describes the transition between two configurations \((\delta, s)\) and \((\delta', s')\); the predicate \(\text{Final}(\delta, s)\) specifies configurations \((\delta, s)\) where the computation is completed. As an example, if the program is a single action \(a\) and the agent is currently in situation \(s\), the transition to the next configuration is defined as \(\text{Trans}(a, s, \delta', s') \equiv \text{Poss}(a[s], s) \wedge \delta' = \text{nil} \wedge s' = \text{do}(a[s], s)\).

Multiple dialects of GOLOG exist: CONGOLOG (De Giacomo, Lespérance, and Levesque 2000) adds concurrency and interrupts to GOLOG. INDILOG (De Giacomo et al. 2009) executes programs on-line with a search operator for off-line execution, and adds sensing actions, which are actions that determine the value of a certain fluent. READYLOG (Ferrein and Lakemeyer 2008) extends INDILOG with passive sensing.

With sensing actions, it is desirable to be able to express the agent’s knowledge, which can be described using the notion of possible worlds (Scherl and Levesque 1993). The binary relation \(K(s', s)\) describes that as far as the agent knows, it might be in situation \(s'\) when in \(s\). Using \(K\), one can define the predicate \(\text{Knows}(P, s)\) which holds iff \(P\) is known to be true in situation \(s\), and the predicate \(\text{Kwhether}(P, s)\) which holds iff the value of \(P\) is known:

\[
\text{Knows}(P, s) \equiv \forall s' K(s', s) \supset P[s']
\]

\[
\text{Kwhether}(P, s) \equiv \text{Knows}(P, s) \lor \text{Knows}(\neg P, s)
\]

As a different approach, Knowledge fluents (Demolombe and del Pilar Pozos Parra 2000) extend the Situation Calculus with a modal operator \(K\), defining fluents \(KP(s)\) meaning “\(P\) is known to be true in situation \(s\)”.

For each ordinary relational fluent \(F\), they define knowledge fluents \(KF\) and \(\neg F\) by successor knowledge axioms (SKA):

\[
KF(\vec{x}, \text{do}(a, s)) \equiv \gamma_{KF}^+(\vec{x}, a, s) \lor KF(\vec{x}, s) \wedge \neg \gamma_{KF}^-(\vec{x}, a, s)
\]

\[
\neg F(\vec{x}, \text{do}(a, s)) \equiv \gamma_{KF}^-(\vec{x}, a, s) \lor K\neg F(\vec{x}, s) \wedge \neg \gamma_{KF}^+(\vec{x}, a, s)
\]

Analogously to SSAs, \(\gamma_{KF}^+(\vec{x}, a, s)\) (or \(\gamma_{KF}^-(\vec{x}, a, s)\)) defines all possibilities to change the knowledge fluent \(KF\) (or \(\neg F\)) to true or false. As an example, after \(cup\) has been sensed on \(table\), \(K\text{at}(cup, table)\) holds. If the agent moves away, the cup may be removed by another agent, thus \(\gamma_{KF}^+(cup, table, \text{goto}(kitchen), s)\) holds and \(K\text{at}(cup, table)\) is false. SSAs can be translated to SKAs (Petrick and Levesque 2002). The SSA of \(F\) is translated to the SKA of \(KF\) by defining \(\gamma_{KF}^+(\vec{x}, a, s)\) (or \(\gamma_{KF}^-(\vec{x}, a, s)\)) defines all possibilities to change the knowledge fluent \(KF\) (or \(\neg F\)) to true or false. As an example, after \(cup\) has been sensed on \(table\), \(K\text{at}(cup, table)\) holds. If the agent moves away, the cup may be removed by another agent, thus \(\gamma_{KF}^+(cup, table, \text{goto}(kitchen), s)\) holds and \(K\text{at}(cup, table)\) is false. SSAs can be translated to SKAs (Petrick and Levesque 2002).

**Planning**

Planning describes the problem of finding a sequence of actions to reach a certain world state, called the goal state, from an initial state. Actions are described by their preconditions and effects. Depending on the formalism, there are restrictions on how the world state, the preconditions, and the effects can be represented. PDDL (McDermott et al. 1998) is a family of planning formalisms which provides a standard language for planning problems. It allows STRIPS-like actions (Fikes and Nilsson 1972), but also allows features such as conditional effects and existential and universal quantification. ADL (Pednault 1989) extends STRIPS by typed objects, disjunctive preconditions, an equality predicate, quantified preconditions, and conditional effects. It can be described as a subset of PDDL. PDDL2 (Fox and Long 2003) extends PDDL with numeric fluents and expressions, durative actions, and plan metrics.

FF (Hoffmann and Nebel 2001) is a heuristic planner which uses forward state space search and a heuristic which ignores delete effects. FF was originally designed for the STRIPS subset of PDDL but has been extended to ADL. FASTDOWNWARD (Helmert 2006) is a PDDL planner which supports the ADL fragment among others. It uses the causal graph heuristic, which splits up the problem into independent sub-problems. TFD (Eyerich, Mattmüller, and Röger 2012) extends FASTDOWNWARD to PDDL2.

While planning is possible in GOLOG, it is generally not feasible (Claßen et al. 2008). Instead, the BAT and the goal can be translated to ADL, the planning problem solved with
Continual Planning

Typical agent environments are dynamic and only partially observable. During planning, the agent’s knowledge is incomplete and missing knowledge has to be obtained by means of sensing. Sensing results are only available after the sensing action has been executed. To overcome this, the agent could create a plan which is independent of the sensing results, which is the approach of conformant planning (Hoffmann and Brafman 2006), or it could plan for every possible sensing outcome, which is the approach of contingent planning (Hoffmann and Brafman 2005). PKS (Petrick and Bacchus 2004), instead of creating a complete plan in the Situation Calculus, for a relational fluent \( F \) is defined as it is unclear whether \( F \) holds iff the value of \( F \) is known. We assume if an action causes a fluent to change, the agent is aware of the change and knows the fluent value in the situation. For each \( F_{KIF} \), we add a SKA:

\[
F_{KIF}(\vec{x}, do(a, s)) \equiv \gamma^+_F(\vec{x}, a, s) \lor \gamma^-_F(\vec{x}, a, s) \\
\lor \xi_F(\vec{x}, a, s) \lor F_{KIF}(\vec{x}, s) \land \neg \gamma^-_{F_{KIF}}(\vec{x}, a, s)
\]

where \( \gamma^+_F(\vec{x}, a, s) \) and \( \gamma^-_F(\vec{x}, a, s) \) are the same as in the SSA for \( F \). \( \xi_F(\vec{x}, a, s) \) holds iff \( a \) is a knowledge producing action for \( F \) and \( \gamma^-_{F_{KIF}}(\vec{x}, a, s) \) holds iff \( a \) causes the fluent \( F \) to be unknown. Note that this is different from knowledge fluents: While \( KF(\vec{x}, s) \) holds if and only if \( F \) is known to be true in situation \( s \), \( F_{KIF} \) holds if the value of \( F \) is known in situation \( s \), independent of the value. However, we can express knowledge fluents using Know-If fluents:

\[
KF(\vec{x}, s) \equiv F_{KIF}(\vec{x}, s) \land F(\vec{x}, s) \\
K\neg F(\vec{x}, s) \equiv F_{KIF}(\vec{x}, s) \land \neg F(\vec{x}, s)
\]

Know-If fluents have several advantages compared to knowledge fluents: First, we only need to add one Know-If fluent for each ordinary fluent instead of two knowledge fluents, thus reducing the total number of fluents. Second, we avoid disjunctive preconditions such as \( KF(\vec{x}, s) \lor K\neg F(\vec{x}, s) \), which generally impair planner performance. This is especially useful when defining assertions, where we typically have replanning conditions which only require a fluent to be known but which are independent of the fluent’s value. Third, we can directly express that an action senses a fluent: an action which senses the fluent \( F \) has as its effect \( F_{KIF} \); with knowledge fluents, this effect cannot be expressed as it is unclear whether \( KF \) or \( K\neg F \) holds after the action. Similar to knowledge fluents, Know-If fluents are not as expressive as the \( K \) fluent.
assertions
In order to deal with incomplete knowledge during planning, we add a new action type assertion to Golog. It is conceptually similar to assertions in MAPL and is a placeholder for an unspecified sub-plan, which guarantees that its effects are achievable when its precondition holds without specifying how the effect is achieved. An assertion is never executed but instead replanned once its replanning condition holds.

In Figure 1, the goal is to clean up the cup: if it is dirty, it belongs into the dishwasher, otherwise on the shelf. Initially, the agent does not know whether the cup is clean. The assertion clean_up_cup represents a conditional sub-plan. After sensing the cup state, the assertion is replaced with a plan where the goal is the assertion’s conditional effect.

To determine when an assertion is replaced by a plan, we require the domain expert to devise an axiom defining the predicate Expandable for each assertion a, typically using conjunctions of Know-If fluents. To guarantee eventual expansion, it should furthermore be entailed that

\[ \text{Poss}(a[s], s) \supset \text{Expandable}(a[s], s). \]

Example axioms for clean_up_cup are depicted in Figure 2. The assertion is expandable if the agent knows whether the cup is clean or dirty. Here possibility also implies expansibility. Finally, the SSA of \( at \) depends on the cup state: If the cup is clean, it is put on the shelf, else into the dishwasher.

Next, we define the notion of permanent expansibility of an assertion \( a \) between situations \( s_1 \) and \( s_2 \) as follows:

\[ \text{PermExpandable}(a, s_1, s_2) \equiv \forall s', s_1 \leq s' \leq s_2 \supset \text{Expandable}(a, s'). \]

Intuitively, we want the agent to avoid replanning when an assertion is only temporarily expandable and may still be rendered non-expandable by subsequent actions. Instead, we want it to wait until the assertion becomes permanently expandable from the current situation. For that purpose we introduce the special situation constant now to denote the history of actions \( \langle \alpha_1, \ldots, \alpha_k \rangle \) executed so far by the agent. This is achieved by adding the axiom:

\[ \text{now} = \text{do}(\langle \alpha_1, \ldots, \alpha_k \rangle, S_0) \]

to the BAT and updating it accordingly after the execution of further actions.

For replanning, we have an operation Replan similar to Plan which translates the effects of assertion \( a \) to a goal and calls the planner to create a plan \( \delta' \). Given a BAT \( D \), a ground action \( \alpha \), and a ground situation term \( \sigma \), let

\[ \text{Adds}(\alpha, \sigma) = \{ \gamma_F(\vec{c}, \alpha, \sigma) \} \]
\[ \text{Dels}(\alpha, \sigma) = \{ \neg \gamma_F(\vec{c}, \alpha, \sigma) \} \]

Then \( \text{Replan}(\alpha, \sigma) \) invokes the planner with goal

\[ G = \bigwedge \text{Adds}(\alpha, \sigma) \land \bigwedge \text{Dels}(\alpha, \sigma) \]

**Theorem 1.** If \( \text{Replan}(\alpha, \sigma) \) yields \( \langle \alpha_1, \ldots, \alpha_n \rangle \) as solution plan for \( G \), then

\[ D \models G[\text{do}(\alpha, \sigma)] \iff D \models G[\text{do}(\langle \alpha_1, \ldots, \alpha_n \rangle, \sigma)]. \]

Note that only \( G \) is ensured to hold after executing the plan, i.e. apart from the assertion’s effects, the plan may have additional side effects. To cope with problems arising from this, we use execution monitoring in order to trigger replanning in situations where a previous plan is rendered invalid through expanding an assertion. It lies in the programmer’s responsibility to devise actions and assertions in a fashion that ensures the possibility of such recovery measures.

Finally, we can define the semantics of assertions in terms of Trans and Final:

\[ \text{Trans}(a, s, \delta', s') \equiv \text{now} \leq s \land \]
\[ \{ \neg \text{PermExpandable}(a, \text{now}, s) \land \text{Poss}(a[s], s) \land \delta' = \text{nil} \land s' = \text{do}(a[s], s) \}
\]
\[ \lor \text{PermExpandable}(a, \text{now}, s) \land \delta' = \text{Replan}(a, s) \land s' = s \} \]

\[ \text{Final}(a, s) \equiv \text{False} \]

That is, for assertions we only consider future and present situations of now. As long as the assertion is not permanently expandable, it is treated as a primitive action. Once it becomes permanently expandable, replanning is initiated.

\[ \text{Expandable}(\text{clean_up_cup}(c), s) \equiv \text{clean}_{KIF}(c, s) \]
\[ \text{Poss}(\text{clean_up_cup}(c), s) \equiv \]
\[ \text{holding}(c, s) \land \text{clean}_{KIF}(c, s) \]
\[ \text{at}(c, l, \text{do}(a, s)) \equiv a = \text{clean_up_cup}(c) \land \]
\[ (\text{clean}(c) \land l = \text{shelf}) \]
\[ \lor \neg \text{clean}(c) \land l = \text{dishwasher} \]

Figure 1: Example for an assertion expansion: the assertion clean_up_cup is expanded and replaced with a new sub-plan. e(clean(cup1), true) denotes the sensing result.

Figure 2: Example axioms for clean_up_cup
An assertion must never be used as a possible action. On the other hand, we generally want to allow the use of assertions during expansion. Therefore, we require the domain to include a (strict) finite partial order $<_A$ on assertions, where $a$ can be used to expand $b$ iff $a <_A b$ holds (read: “$b$ is more abstract than $a$”). As an example, when expanding clean_table to clean up all cups on a table, the planner should be able to use the clean_up_cup assertion, hence we set clean_up_cup $<_A$ clean_table.

**Theorem 2.** Let Trans$^*$ denote the reflexive and transitive closure of Trans as defined in (De Giacomo, Lepérance, and Levesque 2000). If $\alpha$ is an assertion such that $\mathcal{D} \models Trans^*(\alpha, \text{now}, \delta', \text{do}(\beta, \text{now}))$, then $\beta$ is not an assertion.

Therefore, an assertion will never be selected for execution, but rather expansion. After at most finitely many expansions, the next action will always be a non-assertion $\beta$.

As a final remark, note that other definitions than ours for when to expand an assertion are conceivable, e.g. as soon as it is expandable (without the permanency constraint), or only if it is the next action to be executed. Both approaches would simplify the definition, but could lead to more difficult monitoring or even dead ends.

**Evaluation**

In this section, we evaluate our approach to continual planning in GOLOG with two applications. We present an in-depth evaluation of our approach in the household domain and compare it to the GKI CP. Additionally, we sketch how we use continual planning in the RoboCup Logistics League.

**Household Domain**

We evaluate our approach using the clean-up task from the household domain and compare it to the GKI CP. A comparison to MAPL was not possible because our domain relies on conditional effects, which are not supported by MAPL. To compare both continual planners, we run both systems on the same problem. To cope with discrepancies between the actual world and the agent’s representation of the world, both planners use execution monitoring, which detects such discrepancies and adapts the plan accordingly. The GOLOG CP uses a monitor similar to an existing GOLOG monitor (De Giacomo, Reiter, and Soutchanski 1998), the GKI CP has a built-in monitor. In order to analyze planner performance quantitatively, we measured the elapsed real time between the invocation of the planner and its termination, excluding monitoring time. All benchmarks were done on an Intel Core i7-3770 at 3.40 GHz with 4 cores and hyper-threading, resulting in 8 parallel threads. Quantitative benchmarks were done by simulating sensing results and assuming that all actions succeeded. We ran all tasks twenty times and computed the average total time. Both systems have also run successfully on our mobile robot Caesar (Ferrein et al. 2013), which is shown in Figure 3.

**Evaluation Task** Our evaluation task is a clean-up task from the household domain and modifies the setting of the TidyUp-Robot project (Dornhege and Hertle 2013): The robot is supposed to clean up all cups located on a table by putting dirty cups into the dish washer and clean cups on the shelf. There are five relevant locations: dining_table, shelf, kitchen_entrance, dishwasher_side, and dishwasher_front to reach the dishwasher. The dishwasher contains two spots to place cups reachable from the front, and one reachable from the side, where the robot must align before placing any cup. Initially, the robot knows all locations, how to align to all locations and all the spots in the dishwasher. The robot is able to sense the state of a cup if it is holding the cup with the explicit is_cup_clean sensing action. It also relies on passive sensing, e.g. when aligned to and looking onto the table, it can determine whether a cup is located there, which is done implicitly by reading cup positions directly from sensors. The goal is always the same: The robot is supposed to clean up all cups from the dining table. All dirty cups belong into the dish washer, all clean cups belong on the shelf:

$$\neg \exists c (\text{cup(c)} \land \text{holding(c)}) \land \text{looking_at(dining_table)}$$

$$\land \forall c . (\text{cup(c)} \supset \text{at}_{KIF}(c, \text{dining_table}))$$

$$\land \exists l . (\text{location(l)} \land \text{at}(c, l) \supset (\text{clean}_{KIF}(c)$$

$$\land (\neg \text{clean}(c) \supset \text{at}(c, \text{shelf}))))$$

The two tasks only differ in the initial knowledge:

**Task 1** The robot initially knows neither the cup positions nor whether a cup is clean. We vary the number of cups between 1 and 10; we add clean and dirty cups alternately.

**Task 2** The robot does not know the cup positions, but it knows cup states initially and thus does not need to sense them. As before, every second cup is clean, the number of cups varies between 1 and 10 (simplification of Task 1).

**Continual Planning in GOLOG** To evaluate the performance of our approach, we compare it to the GKI CP by running Task 2 with both planners. In Figure 4, the total planning times are shown. We can see that the GOLOG CP plans much faster when using the ensemble planner. For the
problem with five cups, the GKI CP needed a total planning time of $(278.1 \pm 19.9)$ s, while the GOLOG CP only needed $(0.95 \pm 0.02)$ s. When we limit the GOLOG CP to FAST-DOWNWARD, it is still faster with $(183.7 \pm 1.9)$ s. When running Task 1, the GOLOG CP could cope with the incomplete initial knowledge, but the GKI CP did not succeed even for small problems as shown in Figure 5. For the problem with two cups, the GKI CP took $(1190.6 \pm 141.8)$ s, the GOLOG CP with ensemble planning took only $(2.23 \pm 0.02)$ s, but $(634.5 \pm 4.1)$ s when limited to FAST-DOWNWARD. Thus, ensemble planning performs better for this problem.

To analyze plan quality, we investigate the number of actions planned by both planners when running Task 2. Both planners produced plans of similar quality; e.g. for the problem with five cups, the GKI CP needed $65.0 \pm 3.4$ actions, while the GOLOG CP needed $62.0 \pm 0.0$ actions. Thus, there is no significant difference in plan quality. However, the GKI CP could not solve problems with more than five cups, while the GOLOG CP could handle problems with ten cups.

**Assertions** Our continual planner relies on the use of assertions, which guarantee that certain sub-goals are reached while not having all necessary information to create an actual plan. However, continual planning is also possible without assertions: The planner creates a plan for one possible world state and revises the plan when it sensed fluents which differ from its assumptions. As we make the closed-world assumption, the planner simply assumes all fluents not known to be true to be false and plans accordingly.

To measure the performance of assertions, we ran our agent on Task 1 without assertions and with the `clean_up_cup` assertion using the ensemble planner. In Figure 5, total planning times for both cases are shown. For small problems, we can see that planning without assertions is in advantage. This seems reasonable as assertions cause an additional overhead which may surmount their advantage. However, for larger problems, the use of assertions is clearly advantageous. While the planner with assertions could solve problems with 10 cups in $(10.0 \pm 0.06)$ s, planning without assertions took $(326.5 \pm 4.9)$ s for six cups. Problems with more than six cups could not be solved without assertions. When investigating the intermittent planning results, the reason becomes clear: The plan without assertions contains actions which depend on the sensing result. If the sensing result differs from the expected result, the remaining plan becomes invalid and the agent must replan.

Both approaches with and without assertions produce plans of similar length. As an example, for the problem with six cups, the final plan consisted of $93.0 \pm 0.0$ actions when not using assertions and $90.0 \pm 0.0$ actions when using assertions. Thus, assertions do not deteriorate plan length.

**RoboCup Logistics League (RCLL)**

The RCLL is an industry-inspired competition under the RoboCup umbrella. The goal is to maintain and optimize the material flow in a smart factory by a group of three autonomous mobile robots. Before the production can start, the robots must explore the environment and identify the available machines. These machines are distributed in six out of twelve zones (per team). The robots travel to the zones, check whether it is occupied by a machine, and start identification if it is. For details, we refer to (Niemueller, Lakemeyer, and Ferrein 2015). For brevity, we limit our further description to the exploration phase.

In this scenario, we use planning to minimize plan duration. Our agents use local planning, i.e., each agent plans on its own. Full planning for all zones and actions is inefficient. Therefore, a GOLOG procedure as shown below is used to pick some unexplored zone and plan the necessary actions. In order to avoid resource conflicts, the robots coordinate using mutual exclusion locks for zones. Continual planning allows to recover from rejected logs (concurrently operating robots may choose the same zone at the same time).

```plaintext
while some(z, zone, explorable(z)) do
  plan(some(z, zone and explorable(z), explored(z)))
endWhile
```

Within the planner call (`plan`), the necessary steps to explore a specific zone are generated. An assertion is used to insert steps for identification if a machine has been detected within a zone. GOLOG CP for the RCLL shows its useful-
ness in multi-robot scenarios by combining the expressiveness of GOLOG with the efficiency of planning.

**Framework Architecture and Example**

In this section, we describe the architecture of our framework and we give a detailed example of a run in the household domain.

**Implementation**

Our GOLOG interpreter is based on the Prolog implementations of INDIGOLOG and READYLOG. We use ECLiPSe as Prolog interpreter which is integrated into the robot software framework Fawkes (Niemueller et al. 2010). Fawkes provides the functional components and simulation integration. The Lua-based Behavior Engine (BE) (Niemueller, Ferrein, and Lakemeyer 2010) provides the primitive actions. Our implementation is available on https://www.fawkesrobotics.org/p/golog-cp.

As shown in Figure 6, the GOLOG main loop consists of three stages: First, passive sensing is done by reading sensing results from Fawkes' sensing modules. Second, the current program is monitored. During monitoring, all assertions in the program are checked for expandability and are expanded if necessary. The monitor also checks if the current program achieves the goal. If not, it first tries to recover from any exogenous changes and replans if recovery fails. Assertion expansion, recovery, and replanning use the GOLOG-PDDL interface for planning. The monitor uses a goal action of the form ! (goal), which like GOLOG’s test actions has no effects and which succeeds if the goal formula holds. It is used to determine a plan’s validity. After the monitoring stage, the next action of the current program is executed. For plan actions, the external planner is called via the GOLOG-PDDL interface. Other actions are translated to a command for the BE, which takes care of the details of action execution. After the action has been executed, the interpreter continues with the next loop iteration.

**Example**

We present an example of a run of Task 1 with one clean and one dirty cup. The goal is to clean up all cups:

\[
\text{and}(\text{looking}_\text{at(livingroom_table)}, \text{all}(c, \text{cup}, \\
\text{and}(\text{kif}_\text{at(c, livingroom_table)}, \\
\text{implor}(\text{holding}(c), \text{some}(l, \text{location}, \text{at}(c, l))), \\
\text{and}(\text{kif}_\text{clean}(c), \\
\text{and}(\text{impl}\text{neg}(\text{clean}(c), \text{at}(c, \text{dishwasher})), \\
\text{impl}(\text{clean}(c), \text{at}(c, \text{counter}_\text{))})))))
\]

In the following, we abbreviate the goal formula with \(<goal\>). Initially, the program consists of a single plan action, which achieves the main goal, and a goal check.

\[\text{[plan}(<goal>), !(<goal>)]\]

After one execution step, the plan call has been replaced by an actual plan. As the agent has not sensed any cups, it only needs to look at the table in order to accomplish the goal:

\[\text{[goto(dining_table), look}_\text{at(dining_table), !(<goal>)]}\]

After the agent has executed the \(\text{look}_\text{at}\) action, it senses \text{cup1} and \text{cup2} by means of passive sensing. The goal statement does not hold, replanning is initiated. After replanning, the program contains two \text{clean}_\text{up}_\text{cup} assertions:

\[\text{[pick}_\text{up(cup1)}, \text{is}_\text{cup}_\text{clean}(\text{cup1}), \text{clean}_\text{up}_\text{cup(cup1)}, \\
\text{pick}_\text{up(cup2)}, \text{is}_\text{cup}_\text{clean}(\text{cup2}), \text{clean}_\text{up}_\text{cup(cup2)}, \\
!(<goal>)]\]

After executing \text{is}_\text{cup}_\text{clean}(\text{cup1}), the state of \text{cup1} is known and the first assertion is replanned:

\[\text{[pick}_\text{up(cup1)}, \text{look}_\text{at(dining_table)}, \text{goto}_\text{to(counter)}, \\
\text{align}_\text{to(counter)}, \text{look}_\text{at(counter)}, \text{put}_\text{down}(\text{cup2, counter}), \\
\text{pick}_\text{up(cup2)}, \text{is}_\text{cup}_\text{clean}(\text{cup2}), \text{clean}_\text{up}_\text{cup(cup2)}, \\
!(<goal>)]\]

Note that this plan is invalid; in addition to the assertion’s effect, the expanded plan also changes the robot’s position. Thus, executing \text{pick}_\text{up(cup2)} is not possible. However, after monitoring, the new program is again valid:

\[\text{[pick}_\text{up(cup1)}, \text{look}_\text{at(dining_table)}, \text{goto}_\text{to(counter)}, \\
\text{align}_\text{to(counter)}, \text{look}_\text{at(counter)}, \text{put}_\text{down}(\text{cup2, counter}), \\
\text{goto}_\text{to(dining_table)}, \text{look}_\text{at(dining_table)}, \\
\text{pick}_\text{up(cup2)}, \text{is}_\text{cup}_\text{clean}(\text{cup2}), \text{clean}_\text{up}_\text{cup(cup2)}, \\
!(<goal>)]\]

The other \text{clean}_\text{up}_\text{cup} assertion is expanded similarly after executing \text{is}_\text{cup}_\text{clean}(\text{cup2}). After executing the resulting plan, \text{goal} holds and the execution terminates successfully.

**Conclusion**

We combined the expressiveness of GOLOG and the ability to handle incomplete knowledge with the efficiency of PDDL-based plan generation. With the introduction of assertions for planning we improve on a major drawback of previous solutions: not being able to handle incomplete knowledge in the planning part. An assertion specifies conditions when to trigger planning, which could potentially run concurrently while other parts of the GOLOG program are being executed. The conditional effect of an assertion provides the planning goal. The idea is that the planner generates an appropriate plan to achieve the desired effects. We can even run multiple different planners concurrently to benefit of their individual strengths, e.g. shorter generated plans or faster determination that a plan does not exist. By not
relying on the planner for execution, but rather translating the plan back to GOLOG, we can postpone some decisions which rely on sensing and make use of GOLOG’s execution monitoring capabilities.

The presented approach provides a unified modeling framework for robot tasks based on GOLOG that can call PDDL-based planners for efficient plan generation. It allows to encode (partial) domain knowledge into the GOLOG domain and program specification and explicitly model when to generate sub-plans. The evaluation has shown that it provides comparable or even better performance than purely PDDL-based systems. Especially the integration of assertions gives a noticeable performance improvement. The system has been implemented and run on an actual mobile robot solving the described clean-up task in a real environment.

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