RVPLAN: Runtime Verification of Assumptions in Automated Planning

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Abstract: Automated planners use a model of the system and apply state transition functions to find a sequence of actions (a plan) that successfully solves a (set of) goal(s). The model used during planning can be imprecise, either due to a mistake at design time or because the environment is dynamic and changed before or during the plan execution. In this paper we use runtime monitors to verify the assumptions of plans at runtime in order to effectively detect plan failures. This paper offers three main contributions: (a) two methods (instantiated and parameterised) to automatically synthesise runtime monitors by translating planning models (STRIPS-like) to temporal logics (Past LTL or Past FO-LTL); (b) an approach to use the resulting runtime monitors to detect failures in the plan; and (c) the RVPLAN tool, which implements (a) and (b). We illustrate the use of our work with a remote inspection running example as well as quantitative results comparing the performance of the proposed monitor generation methods in terms of property synthesis, monitor synthesis, and runtime verification.

1 INTRODUCTION

Automated planning techniques (Nau et al., 2004) use models of the system to search the state-space for a sequence of actions that can achieve the goals of the application. Existing planners have been developed over many years and as a result are very efficient in solving task planning problems, both in terms of speed as well as quality/length of the resulting plan. However, complex real-world applications can be difficult to model, above all in cyber-physical systems where the environment is dynamic and the information may be incomplete. In these systems, plans can fail due to the use of outdated information or incorrect model abstraction. When this happens, it is crucial for the system to be able to detect plan failure, as well as triggering a replanning (Fox et al., 2006) mechanism using up-to-date information. In this paper, we focus on failure detection, but we plan to extend our approach in future work to integrate with a replanning mechanism (we expand this notion at the end of the paper).

The literature overview on verification and validation of planning and scheduling systems presented in (Bensalem et al., 2014) categorises the verification and validation of plan executions into runtime verification and runtime enforcement. We argue that our approach covers the former, while the latter is related to the use of runtime monitors to aid in replanning and plan repair. There are other formal methods that are better at verifying other areas in planning, such as verification of the models used, verification of the plans (not plan executions), verification of the planners, etc.

Runtime Verification (RV) is a lightweight formal verification technique that checks traces of events produced by the system execution against formal properties (Bartocci et al., 2018). RV can be performed at runtime, which opens up the possibility to act whenever incorrect behaviour of a software system is detected. One of the most common ways to achieve RV is through monitoring. A monitor can be seen as a device that reads a finite trace and yields a certain verdict. It is generally less expensive than other verification techniques, such as model checkers and Satisfiability Modulo Theories (SMT) solvers, since it does not exhaustively analyse all the possible system's executions, but only the execution trace.

RV is suitable in scenarios where there is no access to the system under analysis (black-box), since it only requires to analyse the traces produced by the system execution; it does not require a model of the system nor knowledge about its implementation. It also finds applications in safety-critical scenarios,

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where a runtime failure can be extremely costly. The presence of monitors in such scenarios helps to identify when something goes wrong (possibly reducing/avoiding unwanted side effects).

Since RV can be applied while the system is running, it can be used alongside automated planning to deal with some of the drawbacks of using planning solutions at runtime. If the model of the world used by a planner is imprecise, or the system is dynamic and continuously changes, the system needs to be able to detect plan failure. If the system changes dynamically, the resulting reality gap between the system and the planner abstraction may cause unexpected behaviours. For instance, an action that was rightfully selected to be executed as part of a plan might fail at runtime due to violations of its preconditions, or it might produce unexpected results. Moreover, usually systems are dynamic, and to use a planner in a safe and sound way, we need to recognise when the assumptions made by the planner are no longer met by the system. Checking the assumptions of a plan at runtime is often dealt with ad-hoc methods that have to be specifically designed and implemented for each action. Runtime monitors allows us to perform this failure detection at runtime using formal verification, and in this paper we show how these monitors can be automatically generated from the planning specification, making the process of checking the assumptions completely domain-independent.

In this paper we introduce an approach for failure detection that uses monitors to verify at runtime the assumptions of the actions that are generated by a classical planner. In particular, we show how to automatically synthesise runtime monitors with two different methods: (a) the *instantiated action monitoring* uses the actions of a plan that was generated as a solution to a planning problem, as well as the actions descriptions; or (b) the *parameterised action monitoring* uses only the actions descriptions. Then, we describe how these monitors can be used to detect violations in the assumptions of a plan at runtime. Finally, we discuss the implementation details of our RVPLAN tool and present results of experiments comparing the performance of both methods (instantiated and parameterised) in terms of property synthesis (translation time), monitor synthesis (creating the monitor), and runtime verification (the time it takes to verify the properties).

The rest of the paper is organised as follows. Section 2 contains the related work in automated planning, in particular approaches that deal with plan failure detection. In Section 3 we discuss the necessary background on automated planning and show a running example that we use to exemplify the concepts pertaining to our approach. We introduce our tool, RVPLAN, in Section 4, with the instantiated action monitoring method in Section 4.1, the parameterised action monitoring method in Section 4.2, and our general approach to fault detection in Section 4.3. To evaluate our framework we present the implementation details of our tool as well as some experiments to measure its performance in Section 5. We conclude the paper with our final remarks and discuss future work in Section 6.

2 RELATED WORK

ROSPlan[1] (Cashmore et al., 2015) embeds classical task planning in the Robot Operating System (ROS) through the addition of some ROS nodes for planning. One such node is a knowledge base that is updated with current information related to planning predicates through the use of manually written filters. Actions that are dispatched to be executed are tested before execution to make sure they are still valid (*i.e.*, failure detection).

PlanSys2[2] (Martín et al., 2021) is an alternative to ROSPlan for performing task planning in ROS (in particular ROS2). The novel contributions of PlanSys2 include translating plans into behaviour trees (mathematical model of plan execution), and then auctioning the actions in these plans to components in the system that are capable of executing them.

The main differences between ROSPlan and PlanSys2 to RVPLAN are that our approach is not limited to ROS and our monitors are automatically synthesised, requiring no input from the developer.

In this paper we focus on the use of offline planners, but there are many approaches that deal with planning in an online setting. Several approaches have integrated Belief-Desire-Intention (BDI) agents with planning (Sardina and Padgham, 2011; Meneguzzi and Luck, 2013; Cardoso and Bordini, 2019). Even though all of them support failure detection of plans through the use of BDI agents, they add more computation overhead than simply adding a monitor. Furthermore, some of the translations between agents and planners are not fully automated.

In (Bozzano et al., 2011), the authors propose an approach to on-board autonomy relying on model-based reasoning. They discuss planning under environment assumptions and an execution and monitoring framework. Such a framework is integrated within a generic three layers hybrid autonomy architecture,

[1]https://github.com/KCL-Planning/ROSPlan

[2]https://github.com/IntelligentRoboticsLabs/ros2_planning_system

the Autonomous Reasoning Engine (ARE). The assumptions are controlled at runtime, if the anomaly is due to a change in the environment or in the expected use of resources, then new assumptions can be computed, and the rest of the plan can be validated w.r.t. the new assumptions. If the validation succeeds then its execution can be continued. Otherwise, replanning with the new assumptions can be triggered.

The LAAS architecture for space autonomy applications is described in (Ghallab et al., 2001). Given the targeted domain, the paper highlights two main components of the architecture, failure detection/handling and planning. The decision level of their architecture is particularly relevant here, as it is responsible for supervising the execution of plans. The fault protection is done through a rule-based system that is compiled into an automaton for execution. Execution failure is separate to fault protection and leads to local replanning. It is not clear how failures are detected in their architecture, which is one of the main advantages of our approach (completely automated based on the planning specifications).

In (Mayer and Orlandini, 2015), robust plan execution is presented through plans with flexible timelines. Such flexible plans are translated into a network of Timed Game Automata, which is then verified. Specifically, they verify whether a dynamic execution strategy can be generated by solving a reachability game. Differently from our work, their verifier is used to guide the plan selection, while our contribution is mainly focused on recognising assumption violation. Their framework is also domain independent, but it is less general than ours because their plan representation must comply with the framework proposed in (Mayer et al., 2016). RVPLAN is based upon the PDDL standard (widely supported in automated planning).

Some challenges in changing the models or abstractions used in planning when the execution either fails or produces unexpected outcomes are presented in (Frank, 2015). The author compares these challenges to the concept of computational reflection and shows how to relate planning models to execution abstractions in a case study of a spacecraft attitude planning. No implementation artifact is available and the discussion is limited to describing potential solutions. However, the discussion about abstractions and refinements can be useful for our future work about making changes in the actions from planning models.

None of these works exploit Runtime Verification to validate the planner's assumption at execution time. Indeed, the violation detection, when present, is obtained by manually implementing (hard-coding) such a feature. Instead, in our work, we present fault detection of plans through runtime monitors that are automatically generated based on the plans' assumptions.

3 AUTOMATED PLANNING RUNNING EXAMPLE

In this paper we consider STRIPS (STanford Research Institute Problem Solver) planning (Fikes and Nilsson, 1971). Note that even though we focus on STRIPS-like syntax as a proof of concept for our evaluation experiments, our results are general and can be ported to any planner that supports STRIPS planning. The classical planning problem, also called a STRIPS problem, consists of a set of actions A, a set of propositions S_0 called an initial state, and disjoint sets of goal propositions G^+ and G^- describing the propositions required to be true and false (respectively) in the goal state. A solution to the planning problem is a sequence of actions $a_1, a_2, \ldots, a_n$ such that $S = \gamma(...\gamma(\gamma(S_0, a_1), a_2), ..., a_n)$ and $(G^+ \subseteq S) \wedge (G^- \cap S = \emptyset)$. With $\gamma(S_0, a_1)$ representing the state transition function of applying action a_1 to state S_0. A sequence of actions is called a *plan*.

Formally, let P be a set of all propositions modelling properties of world states. Then a state $S \subseteq P$ is a set of propositions that are true in that state. Each action functor a (*i.e.*, planning operator) is described by four sets of propositions $(\alpha_a^+, \alpha_a^-, \beta_a^+, \beta_a^-)$, where $\alpha_a^+, \alpha_a^-, \beta_a^+, \beta_a^- \subseteq P$. Sets α_a^+ and α_a^- describe disjoint positive and negative preconditions of action a, that is, propositions that must be true and false right before the action a. Action a is applicable to state S iff $(\alpha_a^+ \subseteq S) \wedge (\alpha_a^- \cap S = \emptyset)$. Sets $\beta_a^+$and β_a^- describe disjoint positive and negative effects of action a, that is, propositions that will become true and false in the state right after executing the action a. If an action a is applicable to state S then the state right after the action a will be $\gamma(S, a) = (S \setminus \beta_a^-) \cup \beta_a^+$. If an action a is not applicable to state S then $\gamma(S, a)$ is undefined.

A classical planner is a tuple $\langle P, O, S_0, G \rangle$, with P a set of propositions that model states (the predicates), O a set of planning operators (actions) $\langle a, \alpha_a^+, \alpha_a^-, \beta_a^+, \beta_a^- \rangle \in O$, S_0 the set of propositions which are initially true, and G the set of goals to achieve.

Classical planners take as input *domain* (containing planning operators O) and *problem* (containing initial state S_0 and goals G) files and output a *plan*. In our example we have used the standard formalism for classical planning PDDL (Planning Domain Definition Language) (Mcdermott et al., 1998) which supports STRIPS-like planning. To simplify the representation of the problem we use the *typing* requirement of PDDL, which allows us to assign types to the parameters of predicates. It is straightforward to translate between planning representations with or without typing. The use of typing does not have any influence in our runtime verification approach and is only used to improve readability of the models.

We introduce a planning scenario to motivate our work, and we also use it to exemplify our approach in a later section. In this example, a rover traverses a 2D grid map to perform the remote inspection of tanks containing radioactive material, while trying to avoid cells with high-level of radiation. The domain file is shown in Listing 1. The planning objects in this scenario are robots, grid cells, and radiation tanks. The following list of predicates is used: *robot-at(r,x)* and *tank-at(t,x)* indicate the position of a robot or a tank in a cell; *up(x,y)*, *down(x,y)*, *left(x,y)*, and *right(x,y)* indicate possible movements from cell x to cell y; *empty(x)* is used to mark that cell x is empty; *radiation(x)* denotes that cell x has high radiation; and *inspected(t)* represents when a tank has been inspected.

```
(define (domain remote-inspection)
(:requirements :typing)
(:types robot cell tank - object)
( :predicates
  (robot-at ?r - robot ?x - cell)
  (tank-at ?t - tank ?x - cell)
  (up ?x - cell ?y - cell)
  (down ?x - cell ?y - cell)
  (right ?x - cell ?y - cell)
  (left ?x - cell ?y - cell)
  (empty ?x - cell)
  (radiation ?x - cell)
  (inspected ?t - tank) )
( :action right
 :parameters (?r - robot ?x - cell ?y - cell)
 :precondition (and (robot-at ?r ?x) (right
    ?x ?y) (empty ?y) (not (radiation ?y)))
 :effect (and (robot-at ?r ?y) (not (robot-at
    ?r ?x)) (empty ?x) (not (empty ?y))) )
( :action inspect-right
 :parameters (?r - robot ?x - cell ?y - cell
    ?t - tank)
 :precondition (and (robot-at ?r ?x) (tank-at
    ?t ?y) (right ?x ?y) (not (inspected ?t
    )))
 :effect (and (inspected ?t)) )
)
```

Listing 1: Domain file for the running example.

The domain contains actions for movement in the grid and for inspecting tanks. Movement is separated into four actions, move up, down, left, and right. The parameters for the movement actions are the robot performing the action, the current cell x, and the destination cell y. The preconditions include that the robot is currently at cell x, there is a path between

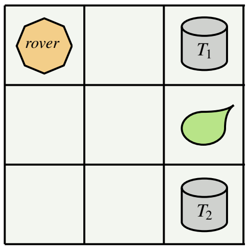


Figure 1: Initial state in a 3x3 grid; *rover* is the robot, T_1 and T_2 are the tanks to be inspected, and the green drop is radiation.

x and y (predicate up, down, left, right depending on the action), y is empty, and there is no radiation in y. The effects are that the robot is no longer at x but it is now at y, cell x is empty, and cell y is no longer empty. Similarly, there are four actions for inspecting a tank, *inspect-up*, *inspect-down*, *inspect-left*, and *inspect-right*. Parameters are the robot, the tank, the cell that the robot is at x, and the cell that the tank is at y. Preconditions are that the robot is currently at x, the tank is at y, there is a path between x and y, and the tank has not been inspected yet. The effect is that the tank has now been inspected. To improve readability we only show the actions to move *right* and to *inspect-right*, but the others are almost identical.

Listing 2 contains the problem description, with the initial state illustrated in Figure 1. The first cell in the grid is *cell_0-0* (top left, first number is x axis, second is y axis) and the last is *cell_2-2* (bottom right). Predicates that are followed by … indicate that these continue to permutate using the remaining cell objects where appropriate. An example of a plan returned by a classical planner is shown in Listing 3.

```
(define (problem p01)
(:domain remote-inspection)
( :objects cell_0-0 cell_1-0 cell_2-0
   cell_0-1 cell_1-1 cell_2-1
   cell_0-2 cell_1-2 cell_2-2 - cell
   tank1 tank2 - tank
   rover - robot )
( :init
   (robot-at rover cell_0-0)
   (tank-at tank1 cell_2-0)
   (tank-at tank2 cell_2-2)
   (empty cell_1-0) ...
   (up cell_0-1 cell_0-0) ...
   (down cell_0-0 cell_0-1) ...
   (right cell_0-0 cell_1-0) ...
   (left cell_1-0 cell_0-0) ...
   (radiation cell_2-1) )
 (:goal (and (inspected tank1) (inspected
     tank2)))
)
```

Listing 2: Problem file for the running example.

```
(right rover cell_0-0 cell_1-0)
(inspect-right rover cell_1-0 cell_2-0 tank1)
(down rover cell_1-0 cell_1-1)
(down rover cell_1-1 cell_1-2)
(inspect-right rover cell_1-2 cell_2-2 tank2)
```

Listing 3: Example of solution found by a planner.

Even though initial sources of radiation can be reported at planning time, at runtime the radiation levels can change. A mechanism for detecting these changes is necessary to ensure the safety of the robot and the correctness of the plan.

4 RVPLAN

In this section, we show how to map the planner's assumptions into a runtime monitor and the theory behind our tool. This monitor can then be used to verify at runtime whether the system satisfies these assumptions. If the system behaves differently from what assumed by the planner, the monitor reports a violation.

RVPLAN is meant to automate the translation from planner's assumptions to runtime monitors. We present two possible methods for automatically synthesising these monitors. The first uses a plan and the set of planning operators to generate a monitor (instantiated method), while the second uses only the set of planning operators (parameterised method). Then, we discuss how monitors generated in such a way can be used for fault detection.

4.1 Instantiated Action Monitoring

The standard formalism to specify formal properties in RV is propositional Linear-time Temporal Logic (LTL) (Pnueli, 1977). Given a propositional LTL property, a monitor can be synthesised as a Finite State Machine (FSM) (Andreas Bauer, 2011). Given a trace where each element is a proposition, the FSM returns the verdict $\top$ or $\bot$, if the trace satisfies (resp. violates) the LTL property[3]. LTL, however, has only future modalities, while it is widely recognised that its extension with past operators (Kamp, 1968) allows writing specifications which are easier, shorter and more intuitive (Lichtenstein et al., 1985).

The definition of linear temporal logic restricted to past time operators (Past LTL for short) is as follows (Manna and Pnueli, 1989):

$$\varphi = true \mid false \mid a \mid p^+ \mid p^- \mid (\varphi \wedge \varphi') \mid (\varphi \vee \varphi') \mid \neg\varphi \mid (\varphi\, S\, \varphi') \mid \ominus\varphi$$

where a is an action, p^+ is a positive proposition, p^- is a negative proposition (both ground without variables), φ is a formula, S stands for *since*, and $\ominus$ stands for *previous-time*. We also write $(\varphi \rightarrow \varphi')$ instead of $(\neg\varphi \vee \varphi')$, and $H\varphi$ (*history* φ) instead of $\neg(true\ S\ \neg\varphi)$. Using this logic, we can describe runtime constraints on the preconditions of the planner's actions. Note that we assume the events generated by the system execution to consist in both positive and negative propositions. Which means, for each proposition p, we have the corresponding observable events p^+ and p^-, which represent the event of observing the proposition p to be true or false, respectively.

For instance, considering our running example, we might have the proposition *empty(cell_0-0)*$^+$, which denotes that *cell_0-0* is empty, or *empty(cell_0-0)*$^-$, which denotes that *cell_0-0* is not empty. Note that, p^- and $\neg(p^+)$ have different meanings (resp. p^+ and $\neg(p^-)$). When we use p^- (resp. p^+), we denote the event corresponding to observing proposition p being false (resp. true). While when we use $\neg(p^+)$ (resp. $\neg(p^-)$), we mean any observable event which is not p^+ (resp. p^-). For example, *empty(cell_0-0)*$^-$ means we observe the *empty(cell_0-0)* proposition to be false (*i.e.*, the cell is not empty). While $\neg$*empty(cell_0-0)*$^+$ means we observe anything but *empty(cell_0-0)*$^+$ (*i.e.*, any event is allowed apart from *empty(cell_0-0)*$^+$), differently from *empty(cell_0-0)*$^-$ where we must observe *empty(cell_0-0)*$^-$.

Given a $Plan = [a_1, a_2, \ldots, a_n]$, for each action a_i we extract the set of preconditions instantiated with a_i values; namely, we get the domain action $\langle a_i, \alpha^+_{a_i}, \alpha^-_{a_i}, \beta^+_{a_i}, \beta^-_{a_i} \rangle \in O$, in which we substitute all variables according to the instantiated propositions in a_i. Considering the running example, the first action in the plan was *right(rover, cell_0-0, cell_1-0)*.

Thus, we need to check at runtime that every time the action *right(rover, cell_0-0, cell_1-0)* is performed, its preconditions are met. This can be represented as the Past LTL formula (with *rover*, *cell_0-0*, *cell_1-0* abbreviated in r, $c0$ and $c1$):

$$\varphi = H(right(r, c0, c1) \rightarrow \ominus((\neg robot\_at(r, c0)^- \ S\ robot\_at(r, c0)^+) \wedge (\neg empty(c1)^- \ S\ empty(c1)^+) \wedge (\neg right(c0, c1)^- \ S\ right(c0, c1)^+) \wedge (\neg radiation(c1)^+ \ S\ radiation(c1)^-)))$$

which says that every time (H) we observe the *right(r, c0, c1)* action, in the previous time step ($\ominus$) its preconditions are met. This is obtained by checking that in the past *robot_at(r, c0)*$^+$ has been observed, and since then (S) its negation *robot_at(r, c0)*$^-$ has not been observed (the same for the other preconditions). Intuitively, we are saying that we observed the robot

[3] Additional verdicts can be used, but, since we check safety properties, we only care about $\bot$ to identify violations. For further readings (Bauer et al., 2010).

Algorithm 1: GeneratePastLTL.

Data: the set of planning operators O, the sequence of actions *Plan*
Result: a set of Past LTL properties
1 $result = \{\ \}$;
2 **for** $a_i \leftarrow Plan$ **do**
3 $\quad \alpha^{+}_{a_i}, \alpha^{-}_{a_i}$ = getPreconditions(a_i, O);
4 $\quad i\alpha^{+}_{a_i}, i\alpha^{-}_{a_i}$ = instantiate(a_i, $\alpha^{+}_{a_i}$, $\alpha^{-}_{a_i}$);
5 $\quad \varphi_p = true$;
6 $\quad$ **for** $pre \leftarrow i\alpha^{+}_{a_i}$ **do**
7 $\quad\quad \varphi_p = \varphi_p \wedge (\neg pre^{-}\ S\ pre^{+})$;
8 $\quad$ **end**
9 $\quad$ **for** $pre \leftarrow i\alpha^{-}_{a_i}$ **do**
10 $\quad\quad \varphi_p = \varphi_p \wedge (\neg pre^{+}\ S\ pre^{-})$;
11 $\quad$ **end**
12 $\quad \varphi_{a_i} = H(a_i \rightarrow \ominus\varphi_p)$;
13 $\quad result = result \cup \{\varphi_{a_i}\}$;
14 **end**
15 **return** *result*;

position proposition, and since then we have not observed its negation (so the rover is still there).

In Algorithm 1, we report the algorithm to automatically synthesise a set of Past LTL formulae. Informally, the algorithm gets as input a set of planning operators O (extracted from a planner's domain), and a *Plan*. First it initialises an empty set, which will be used later on to populate with the Past LTL formulae (line 1). After that, it starts iterating over the plan, one action at a time (line 2). It retrieves the sets of preconditions (line 3) that have to be true ($\alpha^{+}_{a_i}$) and false ($\alpha^{-}_{a_i}$) from O that match the current action a_i. Note that these preconditions contain variables, but Past LTL does not allow them. Thus, the algorithm instantiates the preconditions variables using the values contained in a_i (line 4). It is important to remember that the actions in *Plan* are all instantiated (*i.e.*, ground), which means the action's variables/parameters are set to a certain value.

Then, for each precondition which is required to be true (lines 6-8), the algorithm adds the corresponding Past LTL formula in conjunction with the other Past LTL preconditions (line 7). This is done at a syntactic level, where the two LTL formulae are combined, using the conjunction operator, into a new LTL formula. From an implementation viewpoint, this combination is done by appending strings denoting the different LTL formulae. The Past LTL formula consists in an application of the *since* operator, as we have shown previously with an example. The algorithm continues following the same approach for the preconditions which are required to be false (lines 9-11). Note that lines 7 and 10 swap pre^{+} with pre^{-} (and viceversa). The reason for this is that in the first case (line 7), we want to check that since we saw the proposition to be true, we do not want to see it to be false. In this way, we are checking that *pre* is actually true when a_i is performed. The opposite reasoning is followed for line 10. The final Past LTL for an action a_i is obtained at the end of the loop by creating the implication which links the action a_i to its preconditions φ_p (line 12). We need $\ominus$ to require the preconditions to be met in the previous time step, and H to require the implication to be always checked. In this way, every time the action a_i occurs, we know that the preconditions are met. This Past LTL property is then stored inside the *result* set (line 13). After iterating over all the actions of the plan, the resulting set containing all Past LTL formulae is returned (line 15).

Given a planner $\langle P, O, S_0, G\rangle$ generating the plan $[a_1, a_2, \ldots, a_n]$, we create the corresponding set of Past LTL formulae that check the preconditions, *i.e.*, $GeneratePastLTL(O, [a_1, a_2, \ldots, a_n]) = \{\varphi_{a_1},\ \varphi_{a_2},\ \ldots,\ \varphi_{a_n}\}$. Finally, given the set of formulae generated in this way, we can create a single global Past LTL formula as $\varphi = (\varphi_{a_1} \wedge \varphi_{a_2} \wedge \ldots \wedge \varphi_{a_n})$; since we need to check that all actions' preconditions are always met.

Algorithm 1 concludes in PTIME (specifically linear time) w.r.t. the size of the input plan. This is evidenced by the fact that the algorithm consists of an iteration over the plan's actions, where constant time operations are performed. This is further illustrated with the results shown in Section 5.2.

A monitor for the verification of a Past LTL formula. can be seen as a function $M_\varphi : (P \cup O_{|a})^* \rightarrow Verdict$, which given a sequence of propositions and actions (we denote the set of action's functors of O with $O_{|a}$), returns a verdict denoting the satisfaction (resp. violation) of φ.

Since φ is a Past LTL property, the corresponding monitor function can be computed using an efficient dynamic programming algorithm (Havelund and Rosu, 2004). The algorithm for checking past time formulae like the ones generated by our procedure (Algorithm 1) uses two arrays, *now* and *pre*, recording the status of each sub-formula now and previously. Index 0 in these arrays refers to the formula itself with positions ordered by the sub-formula relation. Then for this property, for each observed event the arrays are updated consistently.

An issue related to the the instantiated action monitoring method is that we can only create monitors for existing plans. Thus, if a new plan is generated at runtime, we will need to recreate the monitor because when a new plan is generated, a new Past LTL property needs to be created. This might not be an issue for many application domains, since the synthesis of Past LTL monitors is not time demanding (Havelund and Rosu, 2004). Nonetheless, it is possible to consider parameterised actions instead of instantiated actions.

4.2 Parameterised Action Monitoring

The advantage of using parameters to synthesise a monitor is that once we create the monitor given a domain specification, we do not need to recreate it as long as we do not change the planning operators in the domain. Since domain actions contain variables, we cannot translate them to pure propositional Past LTL. To verify domain actions' conditions we need a formalism that supports variables. A suitable candidate is FO-LTL (First-Order Linear-time Temporal Logic), an extension of LTL that supports variables and has been recently applied to RV (Havelund et al., 2020). Also in this case, we use its past version, Past FO-LTL.

Differently from Past LTL, in Past FO-LTL we have universal and existential quantifiers to handle variables (Havelund et al., 2020):

$$\varphi = true \mid false \mid a \mid p^+ \mid p^- \mid (\varphi \wedge \varphi') \mid (\varphi \vee \varphi') \mid \neg\varphi \mid (\varphi\, S\, \varphi') \mid \ominus\varphi \mid \exists_{x \in D}.\varphi \mid \forall_{x \in D}.\varphi$$

The quantifiers are read *"for at least one value v, which belongs to a set D, we have that* φ*, where all occurrences of x are substituted with v, is satisfied"* and *"for any value v, which belongs to a set D, we have that* φ*, where all occurrences of x are substituted with v, is satisfied"*. The remaining operators are the same as in Past LTL.

Considering the domain action $\langle$*right(r,x,y)* with preconditions $\{$*robot-at(r,x)*, *right(x,y)*, *empty(y)*, $\neg$*radiation(y)*$\}$, we can translate it to FO-LTL:

$$\varphi^{FO} = \forall_{r \in \{rover\}}.\forall_{x,y \in \{0,1,2\}}.right(r,x,y) \rightarrow \ominus((\neg robot\_at(r,x)^- \; S \; robot\_at(r,x)^+) \wedge (\neg empty(y)^- \; S \; empty(y)^+) \wedge (\neg right(x,y)^- \; S \; right(x,y)^+) \wedge (\neg radiation(y)^+ \; S \; radiation(y)^-))$$

where we use the same LTL operators as for the previous approach. The difference now is that we do not instantiate r, x and y to any specific value, but we use universal quantifiers to constrain for each possible r, x and y in the grid from the problem specification (recall that the grid is 3x3, so our possible values are a permutation of $\{0,1,2\}$).

In Algorithm 2, we report the algorithm to automatically synthesise a set of Past FO-LTL formulae. Informally, the algorithm gets as input a set of planning operators O (extracted from the domain specification). First, it initialises an empty set (line 1), which will later on be populated with the Past FO-LTL formulae. Then, it iterates over the domain actions contained in O (lines 2-14); where, for each action, it extracts the action's functor a_i and the positive/negative preconditions $\alpha^+_{a_i}$, $\alpha^-_{a_i}$. The effects $\beta^+_{a_i}$ and $\beta^-_{a_i}$ are omitted, since they are not used.

Algorithm 2: GeneratePastFOLTL.

Data: the set of planning operators O
Result: a set of Past FO-LTL properties

```
1  result = { };
2  for ⟨a_i, α+_{a_i}, α−_{a_i}⟩ ← O do
3      ⟨x_1, D_1⟩, ⟨x_2, D_2⟩, ..., ⟨x_n, D_n⟩ =
         getParameters(a_i);
4      φ_x = ∀_{x_1∈D_1}.∀_{x_2∈D_2} ... ∀_{x_n∈D_n};
5      φ_p = true;
6      for pre ← α+_{a_i} do
7          φ_p = φ_p ∧ (¬pre− S pre+);
8      end
9      for pre ← α−_{a_i} do
10         φ_p = φ_p ∧ (¬pre+ S pre−);
11     end
12     φ^{FO}_{a_i} = φ_x (a_i → ⊖φ_p);
13     result = result ∪ {φ^{FO}_{a_i}};
14 end
15 return result;
```

Since the preconditions are taken from O, they contain variables (*i.e.*, are not instantiated). Because of this, the algorithm has to obtain the action's parameters (line 3). For instance, if $a_i = right(r,x,y)$ (as in previous examples), then $getParameters(a_i)$ returns the r,x,y parameters. We need to know the variables used by the action in order to create the corresponding universal quantifier in the FO-LTL formula (line 4). Where for each parameter x_i that is extracted, we add a corresponding universal quantifier $\forall_{x_i}$. The algorithm then continues similarly to Algorithm 1, with the creation of φ_p, which denotes the preconditions in Past FO-LTL (lines 5-11).

Note that even though the instructions are the same of Algorithm 1, here the preconditions are not instantiated. Indeed, they are directly extracted from $\alpha^+_{a_i}$ (resp. $\alpha^-_{a_i}$) and may contain variables. Nonetheless, this is not an issue since all parameters were previously extracted and the corresponding universal quantifiers were added (lines 3-4); so, no variable in φ_p is free. The algorithm concludes by combining the different parts of the formula (line 12), which consists in the quantifiers (first), followed by the implication which links the action a_i with its preconditions φ_p. We need $\ominus$ to require the preconditions to be met in the previous time step. In this way, when the action a_i occurs, we know that the preconditions are met. This Past FO-LTL ($\varphi^{FO}_{a_i}$) is then stored inside the *result* set (line 13). After iterating over all the planning operators of O, the resulting set containing all Past FO-LTL formulae is returned (line 15).

We consider a planner $\langle P, O, S_0, G \rangle$ to generate the corresponding set of Past FO-LTL formulae that check the preconditions, *i.e.*,

$GeneratePastFOLTL(O) = \{\varphi^{FO}_{a_1}, \varphi^{FO}_{a_2}, \ldots, \varphi^{FO}_{a_n}\}$. Finally, given the set of properties that are generated, we can create a single global Past FO-LTL formula as $\varphi^{FO} = (\varphi^{FO}_{a_1} \wedge \varphi^{FO}_{a_2} \wedge \ldots \wedge \varphi^{FO}_{a_n})$. Again, we need the conjunction of these formulae because we need to check that all actions' preconditions are always met. Following the monitor for Past LTL formula explained in the previous method, we can then compute the monitor function for φ^{FO} using the algorithm presented in (Havelund et al., 2020) which constructs the monitor as a Binary Decision Diagram (BDD).

Algorithm 2 also terminates in PTIME (specifically linear time) with respect to the size of the planning operator set O given as input. This is further illustrated with the results shown in Section 5.2.

4.3 Fault Detection

Up to now, we have shown two different methods for synthesising temporal properties from actions preconditions. Such properties can then be used for generating runtime monitors to check the system execution. This is usually obtained in RV by instrumenting the system under analysis in such a way that every time something of interest happens, the monitor is informed about it. In our case, the monitor is informed when an action is performed, or when new perceptions are available.

In this work, the monitors have been generated through Algorithm 1 and Algorithm 2 using actions preconditions. Consequently, when a violation is reported by a monitor, we conclude that one of such preconditions does not hold at execution time. This fault detection mechanism can be used by the system to properly react in order to avoid unexpected behaviours. For instance, let us suppose the action to be performed is *right(r, cell_0-0, cell_1-0)*. One of the preconditions for the action to be performed is that *cell_1-0* has to be empty (*i.e.*, *empty(cell_1-0)*$^+$). If at runtime, the monitor looking for the action's preconditions finds that *empty(cell_1-0)* is not true (*i.e.*, *empty(cell_1-0)*$^-$), then the resulting violation can be used to avoid the rover to crash against the object occupying *cell_1-0*. This problem could be caused by an outdated representation of the system used by the planner to generate the plan. The cell was empty at planning time, but not at execution time.

We focused on preconditions because most of the time the effects of an action are preconditions for the next one. In future work we will consider monitoring the effects as well, however, the automatic translation of effects require additional features. For instance, we will need to add a notion of intervals of time in which the effects of an action have to be observed. Differently from preconditions, effects require a glimpse of the future, and even if it is feasible we preferred to focus on a more intuitive and direct transformation of the preconditions. From the viewpoint of safety requirements, preconditions were the most relevant aspect to monitor.

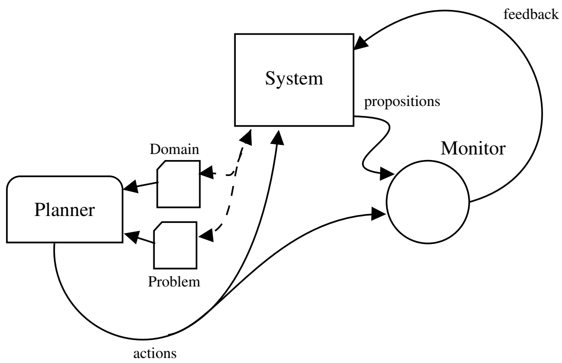


Figure 2: RVPLAN overview. Dashed lines represent relation, solid lines represent communication.

In Figure 2, an overview of the general fault detection approach is shown. In this overview we have the system under analysis, the planner, and the monitor. Using the system, the input files for the planner can be generated (domain and problem files). With these files, the planner creates a plan to be executed on the system (the actions). The monitor is automatically synthesised from the temporal properties generated by translating information obtained from the planner (Sections 4.1 and 4.2), and then deployed to verify at runtime the assumptions made during planning. If the monitor detects a violation, the system is informed about it.

What the system does with the feedback received from monitors and what role the monitors play in further failure handling (*e.g.*, replanning or plan repair) is out of scope for this paper. We discuss some ideas for future work towards tackling some of these topics at the end of this paper.

5 EVALUATION

To evaluate RVPLAN, we implemented both monitor generation methods, as well as simple interfaces between planner, monitor, and environment. Our implementation is validated through the running example we presented in Section 3. Finally, we report the results of experiments about the computation time for the translation of the planner's assumptions, the synthesis of the monitors, and the runtime verification.

5.1 RVPLAN Implementation

We developed[4] our tool in Python and Scala. Specifically, we implemented the property generation (Algorithm 1 and Algorithm 2) in Python, and the monitor synthesis (from the property) in Scala. The Python implementation is straightforward and derives from the algorithms presented previously. The user can select which method to execute by passing different parameters to RVPLAN.

To generate an instantiated monitor, it is required to pass the domain file from which the Python script extracts the O set needed in Algorithm 1, as well as the plan obtained by the planner. We do not restrict which planner is used as long as it handles STRIPS/PDDL, which is the language the Python script expects for the domain file. The script then goes on to instantiate the high-level steps presented in Algorithm 1, and to produce the Past LTL property.

To generate a parameterised monitor, then it is only necessary to pass the domain file, since Algorithm 2 only needs O to extract the domain actions. The script then goes on to instantiate the high-level steps presented in Algorithm 2, and to produce a Past FO-LTL property.

It is important to note that in both cases the Python script generates a `.qtl` file. This is due to the fact that we chose the DEJAVU library[5] (Havelund et al., 2018) to synthesise the monitors. DEJAVU supports both Past LTL and Past FO-LTL, therefore, we can use the same formalism to denote the temporal specifications generated by our algorithms. Once the `.qtl` file has been generated, DEJAVU compiles it into its corresponding Scala implementation. This is the monitor that will then be used at execution time.

5.2 Experiments

We carried out different experiments to evaluate our tool. We focused on three different measurements: (i) the time required to translate the planner's actions into temporal formulae; (ii) the time required to synthesise a monitor from the temporal formulae; (iii) the time required to perform the actual verification with a monitor at runtime.

In Figure 3a, the execution time for synthesising the temporal formulae is reported. Unsurprisingly, the parameterised method performed very well, since it is not influenced by the plan length. While the instantiated method exposed a linear behaviour with respect to the plan length (as pointed out in Section 4.1). Nonetheless, the time required for both methods is less than a tenth of a second.

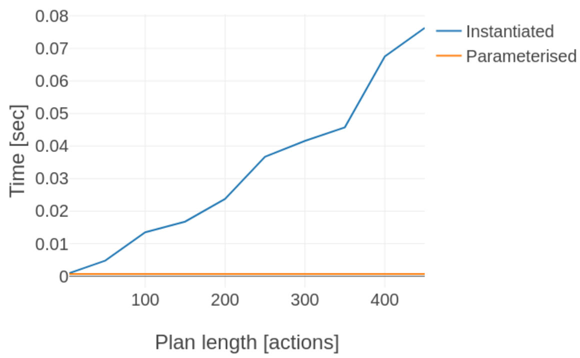
In Figure 3b, we report the execution time for synthesising the monitor given the temporal formulae generated in the previous step. The time required to synthesise the parameterised monitor is constant, since the formula generated at the previous step does not change when changing the plan length (it only considers the set O). The synthesis of the instantiated monitor instead exposed a linear trend once again. This is due to the fact that by increasing the size of the plan, it increases the size of the formulae to use to synthesise the monitor (proportionally). However, here there is a much larger gap between both methods. While the instantiated method is shown to be quicker up until a plan length of around 70, it scales poorly after that point when compared to the constant time of the parameterised method. This brings us to conclude that a hybrid method could be used to improve performance in online scenarios where the generation of the monitors is required to be done on the fly (for example, when the specification of the planning operators can change at runtime and/or new plans are generated). For instance, if we have a plan length of around 70 or less, then it would be better to call the instantiated method, otherwise, the parameterised method should be used. Specifically, we could use the instantiated method by default while we compute the parameterised one in the mean time. By the time the parameterised method is computed, the system has been constantly monitored using the instantiated monitors.

In Figure 3c, the execution time of the actual monitors is reported when scaling the number of events. Both monitors require linear time to verify an event trace; but the instantiated method has a steeper slope. This could be caused by a less optimised internal representation of the monitor, or the fact that we are using Past LTL with the instantiated method and Past FO-LTL with the parameterised method.

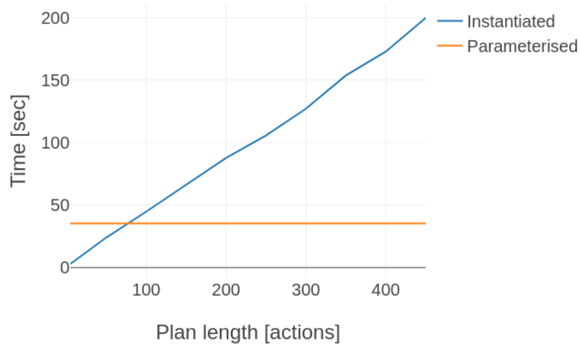
It is important to note that Figure 3b and Figure 3c are related to the performance of the DEJAVU library. Our methods aim to generate the temporal properties, leaving the monitor synthesis and runtime verification to DEJAVU. This means that the first part (Figure 3a) is general and can be reused, while the second part (Figures 3b and 3c) is implementation dependent (we could pick another monitor tool to substitute DEJAVU, which may provide better/worse results).

[4]Zip file with source code: http://www.filedropper.com/rvplan_1 (GitHub repository will be made public if accepted).

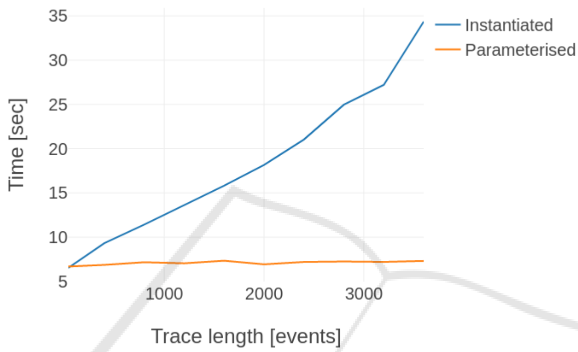
[5]https://github.com/havelund/dejavu



(a) Property synthesis.



(b) Monitor synthesis.



(c) Runtime verification.

Figure 3: Results of experiments.

6 CONCLUSIONS

We have shown how to automatically synthesise monitors to detect failures at runtime in a plan generated by a classical planner. RVPLAN offers two methods for generating monitors: based on instantiated actions in the plan that the planner has sent as output; or based on the actions in the domain specification. The former is best when the plan's length is not large; the latter is more appropriate when the plan's length is large but there are not as many planning operators.

Note that the parameterised approach outperforms the instantiated one, except for monitor synthesis. Because of this, none of the two can be considered the best, in general. Instead, a hybrid combination could be beneficial; where the instantiated approach is used while the parameterised one is synthesising the monitor. In this way, the time needed by the parameterised approach for synthesising a monitor can be covered by the instantiated one. Upon synthesis completion, the instantiated monitor can be swapped with its parameterised counterpart which, as experiments showed, offers better verification performance.

As future work, we want to use the feedback generated by RVPLAN monitors to trigger replanning and use information obtained during verification to update the planning model. Initially, we are looking into only updating the problem representation, that is, updating the values of predicates that could have changed and caused the plan to fail. Eventually, we want to extend these monitors to also be able to aid the planner in plan repair, not only updating the problem specification, but also reconfiguring action specifications in the domain.

We also want to translate the effects of actions as well, but this may require a logic that allows us to define interval properties (such as Metric Temporal Logic (Koymans, 1990)) and could benefit from using durative actions found in temporal planning. Another avenue for future work is to extend our theory to include PDDL requirements such as disjunctive, existential, universal, and quantified preconditions, among others. Finally, we want to apply RVPLAN to realistic case studies. For example, in robot applications developed in ROS[6] we could take advantage

[6]https://www.ros.org/

of the ROSMonitoring (Ferrando et al., 2020) tool to generate our monitors for ROS applications.

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