Plan Execution with Dynamic Goals

Paper #

Abstract

Introduction

Substantial research effort in robot planning has revolved around how plans are executed and how threats to robust execution can be dealt with in-situ. This is particularly important in dynamic and unpredictable real-world environments where plans can and do change rapidly and the robotic agent is expected to be responsive to such exogenous change. Often this focus has been driven by the need to replan given a fixed set of goals a priori, where such objectives are known and do not perturb the planning and execution process.

In this paper, we argue that the impact of asynchronous arrival of goals and their consequent impact on execution is important in dynamic and unpredictable environments especially during robotic exploration. Our robotic domain deals with benthic as well as upper water-column exploration using autonomous underwater vehicles (AUVs), which are untethered and propelled. For instance, in bathymetric surveys of subduction zones, AUVs are used to augment limited ship time to deal with largely unexplored areas of coverage. Even so finding hydrothermal vents is challenging given large spatial areas, noisy sensors and low signal/noise ratio as also the harsh environment in which the AUV has to survive. Identifying vents is painstaking; inadequate sensors and lack of closed loop bathymetric control, requires scientists on ship analyse previous surveys to inform the current AUV deployment. This often means that the vehicle can be re-tasked with new goals while executing one or more current mission objectives. AUV deployment in such cases often occurs over multiple phases (Yoerger et al. 2007); to minimize station time on site, the AUV is redeployed after each phase after a vehicle recharge while data analysis from the past survey continues. Consequent analysis then provides the impetus to retarget when new scientific targets are generated on ship.

While substantial literature exists to deal with agent reactivity and replanning in the face of execution uncertainty, the ability of a robotic agent to systematically deal with dynamic goal is less well studied. In this context, we emphasize the need for planning and plan execution in-situ to enable tight closure of control loops for the robot's responsiveness. Doing so, leverages the ability to dynamically add new objectives to the agent during mission execution instead of being forced to specify them beforehand and is the context of this paper. While such capabilities allow for more flexible and autonomous missions it also makes the overall misson execution more challenging.

In the pursuit of planning in a dynamic environment, earlier work done in `IPEM` (Ambros-Ingerson and Steel 1988), `ROGUE` (Haigh and Veloso 1998), and the LAAS Architecture (Alami et al. 1998) have all helped to make real-world planning possible. Based on these past successes, there have been multiple experiments that have successfully functioned in the real-world, the Remote Agent Experiment `RAX` (Muscettola et al. 1998a), the Autonomous Spacecraft Experiment `ASE` (Chien et al. 1999) and more recently the Teleo Reactive Execution `T-REX`(McGann et al. 2008; Py, Rajan, and McGann 2010). In all these systems, generative plans are dispatched for execution using rich representations that deal with durative actions and resources (Lemai-Chenevier and Ingrand 2004), the focus of our work here.

In particular, our focus is on constraint-based temporal planning (Frank and Jónsson 2003; Lemai-Chenevier and Ingrand 2004) with a demonstrated capability for real-world planning and execution. Most of these approaches often implement least-commitment planning and generate a solution that does not commit to specific values (e.g., action start and end times) unless explicitly required by the model. Such flexibility puts the burden on the plan executive to decide at which time within all possible values, a specific action can be dispatched. The challenge is deciding whether the next possible set of action(s) should be started immediately or if it should be postponed for a later start date.

Starting actions as early as possible avoids procrastination and tends to reduce plan brittleness. This choice is motivated by the intuition that starting actions early provides more room in the future to deal with worst case execution scenarios. While this solution works in the classical case where all the goals of the agent are known a priori, it can be problematical when new objectives are added during the course of mission execution. For example, the agent may prematurely leave an area before new objective for this area are formulated. On the other hand, waiting inordinately could wast time and leave less flexibility for coping with diverse execution scenarios. In this context, it is important for the agent to make a distinction between actions that can be taken proactively versus other actions that may not be urgent.

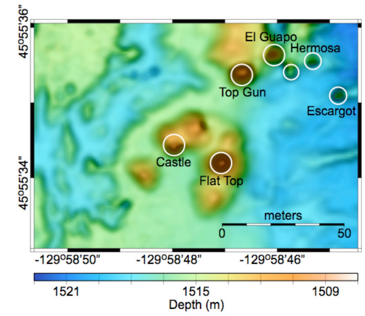
In this work, we propose a systematic approach to allow the agent to make such a distinction for each action by tracing the causal relations between goals within the current plan. This allow us to determine the best dispatch strategy based on the nature of the goals this action contributes to.

The structure of this paper is as follow. We introduce an example illustrating the problem of flexible plan execution. We then discuss previous works and how they tend to focus on a single policy or not consider the possibile emergence of new goals during the mission. We then present algorithmic solutions that allow to decide at execution when actions should be started. Finally, after presenting the results, we conclude and discuss potential directions for future research.

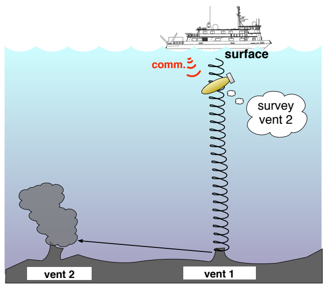
An Illustrative Example We define a simple autonomous underwater vehicle (AUV) mission that will be used to illustrate the benefits of our approach compared to previous ones and the major issues that arise when dispatching. First, the AUV can be at a location or be traveling to one. Second, the AUV has a few basic actions that allow it to function within the environment. It can go to a location, survey a location, and sample a location. In a typical AUV mission, the scientist will want it to survey and sample a location and, if needed, be redirected on the fly to a new location for surveying and surveying.

However, an issue with finding a balanced approach is deciding whether to start an action as early as possible — which we will call *proactive* — or wait until the action should necessary start — called later *deferred*. There is a clear difference between the two approaches but when should, for example, the AUV wait or start early? We demonstrate a scenario where the AUV ideally uses the two approaches at different times. The initial problem is illustrated in Figure 1.

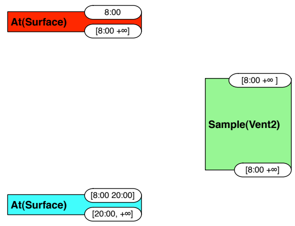
The AUV mission starting at 8 AM needs to *sample vent2* and return to the *ship* by 8 PM. The AUV starts traveling immediately to *vent1*. Considering that that it takes one to two hours to go from the *Surface* to *vent1*, roughly ten minutes to go from *vent1* to *vent2*, and more than two hours in order to *survey* and *sample*, a general plan solution is presented in Figure 2. The plan presented here is partially instantiated giving the



(a) Bathymetry of vent sites off of NW United States



(b) An illustration of our domain



(c) Initial problem

Figure 1: 1a shows bathymetry of actual vent sites off the coast of Oregon. A description of a hydrothermal vent problem with an illustration of the domain (1b) along with the initial partial plan for this problem (1c). In this domain our AUV is initially at *Surface* at 8am, he wants to survey *vent 2* and needs to be back at *Surface* before the end of its mission at 8pm (noted 20:00 here).

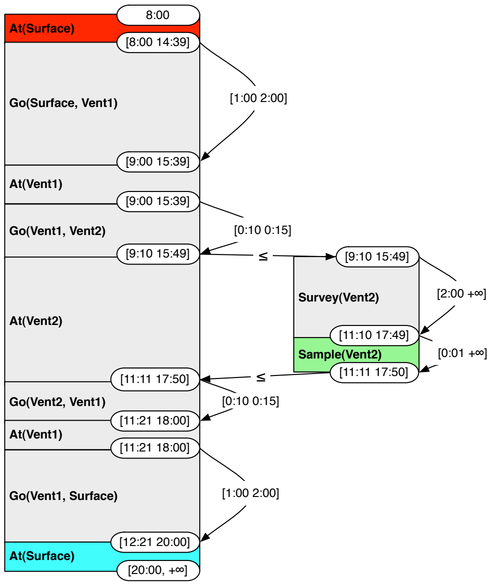


Figure 2: The flexible plan solution of our domain in Fig. 1

AUV the freedom to decide *when* to start each action within the valid boundary of the solution. For example, the AUV should go early in order to *sample vent2* so that the scientists have the a possibility for requesting more tasks. Conversely, heading back to the surface early would waste valuable time, roughly two hours, if the scientists decide they want to *survey* another location. Though by 6pm, it should go to the surface so the scientists can pick it up by 8pm. In this scenario, we see that the AUV alternated between deciding to execute actions early or *defer* them depending on the nature of the action it needed to take next, or more accurately the nature of the objectives related to this action. The AUV was *proactive* on traveling to *sample vent2* because the scientists want it to be completed. On the other hand, the AUV has to return to the surface by 8 PM, however, the scientists don't explicitly want this done, allowing it to procrastinate. By doing so, the AUV is available to complete new tasks given to it by the scientist.

While this example may appear academic at first, it reflects situations we have seen within embedded agent execution in our domain. Indeed, we do daily operations wehere our AUV is deployed and scientists can remotely send new objectives as the mission goes along to the vehicle as they see new areas of interest. Especially in the upper water column the nature of the area to be examined depends highly on the dynamic of the ocean itself and is difficult to predict beforehand. Therefore, scientist can use data sampled by the AUV or other sources (eg satellite data, ship based observations, ...) during the beginning of the operation in order to give it better informed objectives for the rest of the operation. At the same time the vehicle has also operational objectives such as going to a place where its recovery will be easier for operators. This gives a similar distinction between the science objectives and operation objectives. Similarly to our example we do not really want the AUV to get back to recovery area too early as a new science goal could be sent to it which in turn would rather be fulfilled as early as possible.

This paper discusses the problem of dispatching when trying to execute a plan. In particular, dispatching in a dynamic environment where the plan is expected to change due either to unanticipated events or external requests with new directives. External requests can occur at any time which make them in essence uncontrollable events. Specifically, we focus on how these new requests, coming from the external world, alter the way we need to dispatch the plan, rather than how they will be integrated into the plan or any part of the planning process. The reason for our separation from planning is that oftentimes planning and executing are split up into two different jobs. Often times a robotic agent is given an already created plan, and it must then choose when to execute parts of the plan. Therefore, our focus is on developing a method for dispatch a plan, after it has already been created, while understanding that new requests may come in the future.

The approach we have taken on dispatching looks at the token level of a plan, specifically at tokens generated from external requests which we define as goals. Because they have been requested by an external person with the intent of being completed promptly, they have a high priority. In contrast, there are tokens that only describe the evolution of a timeline, which we define as non-goals. In order to keep the plan valid, the agent is obligated to complete the non-goals, but there is no rush. Thus, the non-goals have a low priority. Therefore, we want to complete the goals as early as possible in order to give adequate time for the possibility of new goals, and complete the non-goals as they become necessary for the validity of the plan. Some may argue that finishing the goals early doesn't guarantee that there will be enough time for new goals, however, that is an issue with planning, and our concern is whether dispatching caused the waste of time.

Previous Approaches to Dispatching

Dealing with plan execution is not a new problem and we can find a lot of work that relates to this over several decades. Still, it is pretty rare to see work that envisage that actions could be postponed except when this is necessary to not break the current plan.

The most prominent work is related to the dispatchability of simple temporal networks (STN) (Muscettola, Morris, and Tsamardinos 1998). The core of the problem is to ensure that the temporal constraints can be propagated efficiently within the plan in order to allow the executive to decide quickly whether an action should be started or not while ensuring the plan consistency. In order to accomplish such a task, the STN supporting the plan to be dispatched is transformed into a All-Pairs network and stripped of unnecessary edges, often resulting in a more compact temporal network that lessens the propagation cost of updates. The role of the executive is to select time-points within the current execution bounds and propagate its value within the simplified network. Still, while this work contribute to ensure that execution time are correctly propagated within the plan with a limited cost, it does not directly address how to decide what value should be set for a given time-point in the scope of its possible values. More specifically it is still the role of the executive to decide whether it should start an action as early as possible or consider it as not urgent.

When dealing with least-commitment planning solution this decision is deferred to the plan executive. For example in (Muscettola et al. 1998b), the executive is defined as having two responsibilities: the selection and scheduling of plan events for execution. The executive needs to be highly reactive as it is necessary to function in a real-time environment. One solution offered for dispatching events efficiently is the proactive approach. This approach greatly reduces the plan flexibility, and therefore robustness, as all start time-points are grounded to a specific value which is compatible with the initial constraints.

While in the common case this might be acceptable it may become problematic when put in he context of potential new objectives emerging during the mission. Take our AUV example, and apply the proactive approach globally — assuming that all actions can be completed on their minimum time. As shown in Fig. 3, the proactive approach allows the AUV to *Sample Vent2* before noon but as continue through the plan it results in the AUV getting back to the *Surface* by 12:21 and being stuck in the context of the current plan for the next 7 hours and 39 minutes. Should the scientist want to *Sample Vent1* the AUV will then be forced to re-plan accordingly and go back and forth between the surface and the locations all other again. By being blindly proactive, the AUV made its overall strategy less efficient than if it took the option to procrastinate at *Vent2* until it needs to get back to the surface.

One case we have seen in literature where a time-point is considered to be deferred is related to the dynamic controllability issue with STNs with uncertainty (STNU). In (Morris, Muscettola, and Vidal 2001), they propose an algorithm that during planning insert wait constraints within the solution temporal network that will allow one time-point to wait until an uncontrollable event occurs. In this case, the deterrence of the execution of this time-point is enforced in order to ensure robust plan execution despite exogenous uncontrollable events. In (Gallien and Ingrand 2006), this approach is further discussed along with the Makespan issue while dealing with least-commitment planners which can insert unjustified waits within the plan potentially decreasing in turn the overall performance of the system. Both of these approaches show that when dealing with

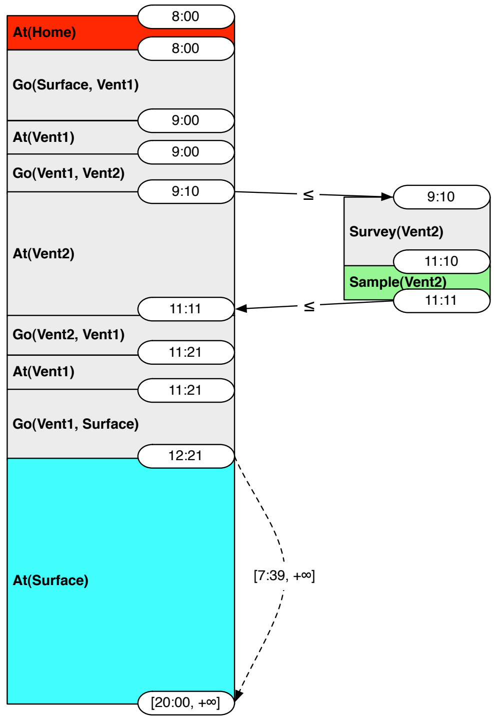


Figure 3: proactive solution for the plan from Fig. 2

uncontrollable temporal constraints – such as for example the duration of a navigation task which depends on external factors – it is necessary to defer some actions in order to ensure the plan execution.

An alternative approach is related to work with soft constraints within the temporal domain indicating preferences on actions timing such as in (Khatib et al. 2001). This should provide a general solution for users to specify whether actions of the plan should be preferably started. One problem with general frameworks dealing with soft constraints though is their poor performances (Bartak 2002) as the general problem is NP-hard. Even though it can be reduced to a more tractable (polynomial) solution by specifying preferences as convex functions (Rossi et al. 2006), the complexity is still cubic in relation to the number of variables. Moreover the solutions proposed do optimize the plan *a-priori* reducing then the plan flexibility which in turn makes it more prone to failure during execution.

Our work is complementary to much of the previous work. While we do not explicitly deal with dynamic controllability, our approach is not inconsistent with that work. In any case, our focus is not on the observation of events during execution but rather on the possibility of new objectives arising at any time, and we want to avoid doing actions that are not “urgent” in order to preserve the context for those objectives. Similarly, we have not implemented temporal preference specification during planning, which has the effect of limiting execution-time flexibility. Our intent is to defer temporal decisions to the executive allowing it to adapt the plan to new objectives without heavily relying on plan-repair or re-planning solutions that could badly impact system reactiveness.

Planning Definitions

To consider the overall planning and plan execution within an agent we use the definition of a temporal domain, planning problem and solution as provided by (Nau, Ghallab, and Traverso 2004):

Definition 1 *A temporal planning domain is a triple* $D = (\Lambda_\Phi, O, X)$, *where:*

- Λ_Φ *is the set of all temporal databases that can be defined with the constraints and the constant, variable, and relation symbols in our representation.*
- O *is a set of temporal planning operators.*
- X *s a set of domain axioms.*

Definition 2 *A temporal planning problem in* D *is a tuple* $P = (D, \Phi_0, \Phi_g)$, *where:*

- $\Phi_0 = (F, C)$ *is a database in* Λ_Φ *that satisfies the axioms of* X. Φ_0 *represents an initial scenario that describes not only the initial state of the domain but also the evolution predicted to take place independently of the actions to be planned.*
- $\Phi_g = (G, C_g)$ *is a database that represents the goals of the problem as a set* G *of tokens together with a set* C_g *of objects and temporal constraints on variables of* G.

Definition 3 *A plan is a set* $\pi = \{a_1, ..., a_k\}$ *of actions, each being a partial instance of some operator in* O. *We define* λ *as the state-transition function.*

π *is a solution of a problem* $P = (D, \Phi_0, \Phi_g)$ *iff there is a database in* $\lambda(\Phi_0, \pi)$ *that entails* Φ_g.

In this work, our focus is on executing a given plan π which was computed by the agent planner. However, in order to reflect the dynamic interaction of the agent with its environment we need to refine the definition of the sets Φ_0 and Φ_g.

Indeed as the world evolves new observations (or refinement of existing ones) are added into Φ_0. Similarly, the agent operator can request new future goals to be added to the agent Φ_g as mission time advance. We note $\Phi_0(t)$ and $\Phi_g(t)$ the value of these sets at the timepoint t. For the sake of simplicity we consider that alteration of these sets is purely additive with time:

$$\forall \{t, t'\} : t \leq t' \Rightarrow \Phi_0(t) \subseteq \Phi_0(t') \wedge \Phi_g(t) \subseteq \Phi_g(t')$$

The dynamically growing nature of Φ_0 reflects the cumulative observation as the agent execute its plan π. In nominal situation new elements of Φ_0 are refinements the plan – for example by asserting that a planned command just started[1]. We also consider that the agent can receive at any point new objectives that will be added to Φ_g. This assumption have an impact on how it is preferable to handle plan execution. Indeed while deciding when to start an action within the plan, one need to make sure that the execution of this action will not limit the ability fo the agent to treat potential future emerging goals. In the light of it the agent should at the best of its knowledge try to balance the impact of the next available action as early as possible or prefer to delay it in the eventuality new goal occur. In our example, it was making sense to go to Vent2 early, but on the other hand going back to the surface too soon would result on the current plan locking the AUV – within its current plan – at Surface until 8 pm. The solution providing the most freedom for the AUV was therefore for it to alternate between the two policies depending on the action impact.

[1]This preclude situations where new observations invalidate the plan which is out of the scope of this paper

In order to help the AUV have a better knowledge on the nature of the goals we do consider that each goal provide information on its priority. In that purpose, we define that Φ_g is partitioned into 2 sets:

- the internal goals Φ_{gi} which represent goals the agent *need* to maintain internally. These goals will be considered as objectives that are not of the higher priority and therefore their actions can be deferred during execution.
- the external goals Φ_{ge} which represents the goal received by the agent externally. As these goals are requested by the user, we consider them as to be of higher important – ie the agent *wants* to execute them. Therefore, their execution should be preferrably proactive.

At any point we need to evaluate an action within our plan π we consider that this plan is up to date and provide a solution of all the goals of both Φ_{gi} and Φ_{ge} that can reasonably be done within the current mission scope.

Proposed algorithms

As a new action can be dispatched for execution, the executive needs to evaluate how it relates to the goals of the plan. Intuitively if this action was generated by (or contribute to) an internal goal of Φ_{gi} it needs to be taken proactively, while otherwise we can consider it as non-urgent. Therefore, when evaluating if the token representing this action within the plan the executive needs to do a forward search on the causal links related to this token to see if they lead to an internal goal as implemented in Algorithm 1

Algorithm 1 The function *DispatchToken* finds if there is a goal in Φ_{ge} that is connected to the token, t, and, if so, dispatches the token.

```
function DispatchToken(Token T)
    BooleanGoal = SearchForGoal(T)
    if Goal = True then
        return Dispatch T
    else if T start upper bound ≤ upper bound for the current tick then
        return Dispatch T
    else
        return Don't dispatch T
    end if
end function
```

Algorithm 2 The function *SearchForGoal* does a Forward search looking for a token that is in the set Φ_{ge}.

```
function SearchForGoal( Token T )
    List Search = Action(s) that T is a Condition
    for all Action(s), A, in Search do
        for all Effect(s), E, of Action A do
            if E is a Goal in Φ_ge then
                return True
            else if E is a Condition of an Action A_c then
                Add A_c to back of list Search
            end if
        end for
    end for
    return False
end function
```

This Algorithm is the central deciding point for how a token should be dispatched. By finding out that a token is connected to a goal in Φ_{ge}, we conclude that the token is a sub-goal, and thus dispatch it immediately being proactive. On the other hand, if the token is not connected to a goal then we defer dispatching it until necessary. This demonstrates our distinction between how we dispatch tokens, proactive or deferred.

A crucial part for deciding how to dispatch a token is finding whether the token in question is connected to a goal in Φ_{ge}, call it G. Algorithm 2 does the function of searching for G in a forward-search manner. We define a causal link within our plan that must be met in order for our search to function.

Definition 4 *A causal link is defined as linking a goal as an effect of an action whose conditions are needed in order to complete the goal and, thus, are subgoals. This link can be recursive as the conditions themselves may be the effect of an action causing a causal chain to build.*

During our search, if we find G then we know that the original token is part of the solution for completing G. As such, we want to be proactive with completing the token early so as to ultimately complete G. If we don't find G then the token has no connection to an external request. The token still needs to be dispatched, however, there is no one explicitly requesting it to be accomplished. Thus, there is no reason to be proactive.

This algorithm is equivalent to a breadth first search along the planning structure starting from the action we need to evaluate. Therefore, its complexity is $O(N+E)$ where N is the number of tokens within the plan and E the number ofcausal links that relate these tokens.

Dynamic solution during planning

Searching for a goal as Algorithm 2 does can be quite computational expensive particularly if there are many tokens that are continuously being dispatched. Completing a full search every time a token needs to be dispatched can severely slow down the execution process, which needs to remain quick to ensure proper execution. Therefore, our next algorithmic approach distributes the full search within the creation of the plan. Resulting in spreading out the full cost of the search. In order to not repeatedly search the plan, we save the tokens that are connected to a goal in Φ_{ge} found during the search. In this way, we acquire a list of tokens, $List_{goals}$, that should be dispatched early.

An alternative solution is to embed the propagation of these value during the planning search. The algorithm uses the same dispatching method as algorithm 1. The difference is that rather than searching for the goal using algorithm 2, it only searches the list, $List_{goals}$, to see if the token is in it. The actually searching for the goals and causally connected tokens happens in algorithms 5, 7.

Algorithm 3 Saves goals as they are added to plan

```
function NotifyAdded( Token T )
    if T is a Goal in Φ_ge then
        Insert T into List_goals
    end if
end function
```

Algorithm 4 Removes the token after it is removed from the plan

```
function NotifyRemoved( Token T )
    Remove T from List_goals
end function
```

Algorithm 5 Searches for tokens connected to goals

```
function NotifyActivated( Token T )
    if T is a goal in Φ_ge or T is linked to a goal through one causal link then
        Recursively search the reverse causal link and add the tokens into List_goals
    end if
end function
```

Algorithm 6 Deactivates token in plan

function NOTIFYDEACTIVATED(Token T)
 if T is not a goal and not one causally linked to a goal **then**
  Remove T from $List_{goals}$
 end if
end function

Algorithm 7 Searches plan when tokens are merged

function NOTIFYMERGED(Token T)
 if T is goal in $List_{goals}$ **then**
  Recursively search the reverse causal link of the active token merged with T and add tokens to $List_{goals}$
 else if The active token of T is in $List_{goals}$ **then**
  Recursively search the reverse causal link of T and add tokens to $List_{goals}$
 end if
end function

Algorithm 8 Removes token when split

function NOTIFYSPLIT(Token T)
 if T is not a goal or not one causally linked to a goal **then**
  Remove T from $List_{goals}$
 end if
end function

In order to distribute the search, we situate our algorithm within the planning search of the Europa Planner,(Frank and Jónsson 2003), which offers callback functions for when a token in the plan is altered. The majority of the searching happens when tokens are either activated or merged. For a token to merge with another token it has to be compatible with another token already in the plan. Splitting happens when they are no longer compatible. We have designed our algorithm around the Europa Planner, however, we believe that the general approach can work on any other planner.

Taking full advantage of the planning search, we use a backwards search from the goal following the reverse causal link to the connected tokens. We fully search from the goals because we know that all the tokens connected through the causal link are sub-goals. By contrast, fully searching each token could be wasteful because there is no certainty that it will be linked to a goal and, therefore, could bring little value to our search. However, some tokens may get added to the plan or linked to a goal after we have already searched the goals. Therefore, for every token we do a local forward search of one causal link to verify if it is connected to a goal in our saved list. If so, we do a full backwards search from the token since it has now proven to be valuable. After the plan has been searched, it is as easy as searching a list for a token to see if it should be dispatched early or be deferred to later.

This approach is potentially more costly than the previous algorithm as it needs to do local updates whenever the plan is altered by the search including retracting past updates if a backtrack occur during the search. Still it is compelling in the fact that this cost occurs during planning reducing the decision problem during execution to simply check if the given action has been marked during planning. It has been the solution we have preferred within our system for this reason as it is functionally equivalent to previous algorithm while reducing extra computation cost as the plan is executed. Planning phases occur within the plan only when either the initial plan failed to execute or the set of goals has been altered. Therefore, it is safe to assume that planning should occur more sporadically than execution decisions which then give an edge to this latter algorithmic solution.

Experimental results

Need to present here both practical results that illustrates the outcome of our solution and how it benefits … eg show a case where new goals are introduced as we go along

Also need some analysis – potentially numerical – on the overhead and impact fo both solutions relative to each other but also potentially to a more direct classic approach. To finally discuss why one solution was preferred on our system

Our experiment follows that of the original plan given in Fig. 2. At the beginning, the AUV need to *Sample Vent2* and it has to return to the surface by the end of the mission. We implemented this on our executive with plans being produced by the Europa planning engine (Frank and Jónsson 2003).. Figure 4 demonstrates the resulting plan from our algorithm and will guide our explanation. Both algorithms will result in the same execution of the plan but their approach is quite different.

For Algorithm 1, the search is quite straight forward. For example in Fig. 4, if we are *At Surface* then the next *Go* token will be dispatched. Because the search will follow the causal links forward, where upon, it will find the goal *Sample Vent2* resulting in dispatching proactively. Similarly, this happens for all of the tokens that are starred. The next token to *Go* to *Vent1* is continuously searched but deferred for later dispatching, because it is not connected to a goal. The resulting AUV stays at *Vent2* rather than heading to the *Surface* immediately like in Fig. 3.

For the distributed algorithm approach, each token is checked during the creation of the plan to see if it is an external goal in Φ_{ge}, or connected to one through a causal link. When the *Sample Vent2* is checked, we immediately find that it is a goal. We then follow the reverse causal link and find *Survey Vent2*. However to better illustrate the algorithm, we can imagine that only the *Survey Vent2* has been causally connected to

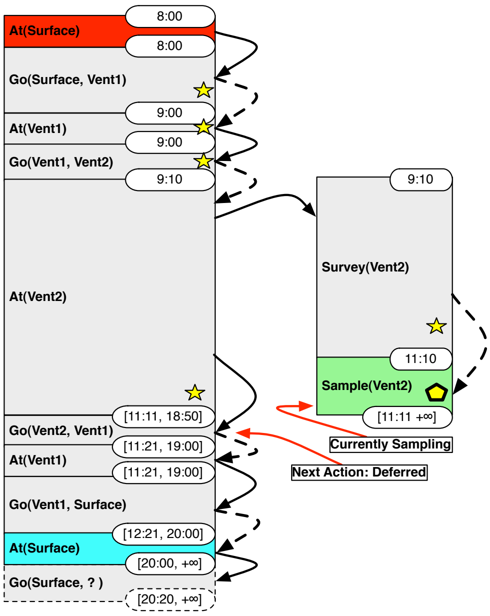


Figure 4: Our algorithm solution for the plan from Fig. 2. Pentagons indicate goals. Stars indicate tokens that were marked as "proactive". Solid lines indicates conditions and dashed lines indicates effects.

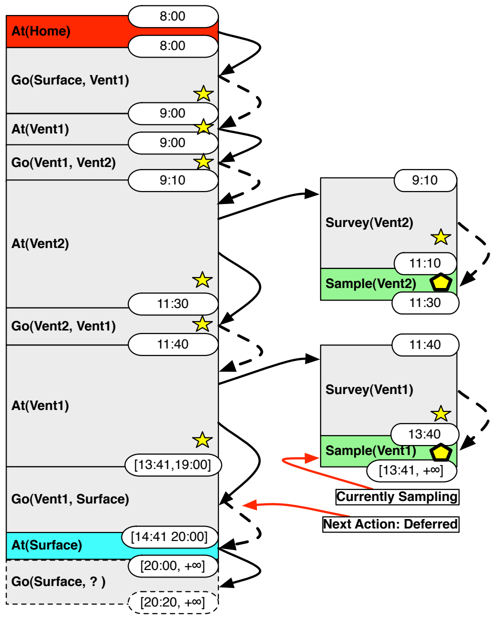


Figure 5: Our algorithm solution after receiving external request for the plan from Fig. 4

the goal so far. Therefore, we only star those two tokens. The path from *Surface* to *Vent1* to *Vent2* has yet to be built. When the path has finally been built, and *At Vent2* is checked, our algorithm searches one causal link and finds *Survey Vent2* which is starred. The search then follows the reverse causal link and stars the rest of the path. The starred tokens will then be proactively dispatched while the non-starred tokens will be deferred until later. Having similar results to Algorithm 1.

Our reasoning for keeping the AUV at *Vent2* is that nothing is requiring it to go *Surface* as soon as possible and that more external requests may come in the near future. To demonstrate this imagine that while the AUV is at *Vent2* it gets a request at 11:30 asking it to *Sample Vent1*. We show the resulting plan in Fig. 5. Again, both algorithms will result in the same conclusion. Algorithm 1 will search from *Go(Vent2, Vent1)* and will now find *Sample Vent1*. The distributed algorithm will find and star the new tokens when the plan gets updated. The resulting new starred tokens will be proactively dispatched.

As the end of the day approaches, the AUV will need to start heading to the surface. At 19:00 both algorithms will find that the *Go(Vent1, Surface)* is still not connected to a goal but that the upper bound time for starting the token has been reached. Therefore, we will dispatch the token because it has become necessary for completing the plan. After returning to the *Surface*, the plan shows that the AUV will then *Go(Surface, ?)* (dashed in the figures). This is an artifact resulting from the plan model which specifies that a *At* token is followed by a *Go*. However, our algorithm will not be dispatching this token as it is not connected to a goal and its upper bound start time ($+\infty$) will not be met.

Conclusion & future directions

As autonomous agents become more and more flexible it becomes difficult to deal with all the possible changes that occur during the mission. While there has already been work around the topic of robust plan execution, they always have been focused on threats coming from execution feedback while not considering how the potential emergence of new goals could impact how the current plan should be executed. In this paper, we discussed this aspect and proposed a solution that relies on extra information on the urgency of an objective. By propagating this through the plan structure, we were able to leverage this information for supporting the plan executive decision starting actions proactively or not. A second algorithm allowed to propagate this information during the planning phase ensuring that the executive can identify this information quickly.

As we stated in the related works our approach does not really address dynamic controllability and has the more classic assumption present in many planning frameworks that time-points are controllable. A side effect of this is that in its current state it may result on the system to decide to defer action as late as possible. In our example, this would result on the AUV leaving Vent1 as late as 19:00 making the rest of its plan brittle to any delay due for example to downward water currents on its way to the surface. This needs to be further addressed in the future and, especially, how our work can be integrated with work presented in (Morris, Muscettola, and Vidal 2001).

Further as of today, we consider that the qualification of the goal is predefined when the goal is submitted by the planner. It is possible though that part of this can be refined on some cases based on the nature of the goal. Looking back at our domain, one can note that the 2 goals provided are constrained differently on their start time; while *Sample Vent2* start time is limited only on its upper bound, the returning to surface conversely is constrained only on the lower bound of its start time. This difference hints on some of the issues we presented. While we do consider that explicit information of these goals help the plan execution to be improved when such information is not initially present. We also are aware that the nature of the constraints within the goal itself can help identify the best policy to be done. It is obvious that for Sampling Vent2 it is better to be proactive on the actions that contribute to this goal. Conversely, the other goal only matter if it appears fairly late in the plan which means that it is probably better to not start completing this part of the plan too aggressively. We plan to further explore how we can refine the distinction between the different policies by using the information provided by the constraints of the different objectives.

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