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A Flexible ANML Actor and Planner in Robotics

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Abstract
Planning in robotics must be considered jointly with Acting. Planning is an open loop activity which produces a plan, based on action models, the current state of the world and the desired goal state. Acting, on the other hand, is a closed loop on the environment activity (to execute command and perceive the state of the world). These two deliberative activities must be integrated and need to handle time, concurrency, synchronization, deadlines and resources. The timeline representation for temporal plan space planning and acting is very expressive; it is also quite flexible for integrating planning and acting. The ANML language is a recent proposal motivated by combining the expressiveness of the timeline representation with the decomposition of HTN methods. This paper reports on FAPE (Flexible Acting and Planning Environment), to our knowledge the first system integrating an ANML planner and actor. Our current focus is not efficient temporal planning per se, but the tight integration of acting and planning, which is addressed by:

(i) extending HTN methods with refinements, given by PRS procedures, of planned action primitives into low-level commands,
(ii) interleaving the planning process with acting, the former implements plan repair, extension and replanning, while the latter follows PRS skills refinements, and
(iii) executing commands with a dispatching mechanism that synchronizes observed time points of action effects and events with planned time.

FAPE has been integrated to a PR2 robot and experimented in a home-like environment. The paper presents how planning is performed and integrated with acting, and describes briefly the robotics experiments and reports on initial performances.

Introduction
Planning is a form of reasoning, through prediction and search, about future changes that can be produced in a system. These changes occur naturally over time. Most contributions to planning abstract away time as state transitions. At an abstract level, this is a legitimate approximation as it simplifies the reasoning. Explicit time is however required in many applications, e.g., for dealing with synchronization with events and others actors, for managing deadlines and time-bounded resources, and for handling concurrency.

Temporal planning comes in two main flavors: extended state space representations and timeline representations. The former is based on states (i.e., snapshots of the entire system) and temporally qualified durations between states. The latter relies on possible evolutions of individual state variables over time (i.e., partial local views of state trajectories), together with temporal constraints between elements of timelines.

Most recent works on temporal planning favor the extended state space representation on the basis of PDDL2.1 (Fox and Long, 2002) with the so-called durative actions. This drive is explained by the wealth of search techniques and domain independent heuristics that have been developed for state space planning, resulting in significant performance improvements. But of a few exceptions, these planners have however a limited handling of concurrency. The timeline alternative representation permits naturally to refer to instants beyond starting and ending points of actions and to handle various kind of concurrency requirements. It is also more flexible in the integration of planning and acting. Timeline planners implement plan-space search algorithms more often than state-space techniques. These algorithms have not scaled up as well as state space planners or HTN planners.

Hierarchical task networks is indeed a planning representation that accounts for numerous deployed applications of significant size. HTN planners benefit from domain specific knowledge expressed as task decomposition methods. In many domains, methods are very naturally formulated. Temporal planning with HTN has not developed as well as with timelines or state space representations.

The Action Notation Modeling Language (ANML) (Smith et al., 2008) is motivated mainly by blending the expressive timeline representation with the decomposition of HTN methods. This paper reports on FAPE, and its planner implementing the ANML language. Our motivation is not efficient planning per se, but the tight integration of acting and temporal planning with task decomposition embedded on a robotic platform. This is addressed by:

• extending planning decomposition methods (Planning)
with refinements of planned action primitives into low-
level commands (Acting), these refinements are currently
brought by PRS decomposition procedures,
• interleaving the planning process with acting, the former
implements plan repair, extension and replanning, while
the latter follows PRS refinements,
• executing commands with a dispatching mechanism that
synchronizes observed time points of action effects and
events with planned time.

The FAPE system currently includes modular compo-
ments to perform Planning and Acting (as introduced in (In-
grand and Ghallab, 2013)).

FAPE includes a first ANML planner that supports a
unique combination of features of least-commitment plan-
space planning, explicit time maintained by a sparse sim-
ple temporal network and hierarchical task decomposi-
tion. There are several motivations for our design choices:
• plan-space planning with least-commitment naturally
supports plan repair, which is essential when acting is a
concern,
• simple temporal network supports efficient consistency
checking and having a sparse network (without saving
constraint propagations) allows us to update temporal re-
lations along with the feedback from execution, and
• hierarchical task decomposition allows for highly scalable
domain adaptable planning.

FAPE has been integrated to a PR2 robot and experi-
enced with in a real home-like environment. This is a work
in progress. A formalization of the planning–acting integra-
tion and a full characterization of the performance of the
system are beyond the scope of this paper. Its contribution is
to present FAPE at the planning, acting, and execution lev-
eels, to describe the robotics experiments and report on initial
performances. The outline of the rest of the paper follows
these steps, preceded by a brief section on the state of the art
and an introduction to ANML.

Related work
Numerous planners implements the PDDL2.1 extended state
space representation with durative actions, e.g., RPG, LPG,
LAMA, TGP, VHPOP and Crickey. Among these planners,
COLIN (Coles et al., 2012) is a notable exception that can
manage concurrency and even linear continuous change.

The timeline approach goes back to the IxTeT plan-
ner (Ghallab and Laruelle, 1994) that reasons on chroni-
cles. A chronicle defines time-points, temporal constraints
between its instants, changes in the values of state vari-
ables, persistence of these values over time, and atem-
poral constraints over state variables parameters and val-
ues. Other planners such as RAX-PS (Jönsson et al.,
2000), ASPEN (Rabideau et al., 1999), Europa/IDEA/T-
ReX (Frank and Jönsson, 2003; Muscettola et al., 2002;
Rajan et al., 2009) and APSI (Fratini et al., 2011), rely on
a similar temporal representation with timelines and tokens
representing change and persistence of the values of state
variables over time. Some of these timelines are directly
connected to actions and percepts (to integrate perception).
These systems express temporal constraints in planning op-
erators using the interval algebra. The organization of the
planner along agents (IDEA) or reactors (T-ReX) offers a
hierarchical representation of the domain. Still the action
models representation with compatibilities (temporal con-
straints over state variables), which tends to spread out the
hierarchical decomposition over more than one compatibil-
ities/reactors, makes them tedious to write and difficult to
debug.

The HTN approach is implemented into several plann-
ers, e.g., Sipe (Wilkins, 1988), SHOP2 (Nau et al., 2003),
SIADEx (Castillo et al., 2006). The latter integrates time to
HTN planning without handling concurrency.

ANML (Smith et al., 2008) extends the languages used
in Europa and ASPEN with recent constructs from PDDL
together with HTN task decomposition methods. We are
aware of ongoing developments on the basis of this lan-
guage\textsuperscript{2}, but to our knowledge, FAPE is the first system
including an ANML planner supporting task decomposition
and temporal planning.

Several systems integrates planning and acting, in partic-
ular with procedure-based approaches to refine actions into
lower level commands with systems such as RAP (Firby,
1987) or PRS (Ingrand et al., 1996). Among these sys-
tems, Cypress (Wilkins and Myers, 1995) (Sipe & PRS),
TCA (Simmons, 1992) (Task Description Language & As-
pen) and XFRM (Beetz and McDermott, 1994) are examples
relevant for our approach. IxTeT-Exec (Lemai-Chenevier
and Ingrand, 2004) and “Configuration Planner” (Di Rocco
et al., 2013) are closer to FAPE since they are based on a
timeline planner, but without decomposition method.

Representation and ANML
The FAPE planner uses ANML as representation language.
ANML is a rich language allowing the user to introduce
planning models in a multitude of ways. While the syntactic
sugar is important from the perspective of knowledge engi-
neering, let us focus this presentation on the fundamental
representations used.

The FAPE planner relies on parametrized state variables,
with typed object variables as parameters, and on time-
lines over these state variables. The advantages of the state
variable representation, as in SAS+ (Bäckström and Nebel,
1995) are well known. The state space represented by state-
variables is significantly smaller (we cut out unreachable
states) and planning algorithms strongly benefit from such
reduction as shown in (Hellmert, 2009).

ANML allows us to specify the state variables directly in
the planning problem definition. Typing is a natural way
to reduce the combinatorics of the parameters in operators.
FAPE supports typing and single inheritance between types,
as illustrated in this simple example (where $<$ denotes inher-
ance):

\begin{verbatim}
type Location;
type Gripper < Location { 
    boolean empty; }
\end{verbatim}
\textsuperscript{2}In particular at NASA Ames Research Center
The function that can be evaluated into a number at the moment of operator application and represents its maximal duration (after which the operator is considered to be failed), \( P \) is a set of typed parameters, \( E \) is a set of temporal statements and \( D \) is a set of decompositions. Parameters of an operator are typed object instances as defined in ANML, they are further used to impose binding constraints between events and decomposition operators. A decomposition is a set of partially ordered and partially instantiated operator references (the action must always occur in the time interval of its parent operator, its parameters are bounded to the values defined in the parent, if any).

The power of hierarchical decomposition (as in HTN) lies in being able to encode expert level knowledge into the domain by making explicit the various possible decompositions of a task, instead of relying on a search mechanism to find these possible decompositions from basic action models. Of course, this also depends on the skill of the programmer, yet, our experiences with various formalisms indicate that HTN are better suited for planning in robotics. While the refinement of the action can be as simple as the action Pick we have introduced, one can imagine going further, e.g., \( \text{Transport} \rightarrow \text{TransportByRobot} \rightarrow \text{Move}, \text{Pick}, \text{Move}, \text{Drop}, \) or even \( \text{PickWithGripper} \) decomposed with motion planning techniques.

**FAPE internal structures**

FAPE planning and acting components rely on several key data structures that provide efficient handling of state variable evolutions, constraints and plans. In the following subsections we present the timelines, temporal network, constraint network and task network.

**Timelines and Chronicles**

To capture the information on the evolution of state variables over time, we use timelines with the same semantics as used in (Ghallab et al., 2004, Sec. 14.3). A timeline is a set of temporal statements related to a unique state variable. A timeline \( \Phi \) is a tuple \((x, F, C)\) where \( x \) is a parameterized state variable, \( F \) is a set of temporal statements and \( C \) is a set of temporal constraints and binding constraints over the time points and object variables in \( F \).

Two essential properties of timelines need to be handled: consistency and causal support. A timeline \((x, F, C)\) is consistent when the constraints in \( C \) are consistent and when no pair of assertions in \( F \) are possibly conflicting. Intuitively,

```plaintext
type Locatable{
    Location myLocation; }

type Robot < Locatable {
    variable float battery;
    variable Gripper left;
    variable Gripper right; }

type Item < Locatable;

instance Location L1, L2, L3;
instance Robot R1;
instance Item I1;
instance Gripper G1, G2;

Temporally annotated statements are for example:
[start] R1.myLocation := L1;
[start, end] I1.myLocation == G1 :-> L3;
[end] I1.myLocation == L3;

A temporal annotation is either a time point or interval defined by two time points. These can be relative to a context (e.g. an operator, or a planning problem), such as \( \text{start, end} \) and \( \text{all, or absolute time points} \).

According to the definitions given in (Ghallab et al., 2004), we define a temporal statement to be an assertion over the evolution of a parameterized state variable. We consider three type of statements:

- an **event** specifies a change of the value of the state variable. For instance, the ANML statement \([t1, t2] r.myLocation == l1 :-> l2\) represents a change of the state variable \( myLocation(r) \) from \( l1 \) to \( l2 \) between time \( t1 \) and \( t2 \), where \( r \), \( l1 \) and \( l2 \) are object variables and \( t1, t2 \) are time points. The value of the state variable is \( l1 \) at time \( t1 \) and \( l2 \) at \( t2 \); it is unspecified in \([t1, t2] \). An event referring to a single time point is considered as being instantaneous, e.g., \([t]\) \( \text{Switch} == \text{On} :-> \text{Off} \) indicates a value of the switch as \( \text{On} \) at time \( t \) and as \( \text{Off} \) right after \( t \).

- a **persistence condition** specifies a constraint on the value of a state variable over an interval. For instance, the ANML statement \([t1, t2] s.myLocation == l3\) states that \( myLocation(s) \) keeps the value \( l3 \) over the interval \([t1, t2]\), where \( s \) and \( l3 \) are object variables and \( t1, t2 \) are time points. For the moment, FAPE only handles equality and non-equality constraints.\(^3\)

- an **assignment** is a special case of **event** specifying a new value to a state variable regardless of its previous one. For instance, the ANML statement \([t] r.myLocation := l3\) states that \( r \) will be at location \( l3 \) at time \( t \) without any condition on its previous location.

Actions are defined as partially instantiated operators that may have several possible decompositions into a partially ordered set of primitive actions. Effects and preconditions are represented as temporally annotated statements occurring between the start and end time of the action. Thus a planning operator is a tuple \((\text{name}, \text{maxDuration}, P, E, D)\), where \text{name} is the unique name of the operator, \text{maxDuration} is

\(^3\)Inequality constraints, e.g., \(<, \leq \) etc., will be added together with the management of resources.
two assertions are conflicting when they specify two possibly distinct values of \(x\) at the same time. This may happen when the two assertions are allowed to overlap in time with possibly incompatible values (with straightforward cases related to conflicts between persistence, events and mixed conflicts). Additional temporal or binding constraints, called separation constraints, may be needed in \(C\) to remove possible conflicts and make the timeline consistent.

A timeline \((x, F, C)\) supports an assertion \(\alpha\) when there is an assertion \(\beta \in F\) that can be used as a causal support for \(\alpha\) and when \(\alpha\) can be added to the timeline consistently. More precisely, when \(\alpha\) asserts a persistent value \(v\) for \(x\) or a change of value from \(v\) to \(v'\) starting at time \(t\), we require \(\beta\) to establish a value \(w\) at a time \(t'\) such that \(t' < t\) and \(w = v\) and that this value can persist consistently until \(t\). Here also additional constraints, i.e., \(t' < t\) and \(w = v\) and separation constraints, can be needed to make the timeline support \(\alpha\).

We define a chronicle as a tuple \((T, C)\) where \(T\) is a set of timelines and \(C\) is a set of temporal and binding constraints. We say that a chronicle is consistent if each timeline in \(T\) is consistent, and the union of constraints in the timelines of \(T\) with those of \(C\) is consistent.

**Temporal Constraint Network**

Dealing with explicit time implies taking into account temporal constraints between identified time points of the planning process (such as the beginning of an action or the occurrence of a contingent event). Repairing plans further requires the ability of removing constraints to reflect real events that might be contradictory with our previous knowledge.

Our temporal network manager is based on the *Simple Temporal Problem* introduced by (Dechter et al., 1991). It is encoded as a directed weighted graph in which an edge from \(t_i\) to \(t_j\) with weight \(w_{ij}\) represents the constraint \(t_j - t_i \leq w_{ij}\).

Consistency is checked on constraint addition by detecting negative cycles in the graph which is a sufficient and necessary condition of STN consistency. This step is performed by running, upon constraint addition or removal, an incremental Bellman-Ford algorithm as presented in (Cesta and Oddi, 1996). This allows us to efficiently check STN consistency while keeping a sparse network containing only constraints that were explicitly stated, thus allowing us to easily remove constraints from the network.

In general, temporal plans include uncontrollable durations (e.g., the time for the robot to go from the kitchen to the living room may vary between 1 and 2 minutes). These durations should not be squeezed by the planner temporal propagation and we must use an approach which guarantee the dynamic controllability (DC) of the plan. We plan to implement the algorithms proposed in (Morris and Muscettola, 2005) to guarantee that the plan remains DC while squeezing controllable duration as needed.

**Binding Constraint Network**

While planning, new object variables are created when a new lifted action is inserted into a plan: every parameter of the action gives birth to a new typed object variable. These variables appear either as parameters of state variables or as values of state variables. Separation and causal support constraints on these object variables are managed as a binding constraint network. This constraint network is consistent iff there exists an instantiation of variables such that all equality and non-equality constraints are satisfied. We use AC-3 to maintain the arc-consistency, which is a well-known trade-off between earliness of the failures and computational performance.

**Task Network**

A task network is a forest of partially instantiated operators, where the branches represent the conjunction of actions into which an action decomposes. We say that the network is decomposed if all leaves are primitives. A single tree corresponds to the decomposition of a single root action. New trees can be added in the task network when new actions are added in the current plan. This mechanism combines HTN techniques with Plan-Space techniques.

The FAPE planner does not support recursive decomposition methods. Recursive methods raise termination and completeness issues, in addition to complexity issues.

**Planning**

The planning component of FAPE relies on two mechanisms: task decomposition, as in HTN, and resolver insertion, as in Plan-Space Planning (PSP). A planning problem is defined as a triple \((V, O, s_{init})\), where \(V\) is a set of state variables, \(O\) is a set of operators and \(s_{init}\) is the initial search node. Since we are in plan-space, we do not define a goal state but an initial search node, which is specified with (i) a set of initial statements, giving the initial values of state variable and the expected events and persistences, and (ii) the plan objectives. The statements in (i) are considered to be causally supported. Those of (ii) need to be supported by the plan to be built. They are given as a set of goal statements, temporally qualified with the end time point, and/or the task to perform (as in HTN), called here the seed action, e.g.,

```plaintext
action Seed(){
   :decomposition{
      Transport(anyRobot_, I1, anywhere_, L2);
   };
}[end] I1.myLocation == L3;
```

In this example, the objective is to achieve the `Transport` task and, at the end to have item `I1` at location `L3`. Note that this specification of the objectives through assertions and a seed action can be redundant, or even inconsistent. It is up to the domain designer to make sure that the domain and problem specification are consistent. While it may be useful to specify goals for one state variable through goal statements and use the seed actions for another state variable, we discourage the domain designer to use both for a single state variable, where the semantics is not clear — there is no syntactical construct to temporarily relate seed actions with goal statements.
The planner search node is a tuple \((\Phi, T)\), where \(\Phi\) is a chronicle and \(T\) is the task network. We say that a search node is consistent if both \(\Phi\) and \(T\) are consistent. Planning proceeds by identifying flaws in a search node and iteratively applying resolvers until a search node is reached that is consistent and with no flaws.

**Flaws and Resolvers**

Planning proceeds as in PSP, by addressing the flaws of a current search node. A search node \(n = (\Phi, T)\) may contain the following flaws:

- **Open goal.** An open goal is any statement in \(\Phi\) that does not have a causal support.
- **Undecomposed actions.** An undecomposed action is a non primitive action appearing as a leaf in the task network; it needs to be decomposed.
- Threats are dealt with incrementally through separation constraints, that maintain each timeline consistent, and through causal support constraints.

The resolvers for an undecomposed action flaw are the existing methods specified for its decomposition. Applying a method as a resolver consists in expanding the action node with its specified decomposition with the temporal and binding constraints inherited by the decomposed action.

An open goal \(\alpha\) may have two types of resolvers:

- any assertion \(\beta \in \Phi\) that can be used to support \(\alpha\); applying such a resolver consists of adding the causal support constraints and the separation constraints required to have \(\alpha\) supported.
- an action that provides an assertion \(\beta\) that can be used to support \(\alpha\). Applying such a resolver requires adding the action together with the support constraints and separation constraints.

The newly added action may in turn bring new unsupported statements.

Notice that there are two ways of inserting an action into a partial plan: through a decomposition, or directly by adding an action as a provider of a support for an open goal. The same action may be added as a provider at some point and appear through a decomposition at a later point. A possible redundancy may result from this. The FAPE planner does not currently implement a merging operation over the task network. This will be the object of future work.

**Search**

Given that a search node \(\pi\) is a solution if it is consistent and with no flaws, search proceeds by identifying flaws of \(\pi\) (i.e. its open goals and undecomposed actions) and applying a resolver for one selected flaw while maintaining the resulting search node consistent. For the purposes of demonstration, we stick, for the moment, to the PSP recursive nondeterministic schema (Ghallab et al., 2004).

The PSP algorithm (See Algorithm 1) at each step of the recursion deterministically chooses a flaw to resolve (selection is done with the simple min-domain heuristic) and then chooses nondeterministically the resolver as follows:

- if the application of a resolver returns a failure then another recursion with a different resolver is performed

**Algorithm 1 Main PSP Algorithm**

```
function PSP(\(\pi\))
    flaws ← OpenGoals(\(\pi\)) ∪ UndecomposedLeaves(\(\pi\))
    if flaws = \(\emptyset\) then return \((\pi)\)
    end if
    select any flaw \(\phi \in\) flaws
    resolvers ← Resolve(\(\phi, \pi\))
    if resolvers = \(\emptyset\) then return failure
    end if
    nondeterministically choose a resolver \(\rho \in\) resolvers
    \(\pi \leftarrow\) Apply(\(\rho, \pi\))
    return PSP(\(\pi\))
end function
```

- if all resolvers were tried unsuccessfully then a failure is returned to the previous choice point.

We can as well modify the non-determinism to reach the optimal solution with regard to some objective function. In practice, our current implementation uses a best-first search strategy, with the number of open goals as a distance evaluation to a consistent search node.

**Acting**

In a system like FAPE, Acting and Planning are integrated. Acting, is more complex than just Execution of platform commands. Often, the actions in the plan are still at a too high level to be directly executed on the platform. From our point of view, we consider in FAPE the basic functions relevant to Acting, and introduced in (Ingrand and Ghallab, 2013), to include: refinement, instantiation, time management and coordination, non determinism and uncertainty, plan repair. In the current FAPE implementation, they are all but one (non determinism and uncertainty) handled.

Acting refines online an action into a collection of closed-loop functions, referred to here as skills; a skill processes a sequence (or a continuous stream) of stimulus input from sensors and output to actuators, in order to trigger motor forces and control the correct achievement of chosen actions. We currently use PRS procedures to refine fully instantiated plan actions into motor commands, as well as to perceive the environment and inform the Planner of important changes. PRS skills also provide some local action recoveries for situations where the procedure can handle an alternative way to perform the action (e.g. to consider an alternative grasping pose, or an alternative path to reach a particular location). For our PR2 implementation, the basic motor commands and perception are provided by ROS actions, nodes and also GenoM3 (Mallet et al., 2010) modules. We plan to integrate other skill execution frameworks which can handle different type of acting representation (MDP, DBN, FSM, etc).

For dispatching, fully instantiated and scheduled actions are passed to the Acting component according to their starting time. The planner maintains a partially instantiated plan (only the necessary binding and temporal constraints are applied), which represents a set of valid plans (time and object variables are instantiated when needed). Actions selected for
execution are found by taking the ones whose preconditions are met and whose start times fit in an execution window (e.g. we want to get actions that can be started in the next \( x \) seconds). The temporal variables and constraints of those actions are instantiated and the actions are then returned. Further calls instantiate more and more actions while the future instantiation of the actions not yet scheduled is kept as open as possible. Once an action is finished, acting reports the actual end date of its execution. This exact date is then integrated in the current plan, and the temporal propagation, as described in the “Temporal Constraint Network” section, is performed. The action fails if it take less or more time than planned. Such temporal failure is reported to the planner which can then attempt to repair the plan accordingly. Note that in the general case, the acting component can also inform the planner that an action is taking too long, yet, wait for the planner to plan and send an abort action as a result of this problem (the acting component does not take the freedom to abort an action which is running late). An action can also fail because the skill failed (e.g. despite multiple attempts, the robot cannot grasp an object, or reach a location). The acting component then retrieves a description of the changes of the world that occurred and send it to the planner which integrate these “unexpected” state variable transitions in its plan.

Considering we have a plan and one of the actions in the plan fails during the execution, the plan-repair consists of the following steps:

1. Removing the action from the task network.
2. Removing all the statements introduced by the failed action from the timelines which shall generate new flaws.
3. Running the PSP algorithm until the flaws are resolved.

Our repair approach is limited to the removal of just the one failing action, we do not consider cascades of other potential failures. There certainly are cases when the repair does not find a plan and we need to replan, making the repairing a wasted effort. However, most of the time repairing the plan is much faster than replanning and the overall benefit for the responsiveness of a real-time system is significant, as we shall show in the following section.

**Experimental Setup and Results**

FAPE is designed to be used as an embedded system. The current implementation has been experimented on a PR2 (Figure 1) to plan service robot type of tasks. For example, the PR2 moves around in an apartment and detects objects which are misplaced (e.g. a video tape in the bedroom, or a book on the dining table) picks them up and stores them away in their proper location (respectively by the TV set, and in the bookshelf).

In the current setup, we rely on some of PR2 basic capabilities\(^4\): navigating in a household like environment; recognizing objects; picking them up and putting them down. Actions are dispatched just in time to PRS which executes them when their start time has arrived. PRS monitors the proper

\(^4\)http://wiki.ros.org/pr2_navigation
http://wiki.ros.org/pr2_tabletop_manipulation_apps
As far as we know, FAPE is the first system including a planner supporting most ANML features – combination of HTN planning and explicit time representation; and plan-space planning. It integrates acting together with planning and both decisional functionalities rely on the same internal representation. Each functionality is critical with regard to the efficiency of the whole system and as such it deserves our attention in future development. The planner shall benefit significantly from the addition of proper resource management similar to the one implemented in IxTeT (Laborie and Ghallab, 1995), a stronger heuristic, as well as the addition of specific and domain dependent planners (e.g. motion or manipulation planner). Meanwhile the Acting system will provide other acting framework than the PRS refinement procedures used for now (e.g. MDP policies (Morisset and Ghallab, 2008), DBN (Infantes et al., 2010), etc). We also plan to implement and compare new models of interleaving planning and acting, where we would concentrate on the decision making between alternative action refinement, repairing and replanning — how to recognize and predict when one is preferred to the other. Similarly, we plan to investigate the inclusion of delayed methods decomposition. The planner, instead of expanding all tasks down to the action leaves may delay and delegate some designated decomposition to the acting component.

We have designed but not yet experimentally tested new control mechanics for decomposition that bring the domain designer more power to fine tune the search and also provide more support for embedded planning. All of the extensions are part of method definition, we call those extensions hard, soft and weak.

The hard extension is an additional condition (a temporal statement) that tells the planner if the method needs to be decomposed (if the condition does not hold then we do not decompose the method and it does not invalidate consistency). The extension allows a multitude of control use-cases to be introduced, e.g. we may start decomposing certain methods only once we get close to their execution — this is the case for the navigation action that can be abstracted as a motion from a to b, until we approach the time of the action and need refine it into a sequence of path following actions that would be otherwise unnecessary to keep in the plan in advance.

The soft extension allows us to define priorities of decompositions — we simply assign a priority to every method then we try expand those with the highest priority first, we can see this extension as an explicit heuristic entered by the domain designed or the real-time environment.

The weak extension represents a look ahead for a decomposition of a method, its main purpose is to propagate new time bounds and constraints. Having a method with several possible decompositions (we call the regular decompositions hard), we add at most one weak decomposition. The weak decomposition method is then always performed when we add the method to the plan and it is non-colliding with any hard decomposition that is chosen later during the search.

We do not directly support conditional decomposition (conditions for each hard decomposition in a method), which can be simulated by using more methods — for each conditional decomposition we instead add a new method having just one decomposition but having the conditional statements as its event, then the original method decomposes into one of the method representing the original conditional decompositions.

While we currently support multi-agent planning (there can be any number of robots in the system that perform their actions in parallel), we are particularly interested in extending the system towards multi-agent planning where actions of some of the entities are not controllable, which shall allow
us to reason and plan human-robot interactions.

Conclusion

We have introduced FAPE, a new framework that integrates Planning and Acting to be embedded in autonomous real-time system such as robots. Using ANML as an input planning language, we have the expressivity to plan for complex temporal plans with respect to concurrent actions in dynamic and changing environments and we also allow the user to improve and fine-tune the efficiency of the system by introducing task decompositions which can efficiently prune the search in plan space. We have experimented both Planning and Acting in simulation with large problems and on a PR2 robot which performs service robot type of activities. The development of FAPE continues as a multi-institutional effort to provide a planning/acting system, which we would like to see positioned as a system capturing the state-of-the-art of planning, integrating domain-specific planners while maintaining the expressivity of ANML and ease of integration with different type of acting components.

References


