APE: An Acting and Planning Engine

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Abstract

A significant problem for integrating acting and planning is how to maintain consistency between the planner's *descriptive* action models, which abstractly describe *what* the actions do, and the actor's *operational* models, which tell *how* to perform the actions with rich control structures for closed-loop online decision-making. Operational models allow for dealing with a variety of contexts, and responding to unexpected outcomes and events in a dynamically changing environment. To circumvent the consistency problem, we use the actor's operational models both for acting and for planning. Our acting-and-planning algorithm, APE, uses hierarchical operational models inspired from those in the well-known PRS system. But unlike the reactive PRS algorithm, APE chooses its course of action using a planner that does Monte Carlo sampling over simulated executions of APE's operational models. Our experiments with this approach show substantial benefits in the success rates of the acting system, in particular for domains with dead ends.

1. Introduction

The integration of acting and planning is a long-standing AI problem discussed by many authors. For example, (Pollack & Horty, 1999) argue that despite progress beyond the restricted assumptions of classical planning (e.g., handle uncertainty, partial observability, or exogenous events), in most realistic applications just making plans is not enough. Their argument still holds. Planning, as a search over predicted state changes, uses *descriptive models* of actions (*what* might happen). Acting, as an adaptation and reaction to an unfolding context, requires *operational models* of actions (*how* to do things) with rich control structures for closed-loop online decision-making.

A recent survey shows that most approaches to integrating acting and planning seek to combine descriptive and operational representations, using the former for planning and the latter for acting (Ingrand & Ghallab, 2017). This has several drawbacks in particular for the development and consistency verification of the models. To ensure consistency, it is highly desirable to have a single representation for both acting and planning. But if this representation were a descriptive one, it would not provide sufficient functionality. Instead, the planner needs to be capable of reasoning directly with the actor's operational models.

Furthermore, several cognitive studies stress the importance of operational models. For example, Dennett's hierarchy of natural beings (Dennett, 1996) refers to the third level as *Popperian creatures*, which have models to simulate their own actions before safely carrying them. Most vertebrates appear to be at least at the Popperian level. It seems clear that these simulation models are operational, since they are used for acting. However, it is unclear whether the Popperian creatures also use or need abstract descriptive models. This may even be true for human, in our everyday actions. We devote significant effort to exhibit descriptive models only for specific actions and purposes, such as planning and optimization, because our operational models are hidden to us. If a designer needs to develop operational models for artificial actors, he or she might want to use them for planning as well.

In this paper, we provide an integrated acting-and-planning system, APE (Acting and Planning Engine). APE's operational representation language and its acting algorithm are inspired by the well-known PRS system (Ingrand et al., 1996). The operational model is hierarchical: a collection of refinement methods offers alternative ways to handle *tasks* and react to *events*. Each method has a *body* that can be any complex algorithm. In addition to the usual programming constructs, the body may contain *commands* (including sensing commands), which are sent to an execution platform in order to execute them in the real world, and *subtasks*, which need to be refined recursively. APE's acting engine is based on an expressive, general-purpose operational language with rich control structures for closed-loop online decision-making.

To integrate acting and planning, APE extends the reactive PRS-like acting algorithm to include a planner, APE-plan. At each point where APE needs to decide how to refine a task, subtask, or event, APE-plan does Monte Carlo rollouts with a subset of the applicable refinement methods. At each point where a refinement method contains a command to the execution platform, APE-plan takes samples of its possible outcomes using a predictive model of what each command will do.

We have implemented APE and APE-plan and have done preliminary empirical assessments of them on four domains. The results show significant benefits in the success rates of the acting system, in particular for domains with dead ends. The related work is described in Section 2. Section 3 briefly summarizes the operational model. APE and APE-plan are presented in Section 4. We present our benchmark domains and experimental results in Section 5. In Section 6 we discuss the results and provide conclusions.

2. Related Work

To the best of our knowledge, no previous approach has proposed the integration of acting and planning by looking directly within the language of a true operational model like that of APE. Our approach is based on the operational representation language and RAE algorithm in (Ghallab et al., 2016, Chapter 3), which in turn were inspired by PRS (Ingrand et al., 1996). RAE operates purely reactively. If it needs to choose among several refinement methods that are eligible for a given task or event, it makes the choice without any attempt to plan ahead. The approach has been extended with some planning capabilities in PropicePlan (Despouys & Ingrand, 1999) and SeRPE (Ghallab et al., 2016). The two systems model commands with classical planning operators; they both require the action models and the refinement methods to satisfy classical planning assumptions of deterministic, fully observable and static environments, which are not acceptable assumptions for most acting systems.

Various acting approaches similar to PRS and APE have been proposed, e.g., (Firby, 1987; Simmons, 1992; Simmons & Apfelbaum, 1998; Beetz & McDermott, 1994; Muscettola et al., 1998; Myers, 1999); some of these provide refinement capabilities. While such systems offer expressive acting environments, e.g., with real time handling primitives, none of them provide the ability to plan with the operational models used for acting, and thus cannot integrate acting and planning as we propose here. Most of the mentioned systems do not reason about alternative refinements.

Finite State Automata (FSA) and Petri Nets have also been used as representations for acting models, e.g.,(Verma et al., 2005; Wang et al., 1991), again without planning capability. For example, the ROS execution system SMACH (Bohren et al., 2011), implements an automata-based approach, where each state of a hierarchical state machine corresponds to the execution of a command. However, the semantics of constructs available in SMACH is limited for reasoning on goals and states, and there is no planning. Cashmore et al. (2015) describes a system called ROSPlan which integrates planning in the ROS architecture. It models tasks into PDDL2.1 and then use a classical planner to generate, instead of the operational models directly for planning. Langley et al. (2017) describes a system that integrates planning with utilities and goals with monitoring and execution. Their models support conditional operators but cannot handle loops or any other programming constructs.

The Reactive Model-based Programming Language (RMPL) (Ingham et al., 2001) is an object-oriented language that allows a domain to be structured through an object hierarchy with subclasses and multiple inheritance. It combines a system model with a control model, using state-based, procedural control and temporal representations. The system model specifies nominal as well as failure state transitions with hierarchical constraints. The control model uses standard reactive programming constructs. RMPL programs are transformed into Temporal Plan Networks (TPN)(Williams & Abramson, 2001), an extension of Simple Temporal Networks with symbolic constraints and decision nodes. Temporal reasoning consists in finding a path, i.e., a plan, in the TPN that meets the constraints. The execution of generated plans allows for online choices (Conrad et al., 2009). TPNs are extended with error recovery, temporal flexibility, and conditional execution based on the state of the world (Effinger et al., 2010). Primitive tasks are specified with distributions of their likely durations. A probabilistic sampling algorithm finds an execution guaranteed to succeed with a given probability. Probabilistic TPN are introduced in (Santana & Williams, 2014) with the notions of weak and strong consistency. (Levine & Williams, 2014) add the notion of uncertainty to TPNs for contingent decisions taken by the environment or another agent. The acting system adapts the execution to observations and predictions based on the plan. RMPL and subsequent developments have been illustrated with a service robot which observes and assists a human. It is a quite comprehensive CSP-based approach for temporal planning and acting; it provides refinement, instantiation, time, nondeterminism, a plan repair. Our approach does not handle time; it focuses instead on decomposition into communicating asynchronous components.

Behavior trees (BT) (Colledanchise, 2017; Colledanchise & Ögren, 2017) aim at integrating acting and planning within a hierarchical representation. Similarly to our framework, a BT can reactively respond to contingent events that were not predicted. The authors propose a mechanism to synthesize a BT that has a desired behavior. The construction of the tree refines the acting process by mapping the descriptive model of actions onto an operational model. Our approach is different since APE provides the rich and general control constructs of a programming language and we do planning directly within the operational model, rather than through a mapping from the descriptive to an operational model. Moreover, the BT approach does not allow for refinement methods, which are a rather natural and practical way to specify different possible refinements of tasks.

Approaches based on temporal logics or situation calculus (Doherty et al., 2009; Hähnel et al., 1998; Claßen et al., 2012; Ferrein & Lakemeyer, 2008) specify acting and planning knowledge through high-level descriptive models and not through operational models like used in APE. Moreover, these approaches integrate acting and planning without exploiting the hierarchical approach based on refinement methods described in this paper.

Our framework has some similarities with HTN (see, e.g., (Nau et al., 1999)), since tasks can be refined with different methods. However, our methods are significantly different from HTN ones since our methods are programs that can encode rich control constructs rather than simple sequences of primitive tasks. This is what allows us to provide a framework for acting and planning.

(Bucchiarone et al., 2013) propose a hierarchical representation framework that includes abstract actions and that can interleave acting and planning for composing web services. However this work focus on distributed processes, which are represented as state transition systems, and does not allow for refinement methods.

Finally, a wide literature on probabilistic planning and Monte Carlo tree search refers to simulated execution, e.g., (Feldman & Domshlak, 2013, 2014; Kocsis & Szepesvári, 2006; James et al., 2017) and sampling outcomes of action models e.g., the RFF algorithm (Teichteil-Königsbuch et al., 2008), FF-replan (Yoon et al., 2007) and hindsight optimization (Yoon et al., 2008). Beyond the fact that all these works are based on a probabilistic MDP framework, the main conceptual and practical difference with our work is that they consider just a descriptive model, i.e., abstract actions on finite MDPs. Their focus is therefore entirely on planning, and do not allow for an integration of acting and planning. Most of the papers refer to doing the planning online – but they are doing the planning using descriptive models rather than operational models. There is no notion of integration of acting and planning, hence no notion of how to maintain consistency between the planner's descriptive models and the actor's operational models. Moreover, they have no notion of hierarchy and refinement methods.

3. Operational Models

Our formalism for operational models of actions is based on the one in (Ghallab et al., 2016, Chapter 3). It has features that allow for dealing with a dynamic environment which has other actors and exogenous events. The main ingredients are *tasks*, *events*, *commands*, *refinement methods*, and *state variables*. Some of the state variables are *observable*, i.e., the execution platform will automatically keep them up-to-date through sensing operations. We illustrate this representation through the following examples.

Example 1. *Consider several robots (UGVs and UAVs) moving around in a partially known terrain, performing operations such as data gathering, processing, screening and monitoring. Let*

Table 1. A refinement method for the task *explore* is shown below.

m1-explore(r, l)
  task: explore(r, l)
  body: get-Equipment$(r$, *'survey'*$)$
    moveTo(r, l)
    if loc$(r) = l$ then:
      Execute command survey(r, l)
      if data$(r) = 100$ then:
        depositData(r)
      return success
    else return failure

- $R = \{g_1, g_2, a_1, a_2\}$ *be the set of robots,*
- $L = \{base, z_1, z_2, z_3, z_4\}$ *be the set of locations,*
- survey(r, l) *be a command performed by robot* r *in location* l *that surveys* l *and collects data*
- loc$(r) \in L$ *and* data$(r) \in [0, 100]$ *be observable state variables that contain the robot* r*'s current location and the amount of data it has collected.*

Let explore(r, l) *be a task for robot* $r \in R$ *to reach location* $l \in L$ *and perform the command* survey(r, l). *In order to survey, the robot needs some equipment that might either be available or in use by another robot. Robot* r *should collect the equipment, then move to the location* l *and execute the command* survey(r, l). *Each robot can carry only a limited amount of data. Once its data storage is full, it can either go and deposit data to the base, or transfer it to an UAV via the task* depositData*(r). A refinement method to do this is shown in Table 1. Inside the refinement method* m1-explore*,* get-Equipment$(r$, *'survey'*$)$*,* moveTo(r, l) *and* depositData(r) *are subtasks which need to be further refined via suitable refinement methods. Only UAVs have the ability to fly. So, there can be different possible refinement methods for the task* moveTo(r, l) *based on whether* r *can fly or not.*

Each robot can hold a limited amount of charge and is rechargeable. Depending on what locations it needs to survey, it might need to recharge by going to the base where the charger is located. Different ways of doing this can be captured by multiple refinement methods for the task doActivities$(r, locList)$. *Two of them are shown in Table 2.*

Note that a refinement method for a task t specifies *how to* perform t, i.e., it gives a procedure for accomplishing t by performing subtasks, commands and state variable assignments. This procedure can include any of the usual programming constructs, e.g., if-then-else, loops and so forth.

The above example illustrates tasks and refinement methods. Let us give the robots a method for reacting to an event.

Table 2. Two refinement methods for the task *doActivities*$(r, locList)$ are shown below.

```
m1-doActivities(r, locList)              m2-doActivities(r, locList)
   task: doActivities(r, locList)           task: doActivities(r, locList)
  body: for l in locList do:               body: for l in locList do:
            explore(r, l)                            explore(r, l)
          moveTo(r, 'base')                          moveTo(r, 'base')
          if loc(r) = 'base':                        if loc(r) = 'base':
            recharge(r)                                recharge(r)
          else return failure                        else return failure
          return success                           return success
```

Table 3. A refinement method for the event *handleAlien*(r, l) is shown below.

```
m-handleAlien(r, l)
  event: alienSpotted(l)
  body: if alien-handling(r) = F then:
            alien-handling(r) ← T
            moveToAlien(r, l)
            Execute command negotiate(r, l)
            alien-handling(r) ← F
            return success
        else return failure
```

Example 2. *Suppose that an alien is spotted in one of the locations $l \in L$ of Example 1 and a robot has to react to it by stopping its current activity and going to l. Let us represent this with an event* alienSpotted*(l). We also need an additional state variable:* alien-handling*(r)∈{*T, F*} which indicates whether the robot r is engaged in handling an alien. A refinement method for this event is shown on Table 3. It can succeed if robot r is not already engaged in negotiating with another alien. After negotiations are over, the methods changes the value of* alien-handling*(r) to F.*

4. APE and APE-plan

Figure 4, APE (Acting and Planning Engine), is based loosely on the RAE (Refinement Acting Engine) algorithm in (Ghallab et al., 2016, Chapter 3). APE's first inner loop (line 1) reads each new *job*, i.e., each task or event that comes in from an *external source* such as the user or the execution platform, as opposed to the subtasks generated by APE's refinement methods. For each such job τ, APE creates a *refinement stack* analogous to a computer program's execution stack. *Agenda* is the set of all current refinement stacks.

Table 4. The pseudocode of APE (Acting and Planning Engine) is given below.

```
APE( ):
Agenda ← empty list
while True do
1   for each new task or event τ in the input
      stream do
        s ← current state
        M ← {applicable method instances
          for τ in state s}
2       T ← APE-plan(M, s, τ)
        if T = failed then
            output("failed to address", τ)
        else
3           m ← the method instance at the
              top of T
            stack ← a new, empty refinement
              stack
            push (τ, m, nil, ∅) onto stack
            insert stack into Agenda
4   for each stack ∈ Agenda do
        Progress(stack)
        if stack is empty then
5           remove it from Agenda
```

```
Retry(stack):
(τ, m, step, tried) ← pop(stack)
add m to tried // the things we
   tried that did not work
s ← current state
M ← {applicable method instances for
  τ in state s}
1 T ← APE-plan(M \ tried, s, τ)
if T ≠ failed then
2   m′ ← the method instance at the top
      of T
    push (τ, m′, nil, tried) onto stack
else
    if stack is empty then
        output("failed to accomplish",
          τ)
        remove stack from Agenda
    else
        Retry(stack)
```

```
Progress(stack):
(τ, m, step, tried) ← top(stack)    // step is the current step of m
if step ≠ nil then                  // i.e., if we have started executing m
1   if type(step) = command then        // step is running on the execution
      platform
        case execution-status(step):
            still-running: return
            failed:        Retry(stack); return
            successful:    pass // continue to next line
        if there are no more steps in m then
            pop(stack); return;
2       step ← next step of m after accounting for the effects of control statements (loops,
          if-then-else, etc.)
        case type(step):
            assignment: update s according to step; return;
3           command:    send step to the execution platform; return;
            task:       pass                          // continue to next line
4       τ′ ← step; s ← current state ; M′ ← {applicable method instances for τ′ in state s};
5       T′ ← APE-plan(M′, s, τ′)
        if T′ = failed then Retry(stack); return;end
6       m′ ← the method instance at the top of T′
7       push (τ′, m′, nil, ∅) onto stack
```

In the second inner loop (line 4 of APE), for each refinement stack in *Agenda*, APE *progresses* the topmost *stack element* by one step. The stack element includes (among other things) a task or event τ and the method instance m that APE has chosen to use for τ. The body of m is a program; progressing the stack element (the Progress subroutine) means executing the next step in this program. This may involve monitoring the status of a currently executing command (line 1 of Progress), following a control structure such as a loop or if-then-else (line 2 of Progress), executing an assignment statement, sending a command to the execution platform, or handling a subtask τ' by pushing a new stack element onto the stack (line 7 of Progress). A method succeeds in accomplishing a task when it returns without failure.

Whenever APE creates a stack element for a task τ, it must choose (line 3 of APE, 6 of Progress, and 2 of Retry) a method instance m for τ. In order to make an informed choice of m, APE calls (lines 2 of APE, 5 of Progress, and 1 of Retry) a planner, APE-plan, that returns a plan for accomplishing τ. The returned plan, T, will begin with a method m to use for τ. If m contains subtasks, then T must include methods for accomplishing them (and so forth recursively), so T is a tree with m at the root.

Once APE has selected m, it ignores the rest of T. Thus in line 4 of Progress, where m has a subtask τ', APE does not use the method that T used for τ'. Instead, in line 5 of Progress, APE calls APE-plan to get a new plan T' for τ'. This is a receding-horizon search analogous to how a game-playing program might call an alpha-beta game-tree search at every move.[1]

The pseudocode of APE-plan is a modified version of the APE pseudocode that incorporates these modifications:

1. Each call to APE-plan returns a *refinement tree* T whose root node contains a method instance m to use for τ. The children of this node include a refinement tree (or terminal node) for each subtask (or command, respectively) that APE-plan produced during a Monte Carlo rollout of m.
2. In line 2 of APE, line 5 of Progress, and line 1 of Retry, APE-plan calls itself recursively on a set $M' \subseteq M$ that contains the first b members of M a list of method instances ordered according to some domain-specific preference order (with $M' = M$ if $|M| < b$), where b is a parameter called the *search breadth*. This produces a set of refinement trees. If the set is nonempty, then APE-plan chooses one that optimizes cost, time or any other user-specified objective function. If the set is empty, then APE-plan returns the first method instance from M' if $|M'| >= 1$; otherwise it returns failed.
3. Each call to Retry is replaced with an expression that just returns failed. While APE needs to retry in the real world with respect to the real actual state, APE-plan considers that a failure is simply a dead end for that particular sequence of choices.
4. In line 3 of Progress (the case where step is a command), instead of sending *step* to the actor's execution platform, APE-plan invokes a predictive model of what the execution platform would do. Such a predictive model may be any piece of code capable of making such a prediction, e.g.,

1. (Ghallab et al., 2016) describes a "lazy lookahead" in which an actor keeps using its current plan until an unexpected outcome or event makes the plan incorrect, and a "concurrent lookahead" in which the acting and planning procedures run concurrently. We tried implementing these for APE, but in our experimental domains they did not make much difference in APE's performance.

a deterministic, nondeterministic, or probabilistic state-transition model, or a simulator of some kind. Since different calls to the predictive model may produce different results, APE-plan calls it b' times, where b' is a parameter called the *sample breadth*. From the b' trial runs, APE-plan gets an estimate of *step*'s expected time, cost, and probability of leading to success.

5. Finally, APE-plan has a *search depth* parameter d. When APE calls APE-plan, APE-plan continues planning either to completion or depth d, whichever comes earlier. Such a parameter can be useful in real-time environments where there may not be enough time to plan all the way to completion.

   The full pseudocode of APE-plan is given the Appendix.

5. Experimental Evaluation

In this section, we will describe our test domains and experiments. We will also present an analysis of our results.

5.1 Domains

We have implemented and tested our framework on four domains. These domains are designed in a way such that they model the common issues that are encountered while acting and planning. Broadly, there are two groups, domains with dead-ends and domains without dead-ends. A domain has dead-ends means that it is possible for the agent to reach a state from which it cannot recover. Without dead ends, a purely reactive system like APE is sufficient for achieving the tasks, but not efficiently. One of our domains illustrates sensing (or information gathering) actions, three involve (centrally controlled) collaboration between actors. All domains have dynamic events and concurrent tasks (see Figure 1).

The Explorable Environment domain (EE) extends the UAVs and UGVs setting of Example 1 with some additional tasks and refinement methods. This domain has dead ends because a robot may run of charge in an isolated location.

The Chargeable Robot Domain (CR) consists of several robots moving around to collect objects of interest. The robots can hold a limited amount of charge and are rechargeable. To move from one location to another, the robots use Dijkstra's shortest path algorithm. The robots do not know where objects are unless a sensing action is performed in the object's location. They have to search for an object before collecting it. Also, the robot may or may not carry the charger with it. The environment is dynamic due to emergency events as in Example 2. A task reaches a dead end when a robot, which is far away from the charger, has run out of charge.

The Spring Door domain (SD) has several robots are trying to move objects from one room to another in an environment with a mixture of spring doors and ordinary doors. Spring doors close themselves unless they are held. A robot cannot carry an object and hold a door simultaneously. So, whenever it needs to move through a spring door, it needs to ask for help from another robot. Any robot which is free can act as the helper. The environment is dynamic because the the type of door is unknown to the robot. But, there are no dead ends.

Domain	Dynamic events	Dead ends	Sensing	Robot collaboration	Concurrent tasks
CR	✓	✓	✓	–	✓
EE	✓	✓	–	✓	✓
SD	✓	–	–	✓	✓
IP	✓	–	–	✓	✓

Figure 1. Properties of our domains are summarized above.

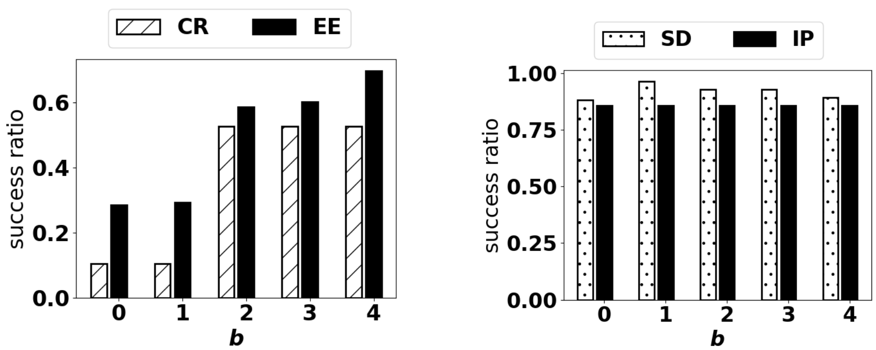
The Industrial Plant domain (IP) consists of an industrial workshop environment, as in the RoboCup Logistics League competition. There are several fixed machines for painting, assembly, wrapping and packing. As new orders for assembly, paint, etc., arrive, carrier robots transport the necessary objects to the required machine's location. An order can be complex, like, paint two objects, assemble them together, and pack the resulting object. Once the order is done, the final product is delivered to the output buffer. The environment is dynamic because the machines may get damaged and need repair before being used again; but there are no dead ends.

These four domains have different properties, summarized in Figure 1. CR includes a model for the sensing action where the robot can sense a location and identify objects in that location. SD models a situation where robots need to collaborate with each other. They can ask for help from each other. EE models a combination of robots with different capabilities (UGVs and UAVs) whereas in the other three domains all robots have same capabilities. It also models collaboration like the SD domain. In the IP domain, the allocation of tasks among the robots is hidden from the user. The user just specifies their orders; the delegation of the sub-tasks (movement of objects to the required locations) is handled inside the refinement methods. CR and EE are domains that can represent dead-ends, whereas SD and IP do not have dead-ends.

5.2 Experiments and Analysis

The objective of our experiments was to examine how APE's performance might depend on the amount of planning that we told APE to do. For this purpose, we created a suite of test problems. Each test problem included one to four jobs to accomplish, and for each job, there was a randomly chosen time point at which it would arrive in APE's input stream. In the CR, EE, SD and IP domains, our test suites consisted of 60, 54, 60, and 84 problems, with the numbers of jobs to accomplish being 114, 126, 84 and 276, respectively. In our experiments we used simulated versions of the four environments, running on a 2.6 GHz Intel Core i5 processor.

The amount of planning done by APE-plan depends on its search breadth b, sample breadth b', and search depth d. We used $b' = 1$ (one outcome for each command), and $d = \infty$ (planning always proceeded to completion), and five different search breadths, $b = 0, 1, 2, 3, 4$. Since APE tries b alternative refinement methods for each task or subtask, the number of alternative plans examined by APE is exponential in b. As a special case, $b = 0$ means running APE in a purely reactive way without any planning at all. Our objective function for the experiments is the number of commands in the plan.



(a) Domains having dead ends (CR and EE)   (b) Domains having no dead ends (SD and IP)

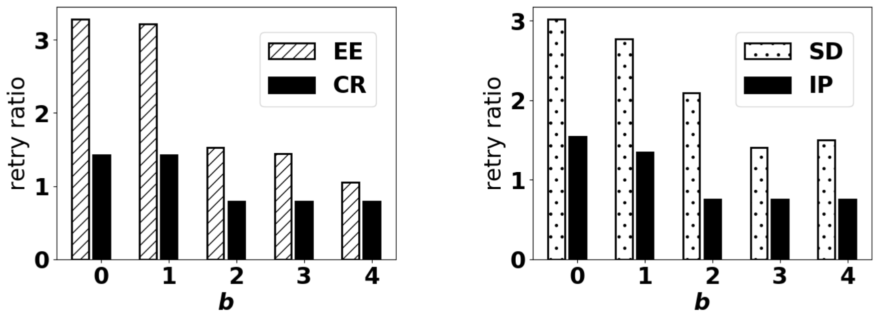
Figure 2. Success ratio (number of successful jobs/ total number of jobs) for different values of search breadth b. CR = Chargeable Robot, EE = Explorable Environment, SD = Spring Door, IP = Industrial Plant.

Hypothesis 1. [SUNANDITA SAYS: *Addressing [Meta Review 2]*] [MALIK SAYS: *This is not a hypothesis in my understanding ?*] *We expect that with the performance of our acting and planning system, APE, measured using three different metrics (success ratio, retry ratio and speed to success) improves with increasing value of the search breadth, b (b is an independent variable). The improvement should be more in domains with dead ends.*

Success ratio. Figure 2 shows APE's *success ratio*, the proportion of jobs that it successfully accomplished in each domain. For the two domains with dead ends (CR and EE), the success ratio generally increases as b increases. In the CR domain, the success ratio makes a big jump from $b = 1$ to $b = 2$ and then remains nearly the same for $b = 2, 3, 4$. This is because for most of the CR tasks, the second method in the preference ordering (in our experiments, this order is decided by the domains' author)turned out to be the best one, so higher value of b did not help much. In contrast, in the EE domain, the success ratio continued to improve significantly for $b = 3$ and $b = 4$.

In the domains with no dead ends, b did not make very much difference in the success ratio. In the IP domain, b made almost no difference at all. In the SD domain, the success ratio even decreased slightly from $b = 1$ to $b = 4$. This is because in our preference ordering for the tasks of the SD domain, the methods appearing earlier are better suited to handle the events in our problems whereas the methods appearing later produce plans that are shorter but less robust to unexpected events. These experiments confirm the expectation that planning is critical in domains where the actor may get stuck in dead ends. It also has benefits in acting costs (the *retry ratio* and *speed to success* measurements).

Retry ratio. Figure 3 shows the *retry ratio*, i.e., the number of times that APE had to call the Retry procedure, divided by the total number of jobs to accomplish. The Retry procedure is called when there is a failure in the method instance m that APE chose for some task τ (see Algorithm4). Retry works by trying to use another applicable method instance for τ that it has not tried already. Although this is a little like backtracking, a critical difference is that since the method m has already been partially executed, it has changed the current state, and in real-world execution (unlike plan-



(a) Domains having dead ends (CR and EE)   (b) Domains having no dead ends (SD and IP)

Figure 3. Retry ratio (number of retries / total number of jobs) for different values of search breadth b. CR = Chargeable Robot, EE = Explorable Environment, SD = Spring Door, IP = Industrial Plant.

ning), there is no way to backtrack to a previous state. In many application domains it is important to minimize the total number of retries, since recovery from failure may incur significant, unbudgeted amounts of time and expense.

In all four of the domains, the retry ratio decreases slightly from $b = 0$ (purely reactive APE) to $b = 1$, and it generally decreases more as b increases. This is because higher values of b make APE-plan examine a larger number of alternative plans before choosing one, thus increasing the chance that it finds a better method for each task. In the CR domain, the big decrease in retry ratio from $b = 1$ to $b = 2$ corresponds to the increase in success ratio observed in Figure 2. The same is true for the EE domain at $b = 2$ and $b = 4$. Since the retry ratio decreases with increasing b in all four domains, this means that the integration of acting and planning in APE is important in order to reduce the number of retries.

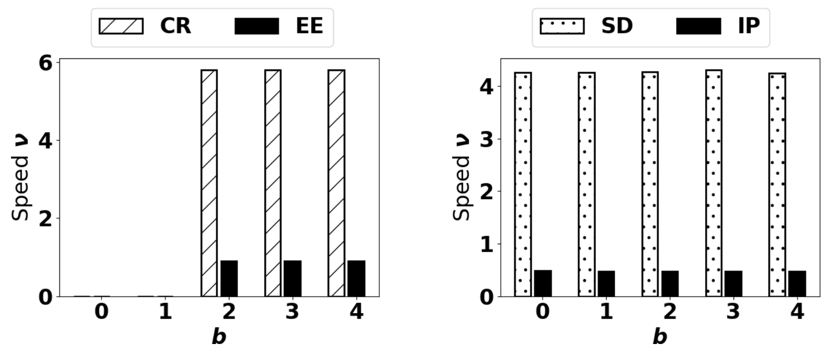
Speed to success. An acting-and-planning system's performance cannot be measured only with respect to the time to plan; it must also include the *time to success*, i.e., the total amount of time required for both planning and acting. Acting is in general much more expensive, resource demanding, and time consuming than planning; and unexpected outcomes and events may necessitate additional acting and planning.

For a successful job, the time to success is finite, but for a failed job it is infinite. To average the outcomes, we use the reciprocal amount, the *speed to success*, which we define as follows:

$$\nu = \begin{cases} 0 & \text{if the job is not successful,} \\ \alpha/(t_p + t_a + n_c t_c) & \text{if the job is successful,} \end{cases}$$

where α is a scaling factor (we used $\alpha = 10,000$ to scale up), t_p and t_a are APE-plan's and APE's total computation time, n_c is the number of commands sent to the execution platform, and t_c the average amount of time needed to perform a command. In our experiments we used $t_c = 250$ seconds. The higher the average value of ν, the better the performance.

Figure 4 shows how the average value of ν depends on b. In the domains with dead-ends (CR and EE), there is a huge improvement in ν from $b = 1$ (where ν is nearly 0) to $b = 2$. This



(a) Domains having dead ends (CR and EE) (b) Domains having no dead ends (SD and IP)

Figure 4. Speed to success ν averaged over all of the jobs, for different values of search breadth b. CR = Chargeable Robot, EE = Explorable Environment, SD = Spring Door, IP = Industrial Plant.

corresponds to a larger number of successful jobs in less time. As we increase b further, we only see slight change in ν for all the domains even though the success ratio and retry ratio improve (Figures 2 and 3). This is because of the extra time overhead of running APE-plan with higher b.

In summary, for domains with dead ends, planning with APE-plan outperforms purely reactive APE. The same occurs to some extent in the domains without dead ends, but there the effect is less pronounced thanks to the good domain specific heuristics in our experiments.

6. Concluding Remarks

We have proposed a novel algorithm APE for integrating acting and planning using the actor's operational models. Our experimentation covers different interesting aspects of realistic domains, like dynamicity, and the need for run-time sensing, information gathering, collaborative and concurrent tasks (see Figure 1). We have shown the difference between domains with dead ends, and domains without dead ends through three different performance metrics: the success ratio, retry ratio and speed to success. We saw that acting purely reactively in the domains with dead ends can be costly and dangerous. The homogenous and sound integration of acting and planning provided by APE is of great benefit for domains with dead ends which is reflected through a higher success ratio. In most of the cases, the success ratio increases with increase in the parameter, search breadth, b of APE-plan. In the case of safely explorable domains, APE manages to have a similar ratio of success for all values of b.

Our second measure, the retry ratio, counts the number of retries of the same task done by APE before succeeding. Performing many retries is not desirable, since this has a high cost and faces the uncertainty of execution. We have shown that both in domains with dead ends and without, the retry ratio significantly diminishes with APE-plan, demonstrating the benefits of using APE-plan also in safely explorable domains.

Finally we have devised a novel, and we believe realistic and practical way, to measure the performance of APE and similar systems. While most often the experimental evaluation of systems addressing acting and planning is simply performed on the sole planning functionality, we devised a *speed to success* measure to assess the overall time to plan and act, including failure cases. It takes into account that the time to execute commands in the real world are usually much longer than the actor's computation time. We have shown that, in general, the integration of APE-plan reduces time significantly in the case of domains with dead ends, while there is not such significant decrease in performance in the case of safely explorable domains.

One limitation of APE is that it finds locally a feasible solution for every task or sub-task that it encounters. It does not take into account the tasks (or sub-tasks) that will surely be performed in future. This is a greedy strategy and may not give the best results. Also, the way in which the algorithm is designed, it is difficult to implement it with any value of sample breadth, b', which is greater than one without having an interpreter for the operational models. [MALIK SAYS: *this point about interpreter needs to be clarified*] This is why we restricted to $b' = 1$ in our experiments. Future work will include improving the algorithm to overcome these limitations and performing more elaborate experiments, with more domains and test cases, and different settings of APE-plan's search breadth, search depth, and sample breadth parameters. We also plan to test with different heuristics, compare APE with other approaches cited in the related work, and finally do testing in the physical world with actual robots.

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7. Appendix: Description of APE-plan

The main procedure of APE-plan is shown in Figure 5. b, b' and d are global variables representing the search breadth, sample breadth and search depth respectively. APE-plan receives as input a task τ to be planned for, a set of methods M and the current state s. APE-plan returns a refinement tree T for τ. It starts by creating a refinement tree with a single node n labeled τ and calls a sub-routine APE-plan-Task which builds a complete refinement tree for n.

APE-plan has three main sub-procedures: APE-plan-Task, APE-plan-Method and APE-plan-Command. APE-plan-Task looks at b method instances for refining a task τ. It calls APE-plan-Method for each of the b method instances and returns the tree with the most optimal *value*. Every refinement tree has a value based on probability and cost. Once APE-plan-Task has chosen a method instance m for τ, it re-labels the node n from τ to m, in the current refinement tree T. Then it simulates the steps in m one by one by calling the sub-routine APE-plan-Method.

APE-plan-Method first checks whether the search has reached the maximum depth. If it has reached the maximum depth, APE-plan-Method makes an heuristic estimate of the cost and predicts the next state after going through the steps present inside the method. Otherwise, it creates a new

Table 5. The pseudocode of APE-plan and APE-plan-Task, a sub-routine of APE-plan. APE-plan is the planner used by APE.

```
APE-plan (M, s, τ):
n ← new tree node
label(n) ← τ
T_0 ← tree with only one node n
(T, v) ←
  APE-plan-Task(s, T_0, n, M, 0)
if v ≠ failure then
  | return (T, v)
else
  | B ← { Applicable method
  |   instances for τ in M ordered
  |   according to a preference
  |   ordering }
  | if B ≠ ∅ then
  |   | n ← Create new node
  |   | label(n) ← B[1]
  |   | T ← tree with only one node
  |   |   n as the root
  |   | return (T, 0)
  | else
  |   | return null, failure
```

```
APE-plan-Task (s, T, n, M, d_curr):
τ ← label(n)
B ← { Applicable method instances for
  τ in M ordered according to a
  preference ordering }
if |B| < b then
  | B' ← B
else
  | B' ← B[1...b]
  | U, V ← empty dictionaries
for each m ∈ B' do
  | label(n) ← m
  | U[m], V[m] ←
  |   APE-plan-Method(s, T, n, M, d_curr+
  |   1)
  | m_opt ← arg-optimal_m {V[m]}
return (U[m_opt], V[m_opt])
```

node in the current refinement tree T labeled with the first step in the method. If the step is a task, then APE-plan-Task is called for the task. If the step is a command, then APE-plan-Method calls the sub-routine APE-plan-Command.

APE-plan-Command first calls the sub-routine SampleCommandOutcomes. SampleCommand-Outcomes samples b' outcomes of the command *com* in the current state s. The sampling is done from a probability distribution specified by the domain's author. SampleCommandOutcomes returns a set consisting of three tuples of the form (s', v, p), where s' is a predicted state after performing command *com*, and v and p are the cost and probabilities of reaching that state estimated from the sampling. We need the next state s' to build the remaining portion of the refinement tree T starting from the state s'. The cost v contributes to the expected value of T with probability p.Now, after getting this list of three tuples from SampleCommandOutcomes, APE-plan-Command calls the NextStep sub-routine.

NextStep (shown in Figure 6) takes as input the current refinement tree T and node n being explored. If n refers to some task or command in the middle of a refinement method m, then NextStep creates a new node labeled with the next step inside m. The depth of n_{next} will be same as n. Otherwise, if n is the last step of m, it continues to loop and travel towards the root of the refinement tree until it finds the root or a method that has not been fully simulated yet. It returns

Table 6. The pseudocode for APE-plan-Method. *pt = APE-plan-Task, pc = APE-plan-Command

```
APE-plan-Method (s, T, n, M, d_curr):
m ← label(n)
if d_curr = d then
    s', cost' ← HeuristicEstimate(s, m)
    n', d' ← NextStep (s', T, n, d_curr)
else
    step ← first step in m
    n' ← new tree node;
     label(n') ← step
    Add n' as a child of n
    d' ← d_curr; cost' ← 0; s' ← s
case type(label(n')):
   task: T', v' ← pt*(s', T, n', M, d')
   command:
 T', v' ← pc*(s', T, n', M, d')
   end: T' ← T; v' ← 0
return (T', v' + cost')
```

```
APE-plan-Command (s, T, n, M, d_curr):
c ← label(n)
res ← SampleCommandOutcomes (s, c)
value ← 0
for (s', v, p) in res do
    n', d' ← NextStep (s', T, n, d_curr)
    case type(label(n')):
       task: T_s', v_s' ← pt*(s', T, n', M, d_curr)
       command:
     T_s', v_s' ← pc*(s', T, n', M, d_curr)
       end: T_s' ← T; v_s' ← 0
     value ← value + (p * (v + v_s'))
return T, value
```

```
NextStep (s, T, n, d_curr):
d_next ← d_curr
while True do
    n_old ← n
    n ← parent(n_old) in T
    m ← label(n)
    step ← next step in m after
     label(n_old) depending on s
    if step is not the last step of m then
        n_next ← new tree node
        label(n_next) ← step; break
    else
        d_next ← d_next − 1
        if d_next = 0 then
            n_next ← new tree node
            label(n_next) ← end; break
        else
            continue
return n_next, d_next
```

```
SampleCommandOutcomes (s, com):
S ← ϕ
Cost, Count ← empty dictionaries
repeat
    s' ← Sample(s, com)
    S ← S ∪ {s'}
    if s' in Count then
        Count[s'] ← 1
        Cost[s'] ← cost_{s,m[i]}(s')
    else
        Count[s'] ← Count[s'] + 1
until b' samples are taken
normalize(Count)
res ← ϕ
for s' ∈ S do
    res ←
      res ∪ {(s', Cost[s'], Count[s'])}
return res
```

`end` when T is completely refined or a node labeled with the next step in T according to s and its depth.

After APE-plan-Command gets a new node n' and its depth from NextStep, it calls APE-plan-Command or APE-plan-Task depending on the label of n'. It does this for every s' in *res* and estimates a value for T from these runs.