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# Combining Probabilistic Planning and Logic Programming on Mobile Robots

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## Introduction

Key challenges to widespread deployment of mobile robots to interact with humans in real-world domains include the ability to: (a) robustly represent and revise domain knowledge; (b) autonomously adapt sensing and processing to the task at hand; and (c) learn from unreliable high-level human feedback. Partially observable Markov decision processes (POMDPs) have been used to plan sensing and navigation in different application domains. It is however a challenge to include common sense knowledge obtained from sensory or human inputs in POMDPs. In addition, information extracted from sensory and human inputs may have varying levels of relevance to current and future tasks. On the other hand, although a non-monotonic logic programming paradigm such as Answer Set Programming (ASP) is well-suited for common sense reasoning, it is unable to model the uncertainty in real-world sensing and navigation (Gelfond 2008). This paper presents a hybrid framework that integrates ASP, hierarchical POMDPs (Zhang and Sridharan 2012) and psychophysics principles to address the challenges stated above. Experimental results in simulation and on mobile robots deployed in indoor domains show that the framework results in reliable and efficient operation.

## Algorithms

Figure 1 presents an overview of the hybrid framework that is described below in the context of *active target localization*, i.e., a mobile robot localizing target objects in indoor domains by planning an appropriate sequence of actions for visual sensing, information processing and interaction (with humans). The *Knowledge Base* (KB) in ASP contains causal rules and facts about the domain. For any specific query (or task), reasoning in the KB results in an *answer set* containing a set of grounded literals. The uncertainty in sensing and actuation is modeled by the POMDP using belief distributions that represent the probability of target occurrence in different regions in the domain. The answer sets from ASP help initialize the POMDP belief or revise the existing belief distribution based on acquired knowledge. The robot makes observations using sensors that are activated by action execution (e.g., visual sensing or processing algorithms) and *passive* sensors that are always in operation (e.g., range finders). Observations made (by the robot) with high certainty update the KB, while the remaining only update the POMDP belief distributions. Human feedback is considered a valuable resource that the robot uses when available and needed. The need for human input is modeled based on the entropy of the POMDP belief distributions.

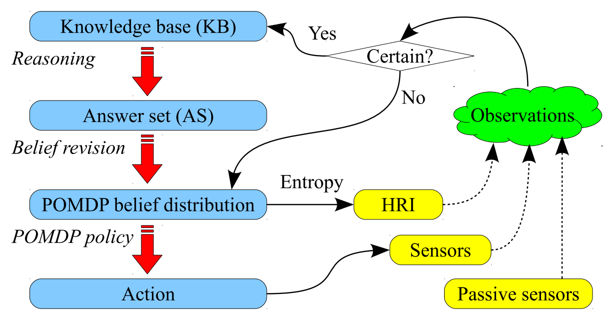


Figure 1: Overview of the hybrid framework.

The probabilistic planning algorithm is based on our prior work on hierarchical POMDPs (Zhang and Sridharan 2012). A high-level POMDP plans the sequence of scenes to analyze (to locate the target) while the lower-level POMDPs choose a sequence of visual processing algorithms to apply on a sequence of images of a chosen scene. The overall hierarchy of POMDPs enables mobile robots to efficiently and accurately localize target objects in indoor environments.

ASP is used for knowledge representation and logical reasoning—domain knowledge is extracted automatically from online repositories (and human inputs) and revised over time. For the illustrative example of a robot localizing targets in indoor domains, the semantic (2D) description has the following elements: `room/1`, a space bounded by walls and doors that can be occupied by the robot and objects; `object/1`, a visually identifiable element in a room; and *category*, a set of objects or sub-categories. The tree of object categories is generated automatically from information in the KB—Figure 2 is an example for office electronics. Categories with objects as children are *primary categories*.

The following predicates represent relations between the elements: (1) `is(X,C)` implies that `C` is an ancestor of `X`, where `X` is an object or a category and `C` is a category, e.g.,

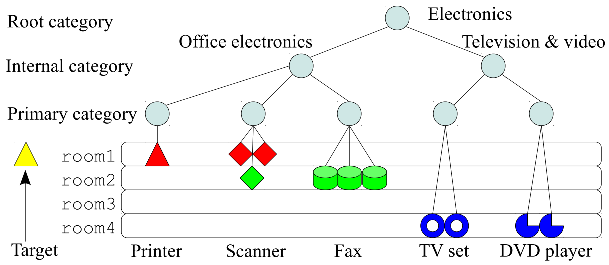


Figure 2: An illustration of object categories.

`is(tv, electronics)`; (2) `observed(O,R,S)` is used to create a fact when object `O` is observed in room `R` at timestep `S`; (3) `located(C,R,S)` implies that objects of category `C` can be (inferred) in room `R` at timestep `S`; and (4) `location(R,X,Y)` states that the coordinates of the center of room `R` (in a learned domain map) are `(X,Y)`, where `X` and `Y` are natural numbers.

The following rules are used for reasoning in this domain[1]: (1) if object `O` is of category `C` and the robot observes `O` in room `R`, then it is believed that objects of category `C` can be in `R`; (2) if objects of category `C` can be in room `R`, then objects of the parent category of `C` (and all ancestor categories of `C`) can be in room `R`; and (3) an object retains its location (i.e., it exists in a room) until it is known to be in some other location (rule of inertia).

```
located(C,R,S)  :- observed(O,R,S), is(O,C).
located(C1,R,S) :- located(C2,R,S), is(C2,C1).
observed(O,R1,S+1) :- observed(O,R1,S),
                 not observed(O,R2,S+1), R1 != R2.
```

The hybrid framework also includes a strategy based on *Fechner's law*[2] to transform the answer set of ASP into a distribution of the same form as the POMDP belief. This strategy captures object co-occurrence properties in the KB—full details are not described due to space constraints. This ASP-based belief distribution is then merged with the POMDP belief distribution, using *weights* to capture the relative trust associated with the two different belief distributions. Consider, for instance, the task of locating a printer, shown as yellow triangle in Figure 2. If ASP and POMDPs are trusted equally, the initial POMDP belief distribution (uniform in the absence of knowledge) would be revised to $[0.3195, 0.2931, 0.1250, 0.2625]$, implying that the target is most likely to exist in `room1`.

## Experiments

As conducting many trials on physical robots is a challenge, a simulated domain was designed to extensively test the framework. Learned object (and error) models were used to simulate realistic motion and perception. The simulation domain has four rooms connected by a surrounding hallway in a $15 \times 15$ grid. There are 50 objects in 10 different primary categories. Each data point in the results described below is the average of performance over 5000 simulated trials. In each trial, the robot's initial position is chosen randomly and one or more objects are randomly selected as target objects, whose locations are hence unknown to the robot. Figure 3 summarizes the experimental results, with the x-axis depicting the extent to which ASP-based beliefs are trusted. When ASP-based beliefs are not included (0 on the x-axis), the accuracy is high ($\approx 0.95$) but the robot travels a significant distance to locate the targets. As the robot starts considering the ASP-based beliefs, there is a marked decrease in the distance traveled—this performance is consistent over a wide range of trust factors. When ASP-based beliefs are trusted significantly more than POMDP-based beliefs, target localization accuracy drops. This decrease in accuracy is partially due to errors in initial knowledge about categories. In addition, the evidence from "related" objects can sometimes overwhelm other facts, e.g., when the `scanner` in `room2` in Figure 2 is the target, `room1` has the highest initial belief based on the answer set. It is a challenge for the robot to recover from these situations, especially when there are false positive target sightings. Similar target localization performance is observed on physical robots in an office domain. Using limited human feedback further improves performance—these results are not shown due to space limitations.

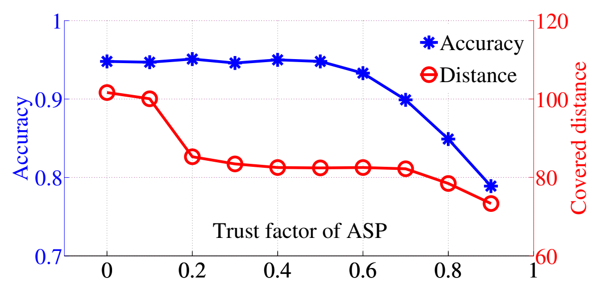


Figure 3: Performance of ASP+POMDP.

## Conclusion

This paper described a novel hybrid framework that integrates ASP and POMDPs to enable a mobile robot to represent and reason with domain knowledge, automatically adapt sensing and information processing to the task at hand, merge logical facts with probabilistic beliefs, and use the information extracted from sensory cues and high-level human inputs to revise the knowledge base. The framework is evaluated in the context of visual target localization—results show that the robot is able to operate reliably and efficiently.

## References


Gelfond, M. 2008. Answer Sets. In Frank van Harmelen and Vladimir Lifschitz and Bruce Porter., ed., *Handbook of Knowledge Representation*. Elsevier Science. 285–316.

Zhang, S., and Sridharan, M. 2012. Active visual sensing and collaboration on mobile robots using hierarchical POMDPs. In *International Conference on Autonomous Agents and Multiagent Systems*.


[1] Variable definitions: `#domain step(S). #domain object(O). #domain category(C;C1;C2).` and `#domain room(R1;R2).`

[2] Fechner's law, introduced in 1860, is the basis of modern Psychophysics. It states that subjective sensation is proportional to logarithm of stimulus intensity.