CLIPP: Combining Logical Inference and Probabilistic Planning

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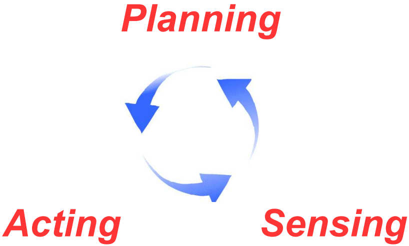
Autonomous Robots

Autonomous robots are intelligent machines capable of performing tasks in the world by themselves, with minimal human control.



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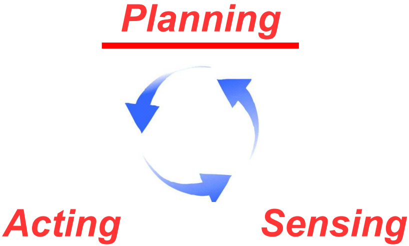

Why Planning is a Challenge for Robots?

- Lack of commonsense knowledge for reasoning.
  - ✓ Example: A robot will never know that "a human cannot appear in two places at the same time" unless it is explicitely defined.
  - ✓ Solution: Answer Set Programming (ASP).
- Unreliable observations and non-deterministic actions.
  - ✓ Example: A robot visually detects a human one-meter in front but actually that may not be the truth.
  - ✓ Solution: Partially Observable Markov Decision Process (POMDP).

How to combine?

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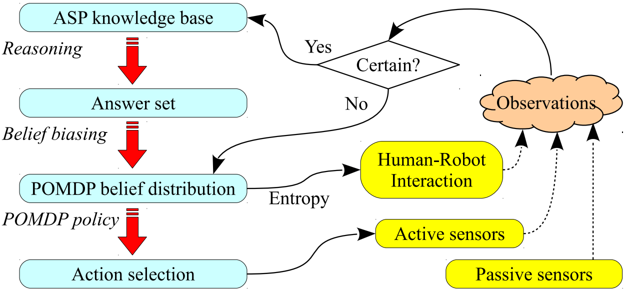
CLIPP Framework: Combining Logical Inference and Probabilistic Planning



ICDL, 2012

Example application: Target Localization

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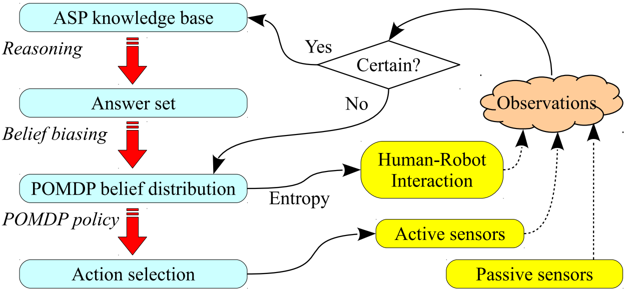

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Example application: Target Localization

Target Localization

Target Localization

- A mobile robot is tasked with localizing target objects in indoor environments.
- The performance is evaluated based on time needed and accuracy.

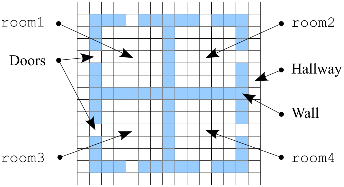

Figure: Simulated domain

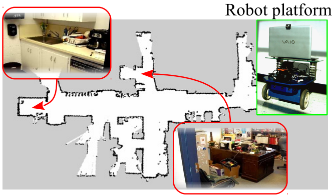

Figure: Realworld domain

ASP → POMDP → Belief biasing → Question asking strategy

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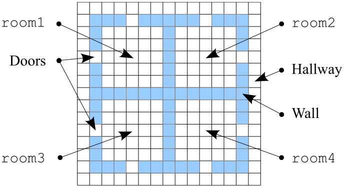

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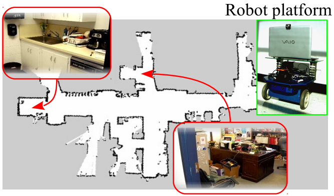

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Target Localization (1/4): ASP Rules

`C`, `C1`, `C2` are categories. `R`, `R1`, `R2` are rooms. `O` is an object. `S` is a timestep.

$$located(C, R, S) :- observed(O, R, S), is(O, C).$$

$$located(C1, R, S) :- located(C2, R, S), is(C2, C1).$$

$$observed(O, R1, S+1) :- observed(O, R1, S),$$
$$not\ observed(O, R2, S+1), R1 != R2.$$

$$accessible(R, S+1) :- accessible(R, S), not\ \neg accessible(R, S+1).$$

Target Localization (1/4): Categorical Tree in ASP

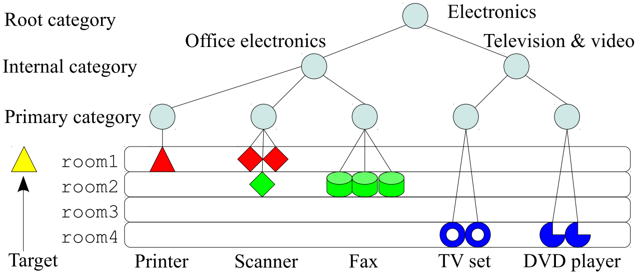
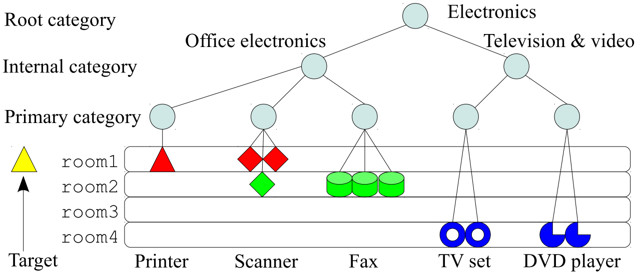


Figure: A categorical tree represented by ASP program

- ✓ Such a tree is automatically constructed and represented in ASP in knowledge base.
- ✓ The answer set can be converted into a distribution b^A: [0.3890,0.3361,0.0000,0.2749].

Details

Target Localization (1/4): Categorical Tree in ASP



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Details

Target Localization (2/4): Hierarchical POMDPs

Markov assumption (first order): state in $t+1$ only relies on the state in t.

⇓

Markov Decision Process (MDP, 1950s): (S, A, T, R).

⇓

Partially Observable Markov Decision Process (POMDP, 1998):
(S, A, O, T, Ω, R).

Our previous work proposed hierarchical POMDPs, where a robot holds a belief distribution b representing the estimation of current state.

AAMAS 2012 Details

Target Localization (3/4): POMDP Belief Biasing

An arithmetic-geometric hybrid merging strategy: r-norm.

$$b'_i = \beta\left\{(1-\Omega)(b_i)^r + \Omega(b_i^A)^r\right\}^{1/r} \tag{1}$$

where, b_i^A is the probability from answer set in room i. b_i and b'_i are the probabilitiess of target occurrence in room i before and after belief merging. β is a normalizer. $\Omega \in [0, 1]$ represents the relative trust of the answer set.

Taget Localization (4/4): When to Ask Human a Question?

When the *entropy* of belief state is *high*, human feedback is needed.

Entropy of distribution b

$$\mathcal{H}(b) = -\sum_{i=1}^{N} b_i log(b_i) \tag{2}$$

Experimental Results: Time Needed and accuracy

Domain

- ✓ Fifty objects of 10 primary categories in 4 rooms are simulated.
- ✓ One of the objects is randomly selected as the target whose position is unknown to the robot.

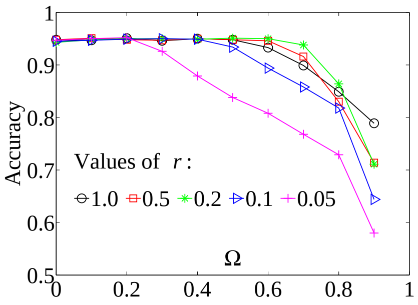

Figure: Accuracy

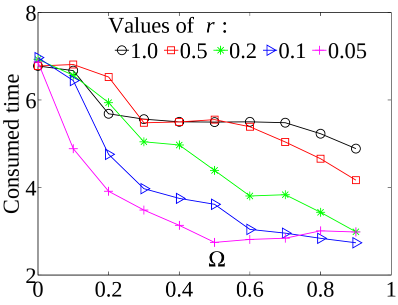

Figure: Time needed

Experimental Results: Time Needed and Accuracy

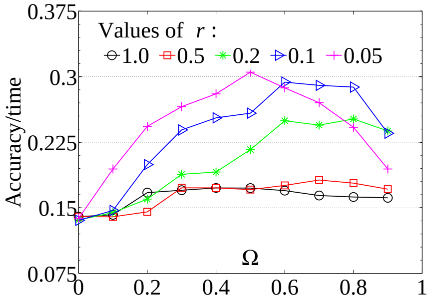

Figure: Accuracy/time

Irrespective of the value of r, the best accuracy-time balance occurs when the value of Ω is neither too high nor too low.

Experimental Results: Question Asking Strategy

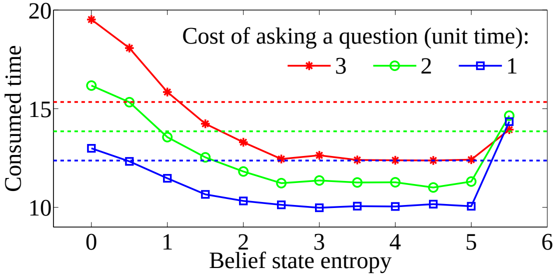

Figure: Entropy-based question asking strategy

Entropy-based strategy performs better than the always-ask (left end) and never-ask (right end) strategies.

Future Research

- ✓ Negative observations to be added in knowledge base.
- ✓ CLIPP for teams with multiple robots.
- ✓ Custumized POMDP belief biasing strategy based on answer sets.
- ✓ Tasks other than target localization.

Thank you!

Appendix *A*: POMDP Bias Generation by Answer Set

Assumptions

1. An object is more likely to be co-located with *close* "relatives", where closeness is defined as the distance to the lowest common ancestor in the tree of object categories.
2. For any category, the influence of "siblings" categories increases as the number of "siblings" decreases. The influence of a "sibling" category increases when there is sufficient support for the sibling's existence (predicate `observed/3`).
3. The relationship between object occurrence probabilities (i.e., belief state entries) and evidence provided by categories (and siblings) is inspired by **Fechner's law**[a].

[a] Fechner's law was introduced in 1860 and serves as the basis of modern Psychophysics.

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Appendix A: POMDP Bias Generation by Answer Set

$$b_i^A = \alpha \ln \left(1 + \sum_{m=1}^{M_i} \frac{N_{i,m}^F}{\prod_{k=0}^{K_{i,m}-1} N_{i,k,m}^S} \right) \tag{3}$$

where b_i^A, the probability that the target is in room i. α is a normalizer. The parameter m is the index of primary category C_m, ranging from 1 to the total number of primary categories with leaf objects known to be in room i (i.e., M_i). Values of M_i and $N_{i,m}^F$ are obtained by counting the number of relevant `located/3` and `observed/3` literals (respectively) in the answer set. $K_{i,m}$ is the height (in object category tree) of the lowest common ancestor of C_m and the target object. The product in the denominator accounts for category nodes along the path from C_m to the lowest common ancestor. Variable k represents the height of nodes along this path, ranging from 0 (object level) to $K_{i,m} - 1$. $N_{i,k,m}^S$ is the number of siblings of the node (including itself) on the path at height k, and $N_{i,0,m}^S = 1$.

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Appendix *B*: Hierarchical POMDPs

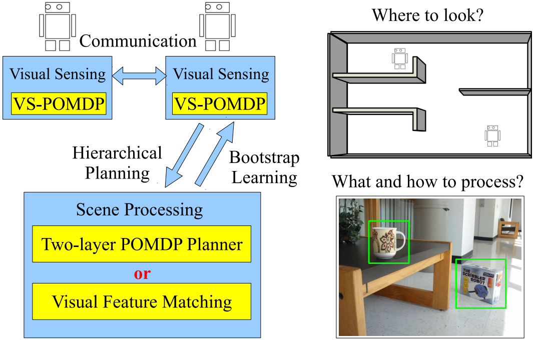

Figure: Sensing and Collaboration on Mobile Robots using POMDPs

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