CLIPP: Combining Logical Inference and Probabilistic Planning

Shiqi Zhang

Advisor: Dr. Mohan Sridharan
Department of Computer Science
Texas Tech University

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Autonomous robots are intelligent machines capable of performing tasks in the world by themselves, with minimal human control.
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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 explicitly 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).
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 explicitly 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?**
CLIPP Framework: Combining Logical Inference and Probabilistic Planning

Example application: Target Localization

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CLIPP Framework: Combining Logical Inference and Probabilistic Planning

Example application: 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

\[\text{ASP} \rightarrow \text{POMDP} \rightarrow \text{Belief biasing} \rightarrow \text{Question asking strategy}\]
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$\text{ASP} \rightarrow \text{POMDP} \rightarrow \text{Belief biasing} \rightarrow \text{Question asking strategy}$
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 ¬accessible(R, S + 1).
✓ Such a tree is automatically constructed and represented in ASP in knowledge base.
✓ The answer set can be converted into a distribution $b^A$: $[0.3890, 0.3361, 0.0000, 0.2749]$. 

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 $b^A$: $[0.3890, 0.3361, 0.0000, 0.2749]$. 

Figure: A categorical tree represented by ASP program.
Markov assumption (first order): state in $t + 1$ only relies on the state in $t$.

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


Our previous work proposed hierarchical POMDPs, where a robot holds a belief distribution $b$ representing the estimation of current state.
An arithmetic-geometric hybrid merging strategy: $r$-norm.

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

where, $b^A_i$ is the probability from answer set in room $i$. $b_i$ and $b'_i$ are the probabilities of target occurrence in room $i$ before and after belief merging. $\beta$ is a normalizer. $\Omega \in [0, 1]$ represents the relative trust of the answer set.
When the *entropy* of belief state is *high*, human feedback is needed.

**Entropy of distribution** \( b \)

\[
\mathcal{H}(b) = - \sum_{i=1}^{N} b_i \log(b_i)
\]
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.

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**Figure: Accuracy**

Values of $r$:
- $1.0$
- $0.5$
- $0.2$
- $0.1$
- $0.05$

**Figure: Time needed**

Values of $r$:
- $1.0$
- $0.5$
- $0.2$
- $0.1$
- $0.05$
Irrespective of the value of $r$, the best accuracy-time balance occurs when the value of $\Omega$ 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.
- Customized 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.
Appendix A: POMDP Bias Generation by Answer Set

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

(3)

where \( b_i^A \), the probability that the target is in room \( i \). \( \alpha \) 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/observed 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 \( N_{i,0,m}^S = 1 \).
Appendix B: Hierarchical POMDPs

Figure: Sensing and Collaboration on Mobile Robots using POMDPs