INTEGRATION OF DIAGNOSTIC CAPABILITIES WITH ASP+POMDP PLANNING

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DISCLAIMER
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OVERVIEW

- Motivation
- Statement of Objectives
- Related Work
- Proposed Tasks
- Current Status
- Summary
Motivation

• Robots work with incomplete domain knowledge
  • Missing or inaccurate information
  • Dynamic environment

• What if something unexpected occurs?

• Intelligent agents still possess a high level of dependency on humans.

• Inability of high-level collaboration between intelligent agents

• Need for intelligent agents to perform more efficiently, so as to incorporate them into more labor-intensive tasks

• Overall, improve current ASP+POMDP planning framework
Answer Set Programming

- Knowledge representation and reasoning
- Non-monotonic reasoning
  - Increasing knowledge base may decrease the number of logical conclusions
- Default reasoning
  - Does an animal fly?
- Reasoning about knowledge
- Belief revision
  - New observations might be inconsistent with older ones

(Gelfond & Kahl, 2013)
Defining kinds and abnormalities

If a book_name is a member of a category that is of a certain kind and that book_name is not believed to be abnormal or is not known to be not of that kind, then it is of the same kind as its super category.

\[
\text{kind_is}(\text{Bkn}, \text{useful}) \leftarrow \text{kind_is}(\text{Cat}, \text{useful}),
\]
\[
\quad \text{is_member}(\text{Bkn}, \text{Cat}),
\]
\[
\quad \text{not ab}(\text{nf}(\text{Bkn})),
\]
\[
\quad \text{not -kind_is}(\text{Bkn}, \text{useful}).
\]

If book_name might be a memoir, it is abnormal

\[
\text{ab}(\text{nf}(\text{Bkn})) \leftarrow \text{not -is_member}(\text{Bkn}, \text{memoir}).
\]

\[
\text{kind_is}(\text{Bkn}, \text{fun}) \leftarrow \text{kind_is}(\text{Cat}, \text{fun}),
\]
\[
\quad \text{is_member}(\text{Bkn}, \text{Cat}),
\]
\[
\quad \text{not ab}(\text{f}(\text{Bkn})),
\]
\[
\quad \text{not -kind_is}(\text{Bkn}, \text{fun}).
\]

Nancy Drew isn't fun

\[
\text{kind_is}(\text{nancy_drew}, \text{fun}).
\]

Initial state/information

\[
\text{bkn_is}(\text{cook_book}).
\]
\[
\text{bkn_is}(\text{dictionary}).
\]
\[
\text{bkn_is}(\text{harry_potter}).
\]
\[
\text{bkn_is}(\text{bossypants}).
\]
\[
\text{bkn_is}(\text{nancy_drew}).
\]
\[
\text{is_child}(\text{cook_book}).
\]
\[
\text{is_child}(\text{dictionary}).
\]
\[
\text{is_child}(\text{memoir}).
\]
\[
\text{is_child}(\text{fantasy}).
\]
\[
\text{is_child}(\text{mystery}).
\]
\[
\text{is_child}(\text{fiction}).
\]

DLV [build BEN/Dec 17 2012 gcc 4.6.1]

\[
\text{trisha@Penguin:~/Desktop/Internship}$
\]

julia_child, useful
webster, useful
harry_potter, fun
bossypants, useful
20 program rules
21
22 % Domain: a 3 room map, a box, a robot cleaner.
23
24 success :- goal(T).
25 :- not success.
26 occurs(A,T) | -occurs(A,T) :- not goal(T).
27
28 % Do not do more than one action per time step.
29 :- occurs(A1, T), occurs(A2, T), A1!=A2.
30
31 % Cleaning rules
32 holds(cleaned(R), T+1) :- occurs(clean(R), T),
33 holds(robot_in(R), T),
34 -holds(box_in(R), T).
35 holds(robot_in(R), T+1) :- occurs(move_robot(R), T).
36 holds(box_in(R2), T+1) :- occurs(move_box(R2), T),
37 holds(robot_in(R1), T),
38 holds(box_in(R1), T).
39 holds(robot_in(R2), T+1) :- occurs(move_box(R2), T),
40 holds(box_in(R1), T),
41 holds(robot_in(R1), T).
42 -holds(robot_in(R1), T) :- holds(robot_in(R2), T), R2!=R1.
43 -holds(box_in(R1), T) :- holds(box_in(R2), T), R2!=R1.
44
45 % Inertia
46 holds(F, T+1) :- holds(F, T), not -holds(F, T+1).
47 -holds(F, T+1) :- -holds(F, T), not holds(F, T+1).
48
49 % Initial state
50
51 holds(box_in(r1), 0).
52 holds(robot_in(r1), 0).
53 -holds(cleaned(R), 0).
54
55 goal(T) :- holds(cleaned(r1), T),
56 holds(cleaned(r2), T),
57 holds(cleaned(r3), T).
**Partially Observable Markov Decision Process**

- *Partial Observability* means the sensed data and measurements are not complete and noisy.

- *Markov Decision Process* in its own, uses the current state and control data to estimate the posterior distribution (the next state) over the possible states.

- POMDP is based off the Markov Decision Process.

- Ergo, *Partially Observable Markov Decision Process estimates a posterior distribution* (what happens next) over possible states, as the current state cannot be fully sensed directly.

*(Probabilistic Robotics, 2006)*
Why ASP+POMDP?

- ASP is good for knowledge representation and default reasoning, but has trouble probabilistically modeling uncertainty.

- POMDPs work effectively well in modeling uncertainties when planning
  - Capable of contingent planning – *able to handle unexpected outcomes*. (Yoon, Fern, Givan, 2007)
  - Capable of conformant planning – *able to achieve a goal regardless of uncertainty in the initial state or action state*. (Palacios, Geffner, 2009)

- Although, including common sense knowledge into POMDP can be a challenge.

- Use ASP to represent and reason about domain knowledge and POMDPs for sensing and information processing

  (Zhang, Sridharan, & Bao, 2012)
OBJECTIVES

• Create a more robust planning system

• Develop an ASP knowledge base that can handle unexpected events

• Estimate probabilistic values for a selection of causal factors for a state – using Partially Observable Markov Decision Processes (POMDPs)

• Integrate diagnostic layer with current ASP + POMDP system
  • Simulation level
  • Physical level (robots)
Current ASP+POMDP framework integrates probabilistic planning, non-monotonic logical reasoning, and human-robot interaction.
Proposed ASP+POMDP framework integrates logical and probabilistic diagnosis to the current framework.

- Shiqi Zhang’s work on programming & probabilistic planning on intelligent agents elucidates the architecture that integrates high-level logical inference with low-level probabilistic sequential decision-making.


- Chen’s work combines ASP with NLP for task planning in service robots.


- Sungwook’s work on probabilistic plannings sheds light on the POMDP’s capabilities of Contingent & Conformant planning.
With respect to **High Through-Put Phenotyping**...

- Peter Biber’s works on autonomous agricultural robots, births ‘Bonibot‘ that performs phenotyping tasks on mazie crops in a field on different days. He gave a detailed insight on the robust and accurate system of algorithms & sensors.

- Ulrich Weiss’ work on detection & mapping for agricultural robots explains the type and effectiveness of sensors used, based on GPS localization & 3D environment sensing.

*MEMs based Light detection & Range sensor (circled) on BoniBot for 3D visualization of the environment.*

*(Biber, Weiss, Dorna, & Albert, 2012)*
PROPOSED TASKS

• Develop diagnostic rules and methods
  • Simulation with ASP only

• Estimate probabilistic values for a selection of causal factors for a state – using POMDPs

• Interface the logical diagnosis layer with the probabilistic diagnosis layer to improve reasoning in intelligent agents

• Simulate using both ASP+POMDP

• Implement overall process on the physical robots

• Set the platform for examining the possible incorporation of the ASP+POMDP Diagnosis & Planning framework into agricultural robotics – the High Through-Put Phenotyping prototype...
  • Implements a possibly effective & optimal method of localizing & mapping cotton plants on a cotton field, to an accuracy of 30cm or less
  • Navigates to a specified cotton plant from any arbitrary position on the cotton field
CURRENT STATUS

• Learning about logic programming

• Working with simple ASP programs

• Understanding Bayes Filter’s implementation into the localization of a mobile robot – Markov_localization
  • In robotics, the Bayes Filter algorithm recursively calculates the probabilities of a sequence of beliefs sensed from measurement & control data, so a robot can infer its position & orientation.
  • The Markov_localization is just a straightforward application of the Bayes Filter to localization problems.

(Probabilistic Robotics, 2006)
Current Status

• Understanding the problem posed by **mapping** for mobile robots – **SLAM**
  • *Robot builds a map of the environment, and simultaneously localizes itself, relative to the built map.*

• Understanding technical functionalities and implementation techniques of state-of-the-art sensors for mobile robots - 3D sensors

• Becoming familiar with the Robot Operating System (**ROS**), which is used to interface with the robot (**Erratic**).
Current Status

• Created an active map of the third floor in the Computer Building at Texas Tech, Lubbock, to simulate a strict indoor domain that’s yet stochastic.

• A series of test runs to observe *Erratic* using POMDP to navigate around obstacles and arrive at a goal set on the map – simulates a mobile robot on an agricultural field navigating to specific plants.
• Research will expand the usability of the current ASP+POMDP project by implementing a diagnosis extension.

• System complete with diagnostic capabilities will be more tolerant of the changing and unexpected environments which are characteristic of real-world scenarios.


QUESTIONS?

Thank you for listening!