A Stochastic Belief Management Architecture for Agent Control

Gavin Rens, Tommie Meyer, Deshen Moodley

Centre for AI Research, CSIR Meraka, South Africa
University of Cape Town, Dept. Comp. Sci., South Africa
{grens,tmeyer,deshen}@cs.uct.ac.za

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Outline

1. Introduction
2. Architecture Components in Detail
3. General Belief Change
4. Conclusion and Future Work
Introduction
Elements and Components

- POMDP theory.
- Logic languages.
- Belief change theory.
- Dealing with ignorance (via entropy optimization).
- Learning and planning assumed present (no detail).
- Observation stream processing.
Conceptual Model of Architecture

- **Background belief base**
  - Decision theory base
  - State base

- **POMDP model**
  - Belief change

- **Decision making**
  - Planner
  - Reasoner

- **Stream processing**
  - Foreground observation buffer
  - Active stream
  - Passive stream

- **Environment**
  - Actions
  - Observations

The SBM Architecture
Architecture Components in Detail
Observation Streams

- Passive stream
  - periodic extraction
  - unsolicited
  - unclear observation cause

- Active stream
  - asynchronous
  - associated with intention
  - observation in context of action
The Background Belief Base

- **Decision Theory Base**
  - environment models (transition, observation & event functions)
  - *Stochastic Decision Logic* (SDL) [Rens et al., 2015]
  - possibly incomplete specifications

- **State Base**
  - probabilistic constraints on possible states
  - P-logic [Zhuang et al., 2017]
  - possibly incomplete specification
Observations are recorded in the order which they were received.

\[ Z = (z_1, z_2, \ldots, z_n) \]

Combining observations from passive and active streams.

\[ z_i \text{ is } \phi \text{ or } (a, \phi) \text{ or } p(\phi) \triangleright t, \]

\[ \text{where } \phi \in L_P \]
The Foreground Observation Buffer

- The SB is modified by $z_1$ via a belief change operation.
- $z_1$ removed from $Z$.
- Then $z_2$ modifies the SB, and so on.
Decision Making

- Reasoner for query answering.
- Asking whether some query posed to the agent logically follows from the BG BB.
- No implementations. (?)
- Not optimized/analyzed with respect to efficiency.
Decision Making

- Planner for action/policy recommendation.
- Online POMDP algorithm employing finite horizon forward search.
- Such algos require a single current (root) belief state and a fully specified POMDP model.
- Entropy optimization (if necessary).
General Belief Change
Dimensions of Belief Change

- Belief revision (⋆) ≠ Belief update (∆).
- Revision: for change w.r.t. epistemic (static) info.
- Update: for change w.r.t. ontic (physical/dynamical) info.
- Active vs Passive.
- Adequacy of transition model specification.
Focus on belief management of the state base (SB).

P-revision (of p-logic) is fine for revision.

Something else required for update.

Update operators typically applied to pd’s, not sets of constraints.

Several candidate methods to extract representative credal sets from SB.
Every observation is assumed *marked* or *raw*.

Marked: accompanied by degree of belief info.

Raw: no extra info.

Epistemic observations are always marked (from both streams).

Ontic observations are always raw (from both streams).
### Operators and Operator Selection

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<th>ontic transition info?</th>
<th>epistemic</th>
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<tr>
<td>active</td>
<td>$\Delta_{atv}^{trn}$</td>
<td>$\Delta_{atv}^{dst}$</td>
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<td>passive</td>
<td>$\Delta_{psv}^{trn}$</td>
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Operators and Operator Selection

\[
\Delta = \Delta_{\text{trn}}^{\text{psv}} \quad \text{trans info?} \quad \Delta = \Delta_{\text{dst}}^{\text{psv}} \\
\Delta = \Delta_{\text{atv}}^{\text{atv}} \quad \text{trans info?} \quad \Delta = * \quad \text{ontic?} \\
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\Delta = \Delta_{\text{atv}}^{\text{atv}} \quad \text{ontic?} \\
\Delta = \Delta_{\text{atv}}^{\text{atv}} \\
\]

FG OB

\[
z_{t+1}, z_{t+2}, \ldots, z_{t+n} \\
\text{atv stream} \quad \text{psv stream} \\
\]
Conclusion and Future Work
Conceptual Model of Architecture

- Background belief base
  - Decision theory base
  - State base
- POMDP model
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  - Planner
  - Reasoner
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  - Active stream
  - Passive stream
- Belief change
- Environment
  - Actions
  - Observations

The SBM Architecture
1. We proposed a coherent framework for general agent knowledge management and decision-making under uncertainty and ignorance.

2. We presented a means to deal with two kinds of streams of observations: *active* and *passive*, where observations from different streams are dealt with differently.

3. We presented a technique for belief maintenance which takes into account whether beliefs should be revised (due to erroneous beliefs) or updated (due to changes in the environment).
Remarks

- Preliminary proposal for an architecture.
- Only a basic framework.
- Generate a discussion and ideas for its improvement.
Remarks

- Many ways to sophisticate the architecture.
- Environment model learning.
- New states learning.
- Case-based reasoning.
- Etc., etc.
Future Work

- Newest findings in probabilistic/possibilistic belief update.
- Issues with knowledge/memory embeddedness.
- W.r.t. real-time planning,
  - Hybrid POMDP-BDI agent architecture [Rens & Moodley, 2017].
  - Partially Observable Monte-Carlo Planning (POMCP) [Silver & Veness, 2010].
- Current work to be incorporated:
  - More robust, generally applicable belief revision,
  - More robust, generally applicable belief update.
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