Probabilistic Multiple Hypothesis Anchoring

Jos Elfring
Sjoerd van den Dries

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Workshop on Knowledge Representation for Autonomous Robots
Scenario

A world model is needed to deal with the uncertainties in unstructured environments.

cup-1

$k - 1$
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Requirements of a World Modeling Algorithm

- Data association in presence of:
  - Unknown and varying number of objects
  - Dynamic scenarios
  - Inaccurate, false and missed detections
- Correcting previous decisions based on new measurement data
- Objects must have semantic meaning
- Exploiting (object specific) prior knowledge
- Probabilistic framework to deal with uncertainties
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Inspired by:

- Multiple Hypothesis Tracking

- Anchoring
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- Multiple Hypothesis Tracking
  - Reid (1979)\(^1\), Cox & Hingorani (1996)\(^2\)
- Anchoring
  - Coradeschi & Saffiotti (2003)\(^3\)

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\(^1\) D. B. Reid, An algorithm for tracking multiple targets, IEEE Transactions on Automatic Control AC-24 (6), (1979), pp 843-854


Probabilistic Multiple Hypothesis Anchoring

Objects are implemented by anchors

- Each anchor contains:
  1. An individual symbol:
     • $\text{cup-1}$
     - Individual symbols have predicate sets, e.g., \{white, small\}
  2. A sequence of measurements:
     • $(z_1(1), z_3(2), z_2(4))$
     - Measurements have attributes and attribute values, e.g., $\text{hue} = 20$
  3. A signature mapping attributes to attribute values, implemented by a mixture of pdfs,
     - A constant position model Kalman filter
     - A pdf representing locations the object can be moved to

Predicate grounding relations link attribute values of measurements to predicate symbols
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Anchor = ( , , , )

z_1(1), \ldots, z_2(4)

area = 250
hue = 12

attributes

Individual symbols

cup-12

Predicate symbols

\{white, small\}

pred attr values

<table>
<thead>
<tr>
<th>red</th>
<th>hue</th>
<th>[-20, 20]</th>
</tr>
</thead>
<tbody>
<tr>
<td>small</td>
<td>area</td>
<td>[10, 200]</td>
</tr>
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... ... ...

/department of mechanical engineering
Probabilistic Multiple Hypothesis Anchoring

Each measurement can be:

- A new object
- A previously observed object
- A false detection
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All possible associations are considered → hypothesis tree:

```
  k
  /|
 k-1 | k-2
  |
 k-2
```

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Probabilistic Multiple Hypothesis Anchoring

- Each hypothesis represents a possible set of associations

number of hypotheses increases rapidly

prune hypotheses in past based on most recent data

allows revising previous decisions
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The probabilistic models are used to incorporate prior knowledge:

- How often do new objects appear? Uniqueness of objects
- Where do new objects appear? Typical locations
- Which objects are expected to appear? Experience-based relations
- How do objects move? Motion models
- Is an object moved, if yes, how? Passive vs. active objects
- How often are false positives detected? Reliability object detector
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Hypothesis tree allows probabilistic answers to queries:

- "How many cups on the table":
  - > 3 (p = 0.8)
or
  - = 4 (p = 0.2)

- "Where is John’s cup":
  - > On the table (p = 0.75)
or
  - > On the sink (p = 0.25)
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Conclusions and Future Work

Conclusions:

- Combined Multiple Hypothesis Tracking with anchoring:
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Future work:

- Preparing ROS implementation
- Extend, learn, share probabilistic models
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Questions

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