World Modeling in Robotics: Probabilistic Multiple Hypothesis Anchoring

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I. Introduction

Domestic robots are typically confronted with a complex, dynamically changing and unstructured environment. In order to adequately perform tasks such as safe navigation and object manipulation, robots need an accurate description of the world. Such an environmental description, here referred to as *world model*, is constructed based on perceived object features and must store and keep track of the objects in the world and their attributes.

Requirements of such a world modeling algorithm are: **(1)** *semantic richness:* object descriptions must be semantically annotated, *i.e.*, stored with human-readable attributes such as *position*, *color* and *class* such that human-defined tasks can be mapped to the world description, and the algorithm must allow multiple attributes to be stored and maintained simultaneously; **(2)** *probabilistic nature:* due to sensor limitations and prediction uncertainty, uncertainty must be explicitly represented and dealt with in the system by using probabilistic representations and calculations; **(3)** *data association and attribute maintenance:* measured object features must be linked to and update object descriptions, while dealing with possible ambiguities; **(4)** *exploitation of prior knowledge:* existing knowledge about the behavior of objects, *e.g.*, movement, expected locations, should be used as much as possible; **(5)** *computationally feasible and scalable:* the system must run real-time on a robot, even in cluttered scenarios with many objects.

We present Probabilistic Multiple Hypothesis Anchoring (PMHA), a world modeling algorithm that fulfills these requirements by uniquely extending perceptual anchoring ([2]) with an efficient Bayesian multiple hypothesis framework ([3], [1]) and a generalized multiple-model object tracking approach ([4]).

II. Probabilistic Multiple Hypothesis Anchoring

The PMHA algorithm works as follows:

- Measured object features are received as input from perception routines. These features are assumed to have a probabilistic representation, explicitly stating the amount of uncertainty. (*Req. 2*)
- The measured features are mapped to semantically rich structures using a predicate grounding relation known from anchoring, *e.g.*, certain hue-saturation-value color ranges are mapped to the color 'blue', relative coordinate frames are mapped to absolute coordinate frames. (*Req. 1*)
- Semantic features are associated to new objects or existing objects in the world model by generating multiple association hypotheses according to the multiple hypothesis framework. Hypothesis probabilities are calculated using a Bayesian prior-likelihood calculation. (*Req. 2, 3*)
- Within each hypothesis, object attributes are updated based on the probabilistic semantic features. The object attributes are also stored in a probabilistic way, *e.g.*, the Cartesian position is stored as a Gaussian. (*Req. 2, 3*)
- Non-measured object attributes are predicted using a multi-model approach: multiple *behavior models* may predict future states of different attributes, *e.g.*, position or color, again generating multiple hypotheses. The behavior models can be both *physics-based*, *e.g.*, a constant-velocity model, and *common-sense based*, *e.g.*, a model stating that *John comes home at 5pm*. (*Req. 4*)

To ensure computational feasibility (*Req. 5*), gating, limited hypotheses generation and hypothesis pruning are used, as well as efficient implementation of the algorithm using track trees and clustering ([3], [1]).

III. Experiments and Future Work

The potential of the algorithm has been demonstrated in several experiments, including the tracking of multiple people in a room, solving ambiguities about the identities of objects, and verification and falsification of object positions and colors based on cheap perception routines. Future work includes extending the behavior models and predicate grounding relations used, as well as combining the multiple hypothesis framework with more efficient methods for storing and retrieving object descriptions.

References

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