Building and Exploiting Semantic Maps

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ICRA 2011 Workshop on Semantic Perception, Mapping and Exploration

They did the work

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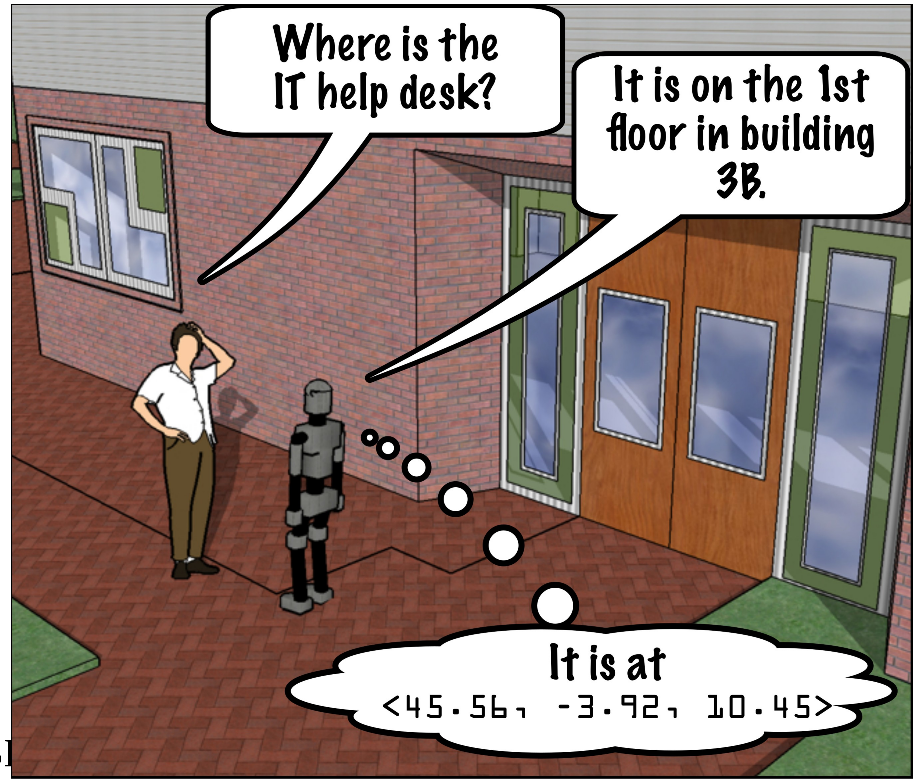
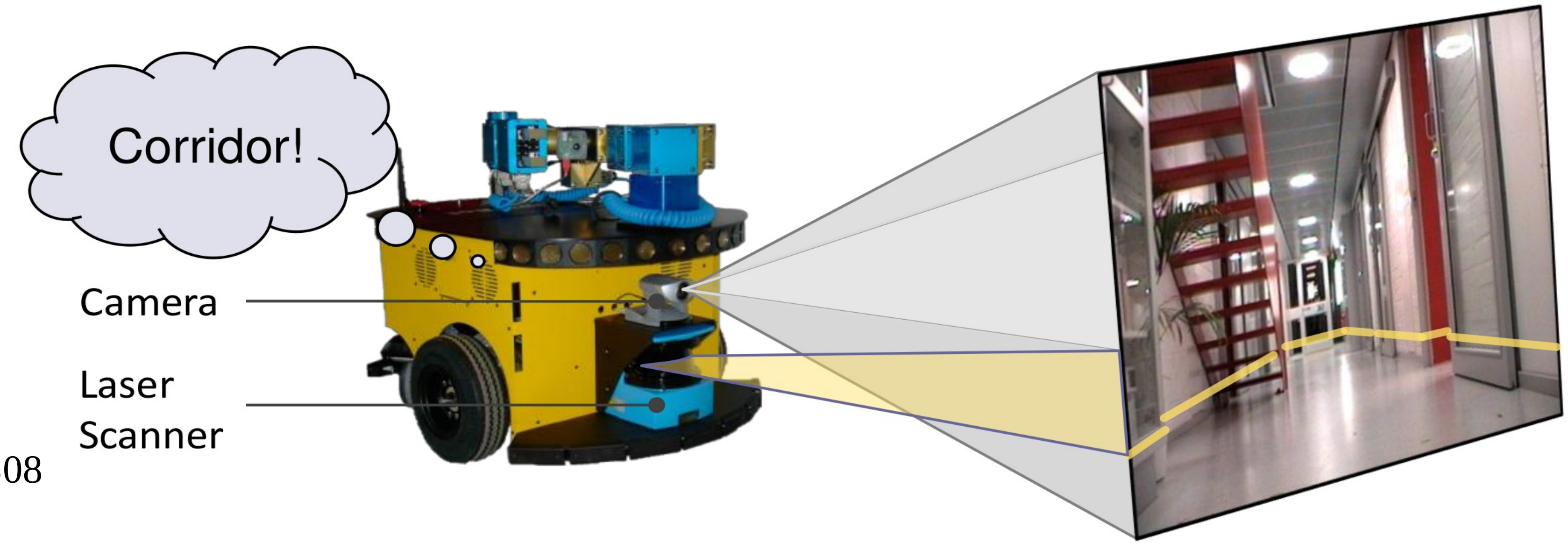
Motivation : the big picture

- Help in the "leap"
  - Industrial → domestic and office environment
  - No / trained users → ordinary people
- Understanding space is a fundamental ability



Target task 1
Place categorization

- Problem: Estimate the semantic category of space
- Very useful when operating in human environments



Scene categorization
Object categorization

Torralba et al, ICCV03
Pronobis et al, IROS 06
Vasudevan & Siegwart, RAS08
Wu et al, ICRA09
Ranganathan, RSS10

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Target task 2
Object search

- We believe that objects are key to understand and to operate in human habitats.
- Likely that fetch-n-carry tasks will be important for service robots
- → **Need to find the objects!**

Garvey, SRI Tech 1976
Tsotsos, IJCV92
Ekvall et al, IROS06
Andreopoulos et al, ICCV09
Kollar & Roy, ICR09
Aydemir et al, ICRA10
Ma & Burdick, ICRA10
Joho & Burgard, RAS11
Kanezaki et al, ICRA11

Observation when modeling the world

- Whatever we do the model of the world will be
  - Imperfect
  - Incomplete
  - Inaccurate
  - Invalid

  → Map must support
  - Revised decisions
  - Uncertainty

- We think it is important to model aspects of the env. at the right level of abstraction → multiple layers

Modeling space

- Abstract the spatial knowledge to keep complexity down

- We discretize space into a graph of connected places
- Places are grouped into rooms based on observed doors

Modeling space

- Using functional spatial relations (IN and ON) to model object-object relations and object-location relations.
  - The apples are IN the bowl ON the table
    - → Hierarchical decomposition.
    - → Abstraction of spatial knowledge

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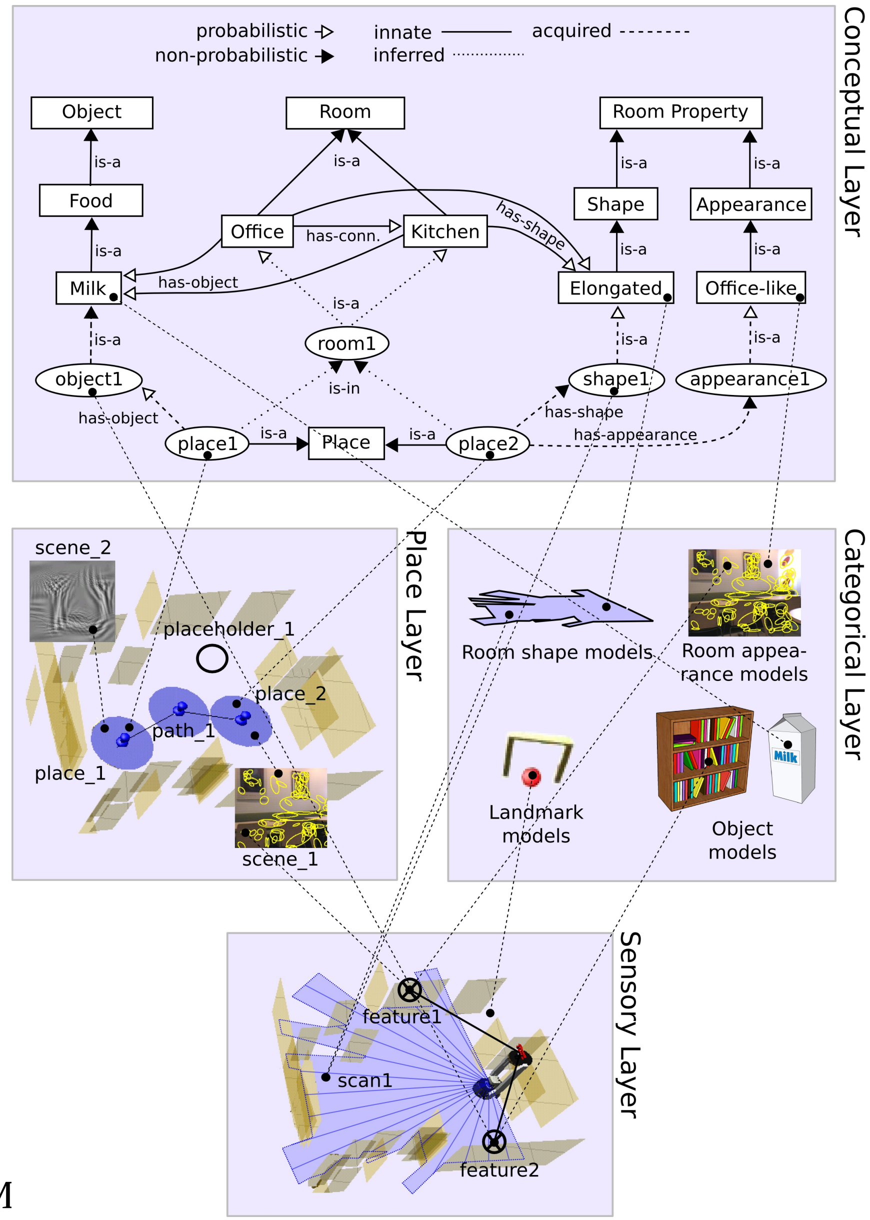
Structuring the map
→ Layered representation

- High level knowledge
  - Human level concepts (e.g. rooms, obj-obj relations,...)
- Long term categorical knowledge
  - Object models, ...
- Discretized space
  - Places, paths,...
- Low level sensor data
  - Navigation, manipulation, …



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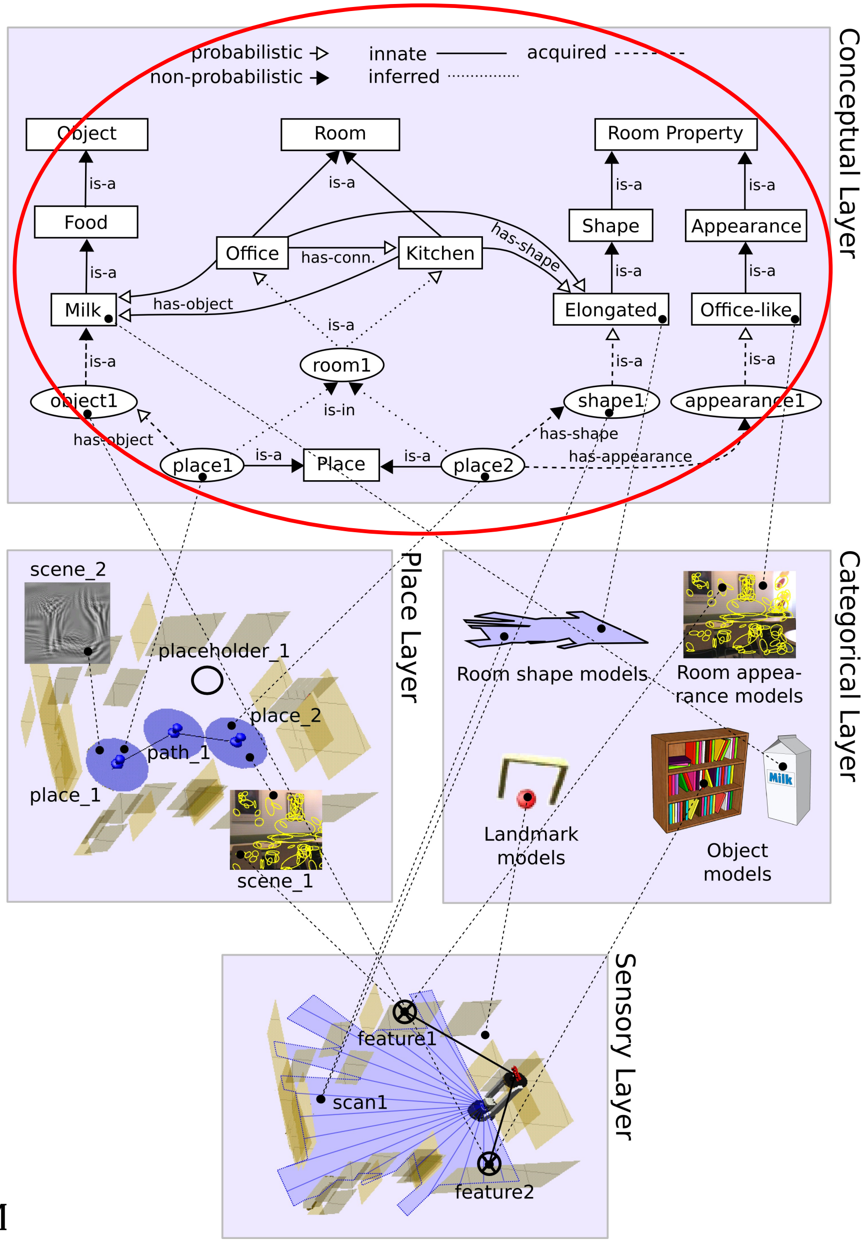
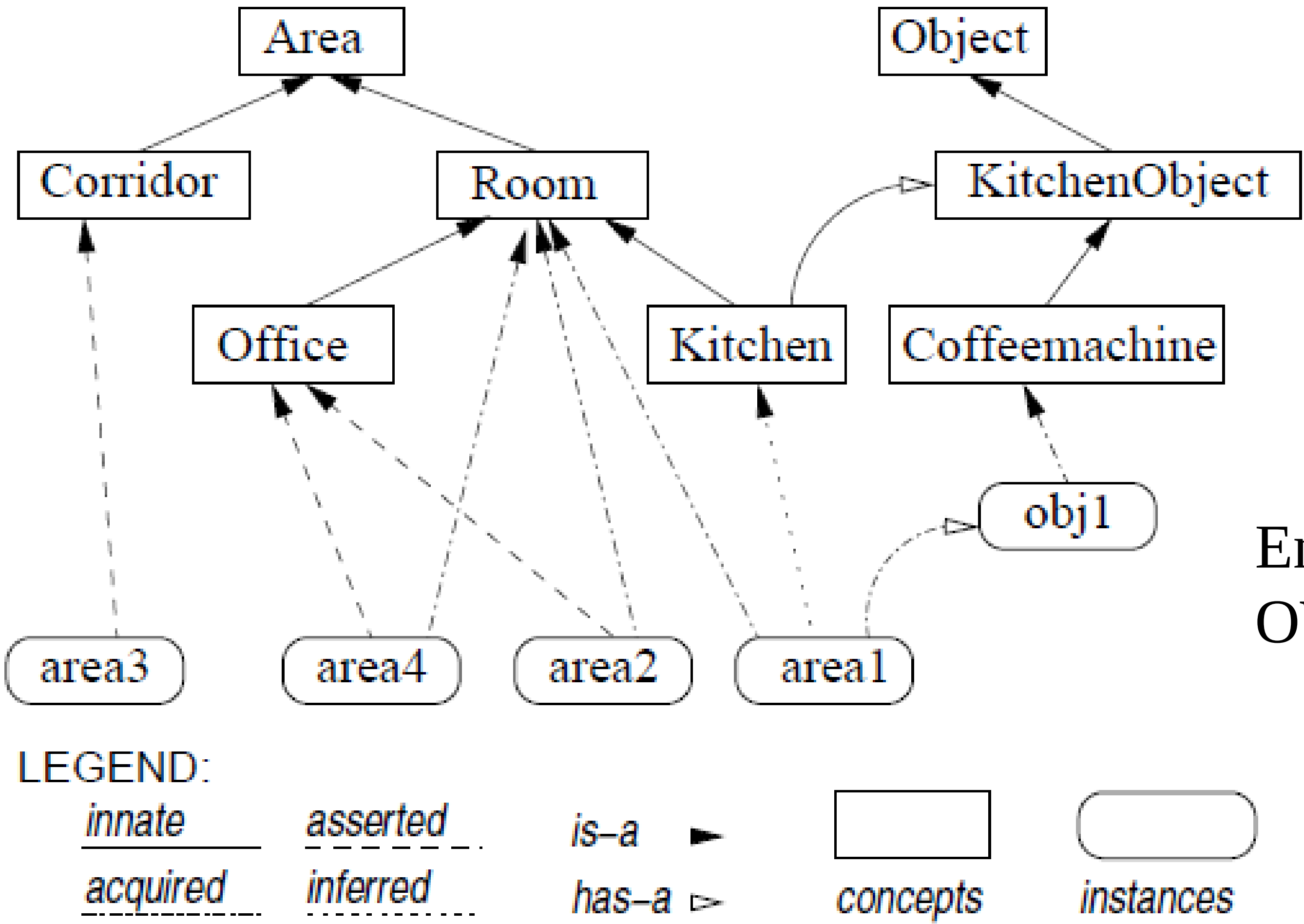


Our previous work



Encoded in OWL-DL

Zender et al, RAS 2008
"Conceptual Spatial Representations for Indoor Mobile Robots"

Tasks 1 & 2 with this

- Place categorization
  - Laser data to infer corridor or room
  - Room category inferred based on observed objects
  - Ex: Living room if seen couch and TV
- Object search
  - Visual attention system to focus on parts of the image
  - Room category can cut down possible objects

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Analysis

- Pros:
  - Combines high level concepts such as objects and low level information from laser
  - Simple to define new room categories
  - Understandable for humans
- Cons:
  - Only works conceptually
  - The ontology is not crisp in reality!
  - Nothing guiding the object search (just cover space)

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A new stab at it
Hierarchical place categorization

- Create a middle layer of "spatial properties"
  - Size of room (small, medium, large)
  - Shape of room (e.g. elongated)
  - Appearance of room (kitchenlike, officelike, …)
  - Combination of objects

- Room categorizes defined based on these properties
  → keeping that pro from before!

- Need to deal with the non-crisp ontology

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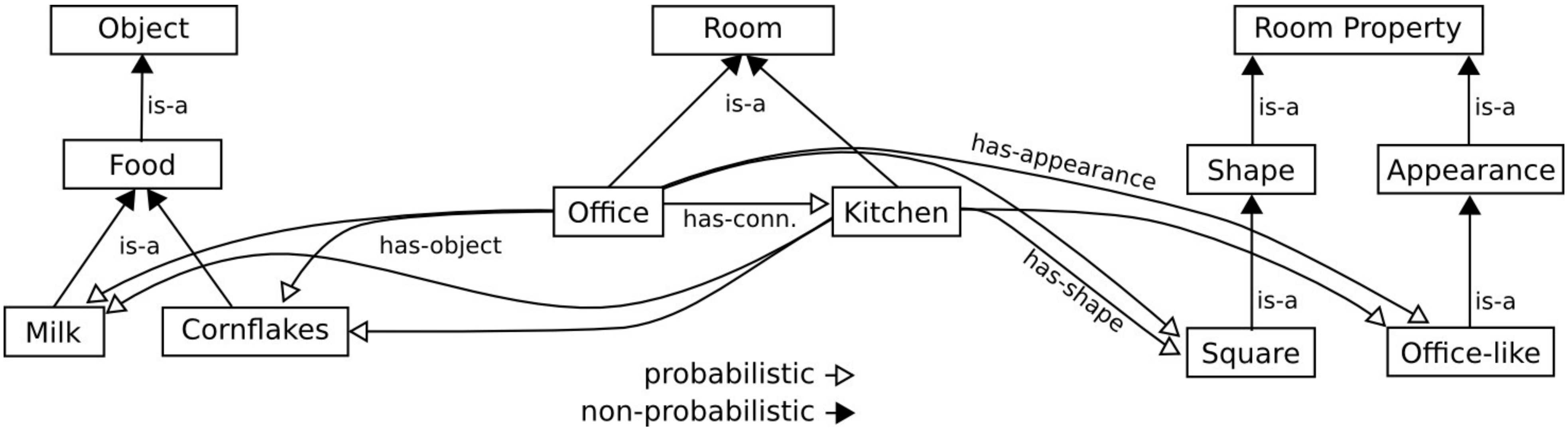
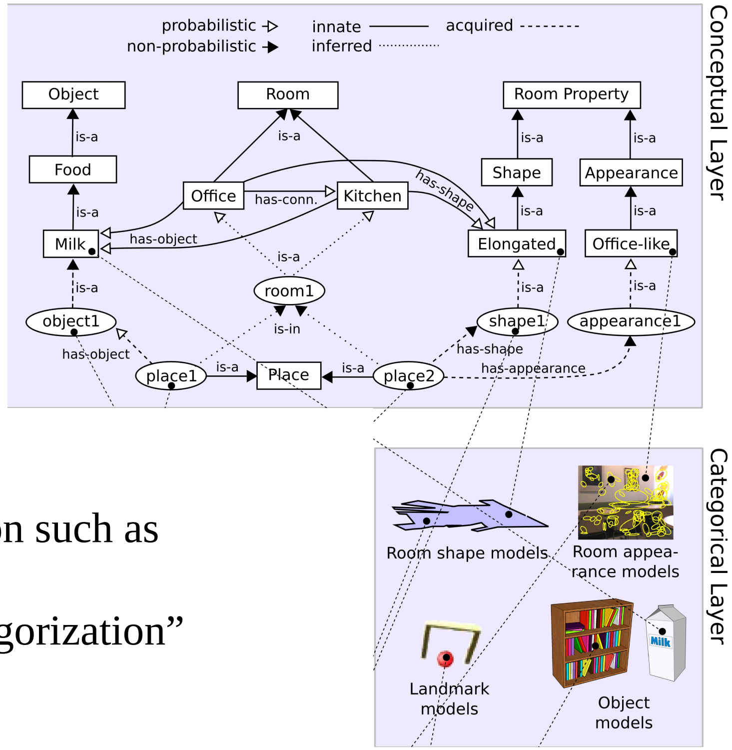
Uncertain ontology



- Probabilistic ontology incorporating
  - Taxonomy
    - “milk is-a food”, “food is-a object”
    - “office is-a room”, “square is-a shape”, “office-like is-a appearance”
  - Uncertainty
    - p(“kitchen has-object cornflakes”) = X
    - p(“kitchen connects-to corridor”) = Y

Property based categorization

- Probabilities for ontology bootstrapped from databases
- Models for properties learned based on sensor data



categories

properties

sensor data

Compare to part-based object categorization such as
Bouchard & Triggs, CVAP'05,
“Hierarchical part-based visual object categorization”

Property based categorization

- Probabilities for ontology bootstrapped from databases
- Models for properties learned based on sensor data

- Human understandable properties

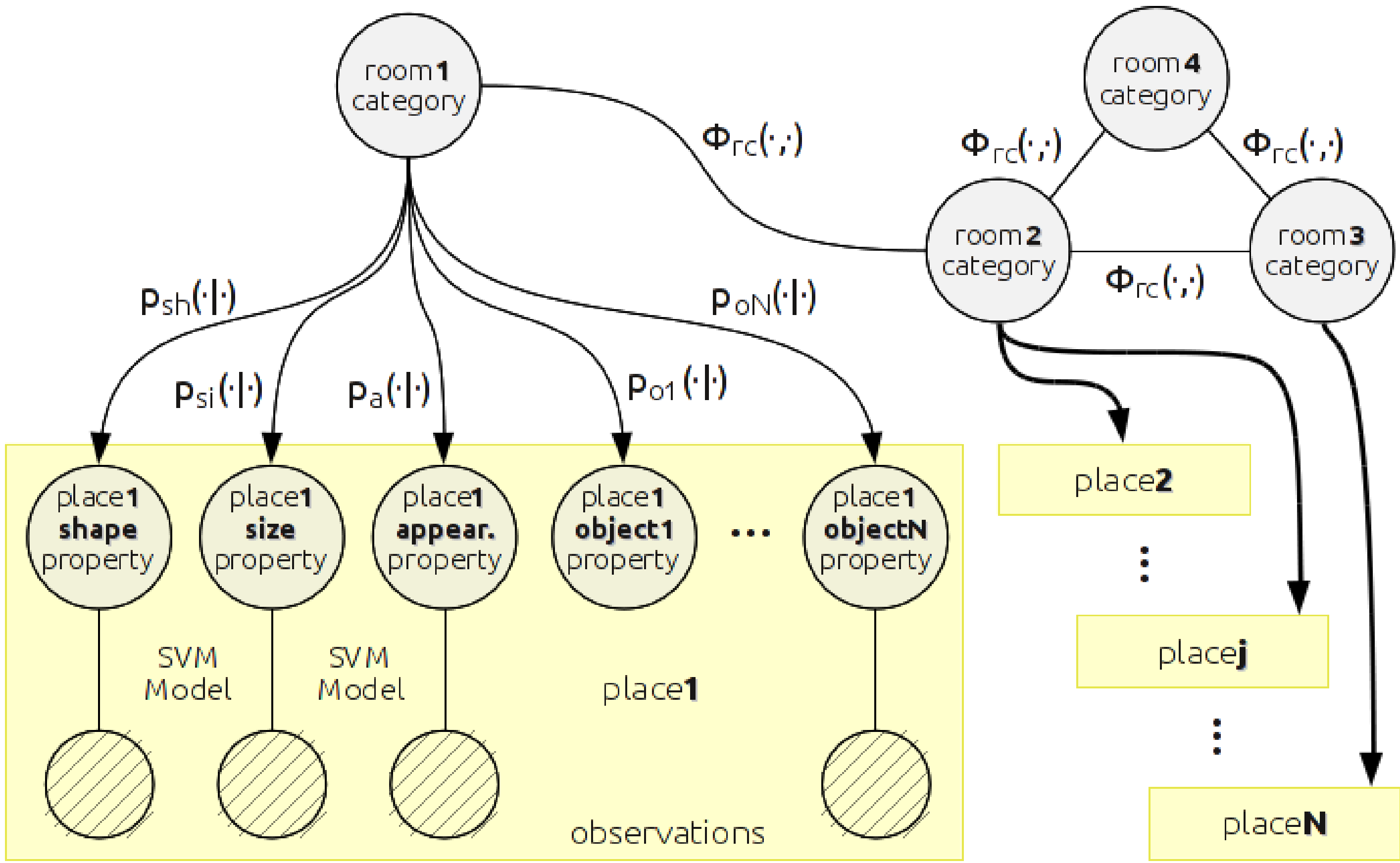
  → human can define categories

  “A professor's office is similar to a two person office in size but only has objects for one person”

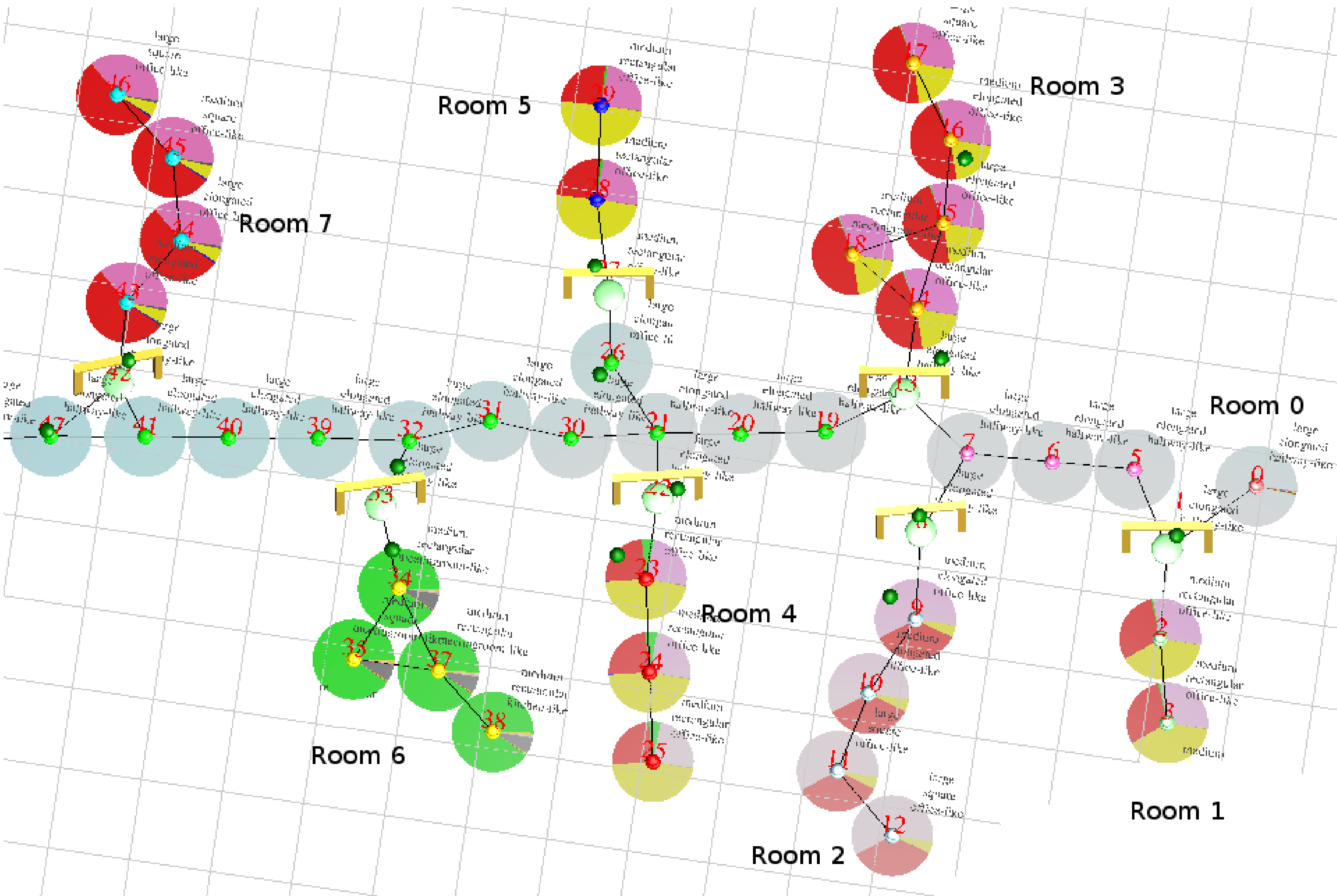
- Additional pros:
  - Do not have to re-train from sensor data level when adding new room categories
  - Massive dimensionality reduction
  - Decouples high and low level information

Probabilistic inference

- Incorporating all information in a chain graph
- Including the topology (connectivity of places)



Results: Place categorization



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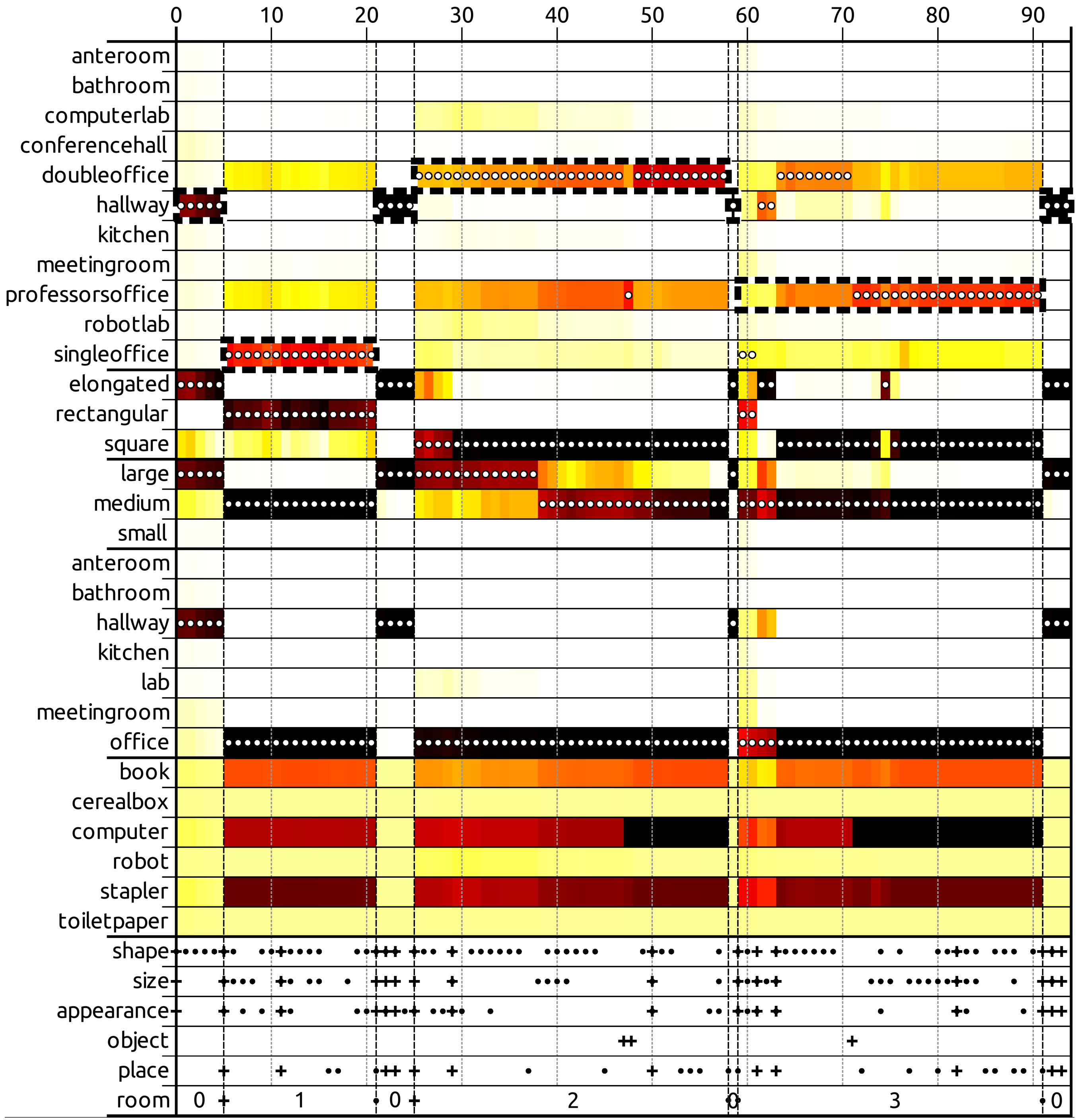
Results



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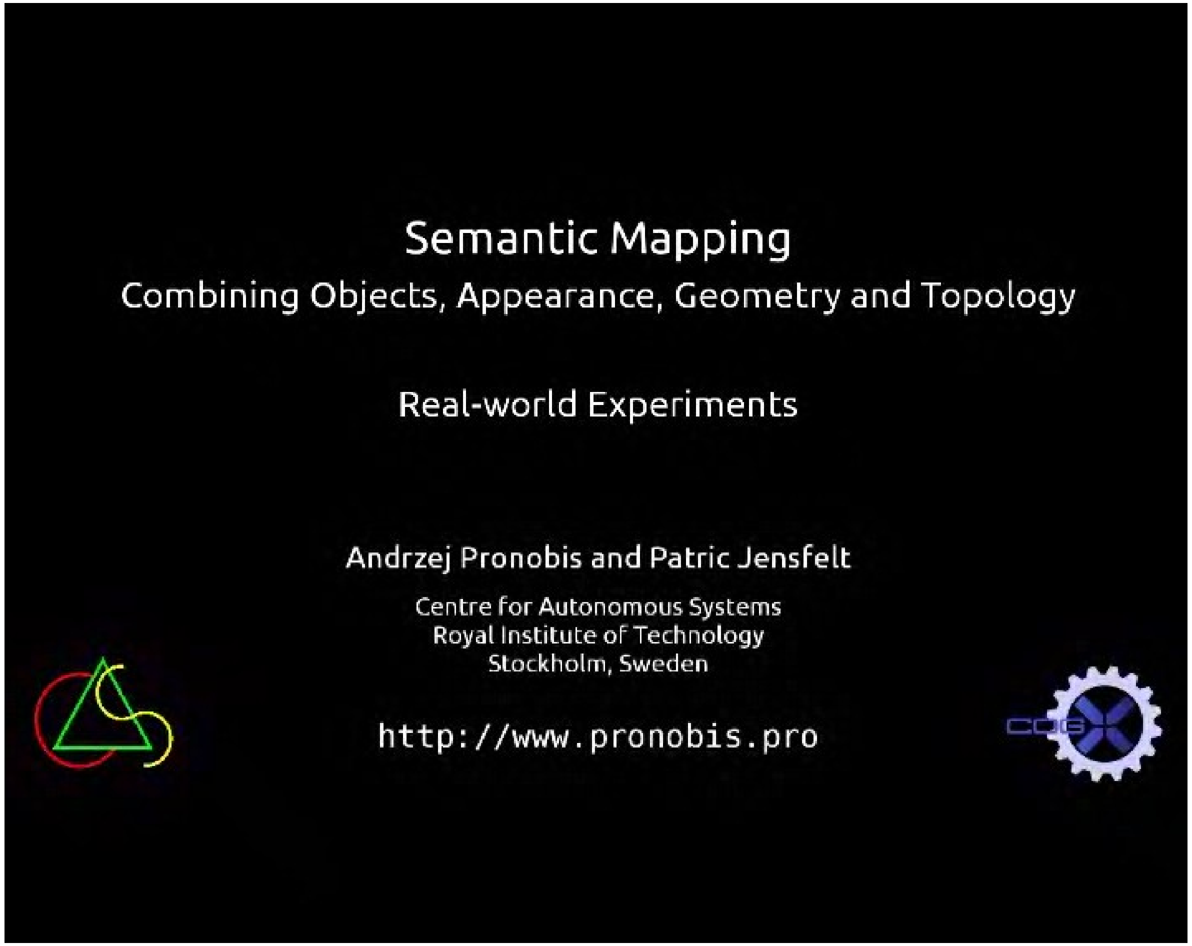
Video


Semantic Mapping
Combining Objects, Appearance, Geometry and Topology
Real-world Experiments
Andrzej Pronobis and Patric Jensfelt
Centre for Autonomous Systems
Royal Institute of Technology
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Advantages of the approach

- Incorporates all information (objects, shape, appearance, etc) in a single framework
- Scales well with number of categories
- Do not need to re-train property models with new cat.
- Human understandable properties

  → well suited for HRI
- Generative models of room categories
  - What does a kitchen look like and what objects to expect there? (default knowledge)
  - How likely is it to find cornflakes in *room42?* (incorporating <u>**all**</u> spatial knowledge)
  - Novel category detection (would the categories I know of generate what I see now?)

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Target task 2
Object search: Our initial approach

- Object detection in cluttered scenes is very tough
- Recognition requires enough resolution
- Use visual attention to guide search
- Robot searches by looking at every part of the environment sequentially

  → will look at object at some point

  → uninformed search!

Ekvall et al, IROS06

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Exploiting the semantic map

- (Partial) semantic map gives us
  - Probability for objects per place
  - Place categories

- Indirect direct search [Garvey 1976]
  - Make use the of the spatial relations
    - Look for stapler then for table

- Possible worlds
  - By extending the topological graph with places at the frontiers of the explored space we can make the semantic map predict existence of new rooms.

    → Can better trade exploration vs exploitation

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Planning the search

- Actions
  - Search(Location)
  - MoveTo(Location)

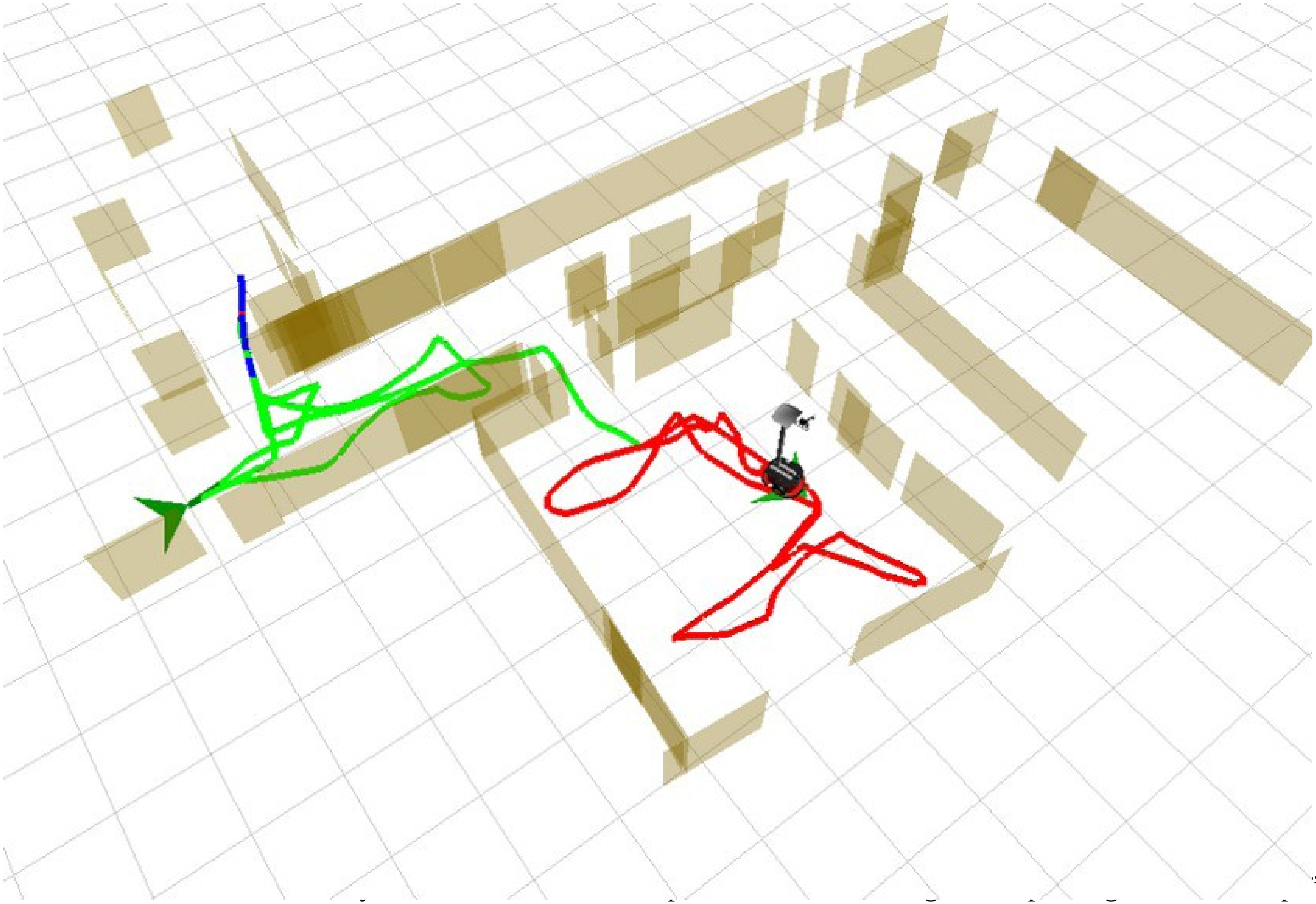
- Ideally decision theoretical planner in continuous space
  - → intractable

Switching planner

- Combines
  - Continual planner
    - Interleaves planning and plan monitoring to deal with uncertainty.
    - Performs the large scale planning
  - Decision theoretic planner
    - Used to plan the search at a specific location

- Trades exploration vs. exploitation in a principled way

Example run



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Want more on object search?

- IROS 2011 Workshop
  "Active Semantic Perception and Object Search in the Real World"

- Check MW7 at www.iros2011.org

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- EU FPF IP Project “CogX”

COGX

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