Simultaneous Activity Recognition and Monitoring for Robot Assistants

TUM CVPR Group Seminar

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Outline

1. Robot Assistants in Human Households
2. Spatio-Temporal Plan Representations
3. Simultaneous Plan Recognition and Monitoring (SPRAM)
4. Summary

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Robot Assistants in Human Households...

Should:

- Carry out heavy and tedious tasks for humans
- Assist humans in tasks they cannot or do not want to perform
- Carry out tasks self employed

Should not:

- Hinder humans in any way
- Be annoying (vacuum bedroom while human sleeps)

Service Robots in Human Households...

- Need to know what their human partner is doing even without beeing explicitly told
- Need to react adequately to human behavior
- Should learn from observations

Human Belief State Module

The robot should have a module that maintains a belief-state about the activities of its human partner!

Challenges for a Human Belief State Module

- High uncertainties
- World is not static any more
- Human behaviour is hard to model and interpret
- Human might change his mind or perform several tasks simultaneously

Idea: Simultaneous Plan Recognition and Monitoring

Probabilistic framework that keeps track of activities that are likely to be executed and constantly allow for changes.

Cognition-Endabled, Reactive Robot Control

- ROS middleware
- CRAM - Cognitive Robot Abstract Machine for flexible, reliable, and general robot control
- CPL plan language (based on CommonLISP)
- Knowrob knowledge processing system (based on Prolog)

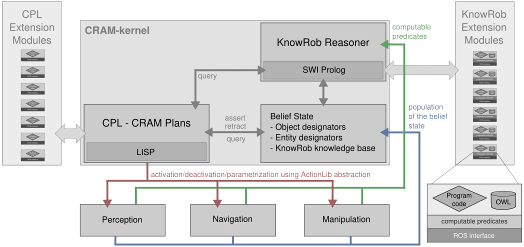


Image courtesy of Michael Beetz / TUM-IAS group

The KnowRob Knowledge Processing System

- Work by Moritz Tenorth et al.
- Tools for knowledge acquisition, representation and reasoning that are tailored to the demands in mobile robotics
- Combines knowledge about the environment, objects, actions etc. obtained from observations or the Web (OpenCyc, WikiHow, ...)
- Knowledge represented Ontolgies using Web Ontology Language (OWL)
- Describe relational knowledge using Description Logics
- Allows queries about e.g. likely storage locations of objects based on the type of object and the container and how to open the specific container

Semantically Annotated Environment Information

- Objects and environment map represented in knowledge base
- Furniture pieces as object instances inherit properties of their type
- Articulation models for opening containers (Jürgens work)
- Spatio-temporal representation of object-poses

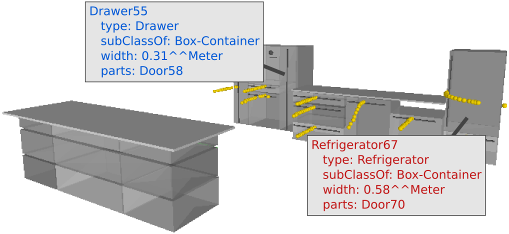


Image courtesy of Moritz Tenorth

Example-query: Where is the Pancake-Mix?

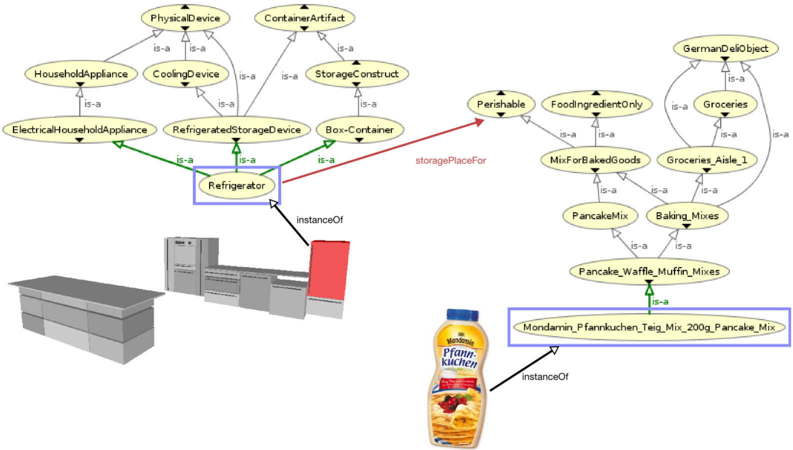


Image courtesy of Moritz Tenorth

Outline

Spatio-Temporal Plan Representations

- Model for human activities based on observation of human task performance
- General, humanlike representation of locations based on semantic environment maps
- Transferable to other environments given a semantic map
- Allow for plan monitoring and -recognition in different environments

Goal:

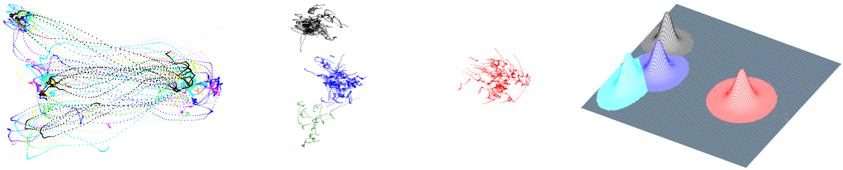
A general, transferable representation of human tasks that allows a robot to explain its observations

The TUM Kitchen Dataset

- Labeled motion-tracking data of humans performing a table-setting-task in a kitchen environment
- 6 objects stored in 3 different locations (cupboard, drawer, stove) plus goal location (table)
- Labels for actions of both hands and body in general

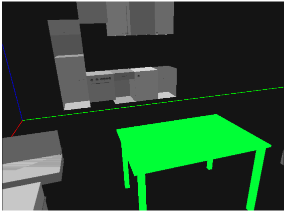
Spatial Model Generation

- Assumption: Human most of the time is standing still while interacting with objects
- Estimate positions where human is standing still and interacts with objects using motion tracking data and labels
- Perform clustering using Expectation Maximization Algorithm



Spatial Model Generation

- Idea: Represent locations relative to furniture objects in the environment
- Assumption: Storage locations of objects known
- Query KnowRob to find storage locations of objects involved in plan
- Put 2D-Gaussians into reference to nearest storage location



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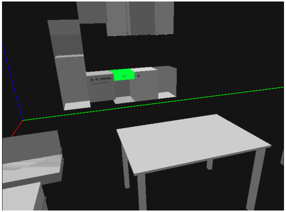

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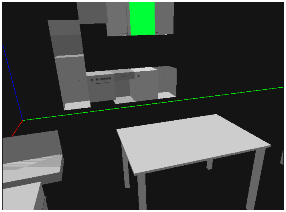

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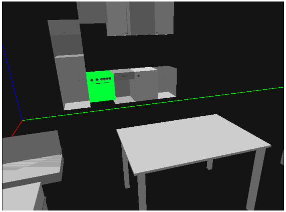

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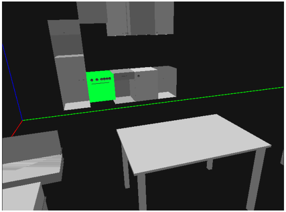

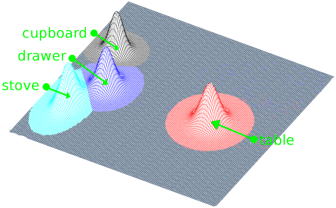

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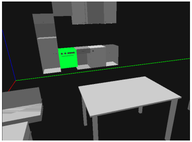
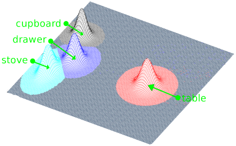




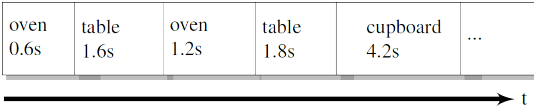
General Spatial Model of locations a human visits during a table-setting task.

Spatio-Temporal Plan Representations (STPRs)

- Representation of human activities based on spatial model using KnowRob-linked locations
- Sequence of n tuples with location l_i and duration t_i:

$$p_n = ((l_1, t_1), (l_2, t_2) \ldots, (l_n, t_n))$$

- Visualization: Timeline-like representation

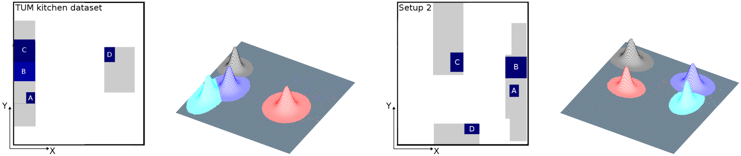


Generation of STPRs

- Analyze human motion tracking data with regards to spatial model
- Create sequences of location/duration tuples

Transferring Spatial Models to Other Environments

- Spatial model can be transfered to other environments given a semantic map and storage locations of objects
- Obtain locations of objects and their orientation from semantic map
- Create gaussians relative to container objects using the learned relations



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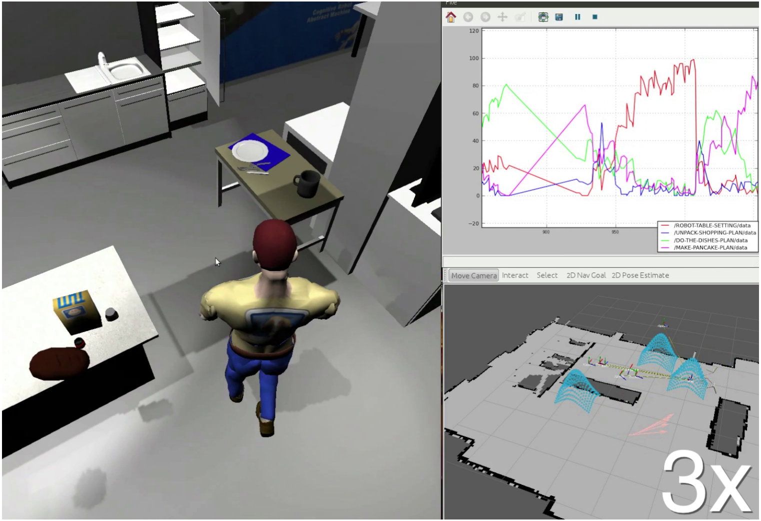
Challenges in Plan Recognition

- High uncertainties
- Only partial observations of objects/human position might be available
- Human might suddenly change its plans or abandom it
- How to detect plan-endings despite only partial observations?

Idea:

Generate a SPRAM module that maintains a posterior probability distribution about human task execution.

Video: Probabilistic SPRAM Module in Action



A High-Level Particle Filter for SPRAM

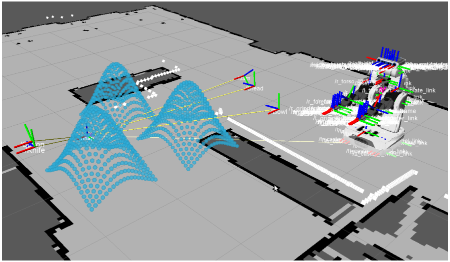
- Model estimation using a High-Level Particle Filter
- Describes posterior probability distribution by a set of particles
- Particles include STPRs (with spatial model) as human task models
- Monte-Carlo based filtering approximates the posterior $p(x_t|z_{1..t})$ by:

$$\int f(x_t)\, p(x_t|z_{0..t})dx_t \approx \frac{1}{P}\sum_{L=1}^{P} f(x_k^{(L)})$$

where x_t are the human activites, $z_i = (location_i, duration_i, objects_i)$ and $f(...)$ represents the weighting function.

A High-Level Particle Filter for SPRAM

- Random Particle Injection prevents degeneration (human might change his plan, plan ending might not be detected)
- Weighting function combines locations, durations, object-detections and overall execution time
- Simultaneous monitoring of most-likely task(s)
- Prediction of places that are likely to be visited by human in the next time



Work In Progress

- Monitoring of several likely tasks
- Combination of STPRs with partial order-models from KnowRob would allow for more elaborate reasoning and improve recognition
- Set up realistic ontology about a “normal” day of a human based on real-world data
- Improve performance using a Relational Particle Filter (Assumption: Obervations conditionally independet which they are NOT!)
- Include paths between places into prediction of places

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Summary

- We use Spatio-Temporal Plan Descriptions (STPR) for plan monitoring and recognition in human centered environments
- We set up a module that performs Simultaneous Plan Recognition and Monitoring based on STPRs and semantic environment information
- STPRs can be used accross environments given a semantic map (e.g. from RoboEarth)
- First experiments look promising and there is more to come!

The end

Any questions?

Video: The MORSE Simulator

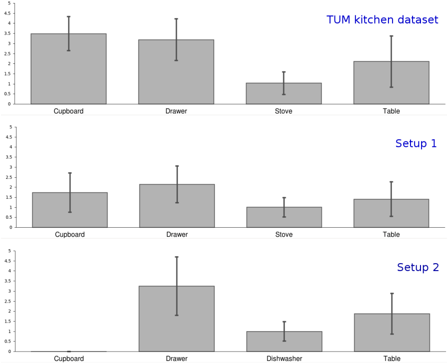
Application Example: Basic Plan Monitoring

- Durations a human spends at places while performing pick and place tasks should be similar in different environements
- Assumption: Durations a human spends at one location depends on amount of manipulation that has to be performed

Question

Are durations a human spends at different types of storage locations comparable?

Application Example: Basic Plan Monitoring



Question

Can we use this information to distinguish a pick and place task from other tasks?

Application Example: Basic Plan Monitoring

- Use durations from TUM Kitchen Dataset as model and calculate confidence value based on durations at storage locations

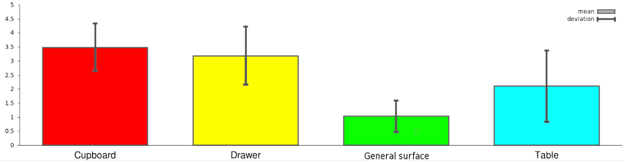


Table setting task:

stove 0.9 s	table 1.2 s	stove 1.0 s	table 1.4 s	cupboard 3.3 s	table 1.9s	...

Cleaning task:

table 1.9 s	stove 3.1 s	drawer 3.3 s	table 2.2 s	...

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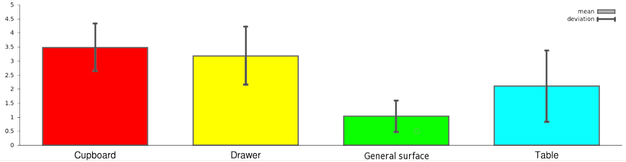

Table setting task:

stove 0.9 s	table 1.2 s	stove 1.0 s	table 1.4 s	cupboard 3.3 s	table 1.9s	...

Confidence: 0.593

Cleaning task:

table 1.9 s	stove 3.1 s	drawer 3.3 s	table 2.2 s	...

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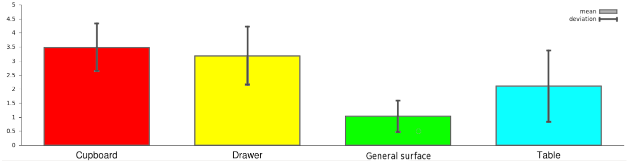


Table setting task:

stove 0.9 s	table 1.2 s	stove 1.0 s	table 1.4 s	cupboard 3.3 s	table 1.9s	...

Confidence: 0.593

Cleaning task:

table 1.9 s	stove 3.1 s	drawer 3.3 s	table 2.2 s	...

Confidence: 0.350

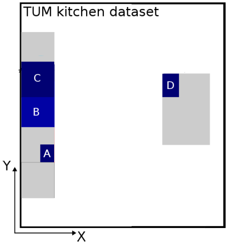
Application Example: Basic Plan Monitoring

- Experiments in two different environments (setup 1, setup 2) using model of TUM Kitchen Dataset
- Recorded motion tracking data of 10 participants performing 3 different tasks:
  - Robot-like table setting
  - Human-like table setting
  - Cleaning task
- Results:

Task	c_p Setup 1	c_p Setup 2
Robot-like table setting	0.524	0.593
Human-like table setting	0.448	0.506
Cleaning task:	0.191	0.350

Application Example: Basic Plan Monitoring

- Use plan patterns to calculate confidence value based in string comparison methods (e.g. Levenshtein distance)



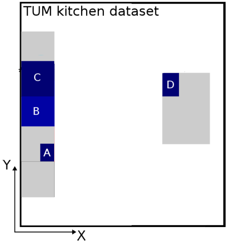
- A: Initial location of placemat and napkin
- B: Initial location of cutlery
- C: Initial location of plate and cup
- D: Goal location

Table setting task:

stove	**table**	**stove**	**table**	**cupboard**	**table**	**...**
0.9 s	**1.2 s**	**1.0 s**	**1.4 s**	**3.3 s**	**1.9s**	

Application Example: Basic Plan Monitoring

- Use plan patterns to calculate confidence value based in string comparison methods (e.g. Levenshtein distance)



- A: Initial location of placemat and napkin
- B: Initial location of cutlery
- C: Initial location of plate and cup
- D: Goal location

Table setting task:

A	**B**	**A**	**B**	**C**	**B**	...

Application Example: Basic Plan Monitoring

Use Generalize Levenshtein Similarity to calculate confidence value:

Table-setting model learned from TUM kitchen dataset:
ADADCDBDBDBDCD

Table-setting task observed in environment 2:
ADADCBDBDBDBDCD

Cleaning-task observed in environment 2:
DACDADBC

Application Example: Basic Plan Monitoring

Use Generalize Levenshtein Similarity to calculate confidence value:

Table-setting model learned from TUM kitchen dataset:
ADADCDBDBDBDCD

Table-setting task observed in environment 2:
ADADCBDBDBDBDCD

Confidence: 0.943

Cleaning-task observed in environment 2:
DACDADBC

Confidence: 0.342

Application Example: Basic Plan Monitoring

Generalized Levenshtein Similarity for 3 different tasks in 2 different environements using model of table setting task in TUM Kitchen environment:

Task	GLS $_{\text{Setup 1}}$	GLS $_{\text{Setup 2}}$
Robot-like table setting	0.982	0.943
Human-like table setting	0.429	0.429
Cleaning task:	0.357	0.340

Conclusion:

We can distinguish different tasks according to their patterns and durations using spatio-temporal plan descriptions!