From Symbolic Reasoning to Autonomous Robots

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Technical Aspects of Multimodal Systems

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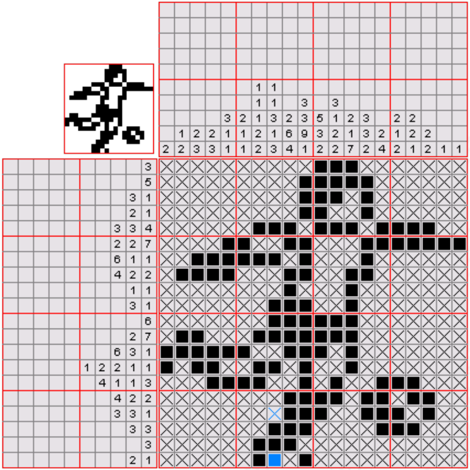
Outline

PICTURE

Institute of Computer Science / University of Potsdam

5	3			7				
6			1	9	5			
	9	8					6	
8				6				3
4			8		3			1
7				2				6
	6					2	8	
			4	1	9			5
				8			7	9

```
pos(0..8).
input(1..9).
block(0..2).
1{in(X, Y, Z): input(Z)}1 :-
  pos(X); pos(Y).
1{in(X,Y, Z): pos(Y)}1 :-
  pos(X); input(Z).
1{in(X,Y, Z): pos(X)}1 :-
  pos(Y); input(Z).
1{in(X,Y, Z):
  pos(X), X/3 == Xb,
  pos(Y), Y/3 == Yb}1 :-
   block(Xb); block(Yb);
   input(Z).
```


2
1 2
2 3
2 3
3 1 1
2 1 1
1 1 1 2 2
1 1 3 1 3
2 6 4
3 3 9 1
5 3 2
3 1 2 2
2 1 7
3 3 2
2 4
2 1 2
2 2 1
2 2
1
1
3
5
3 1
2 1
3 3 4
2 2 7
6 1 1
4 2 2
1 1
3 1
6
2 7
6 3 1
1 2 2 1 1
4 1 1 3
4 2 2
3 3 1
3 3
3
2 1

PICTURE

Institute of Cognitive Science / Osnabrück University

Calvin

MUFFIN

Video

Motivation

Demos in autonomous robotics require a tremendous amount of **hard-coded knowledge** of the environment. However, the goal is to make them perform in **unknown** mundane environments.

The robot should autonomously explore the environment and extract useful concepts.

This requires successful...

- Perception
- Exploration
- Model Construction
- Unsupervised Learning

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Tabletop Segmentation

Assumptions

- Objects are opaque, non-reflecting entities
- Objects lie on top of supporting planes such as tables
- Different objects can be visually separated by distance
- Orientation and height of the camera w.r.t. the floor are known
- Supporting planes are convex
- Objects between some minimum/maximum height above a supporting plane lie on top of it

These can be violated, but the framework does not account for errors because of such violations.

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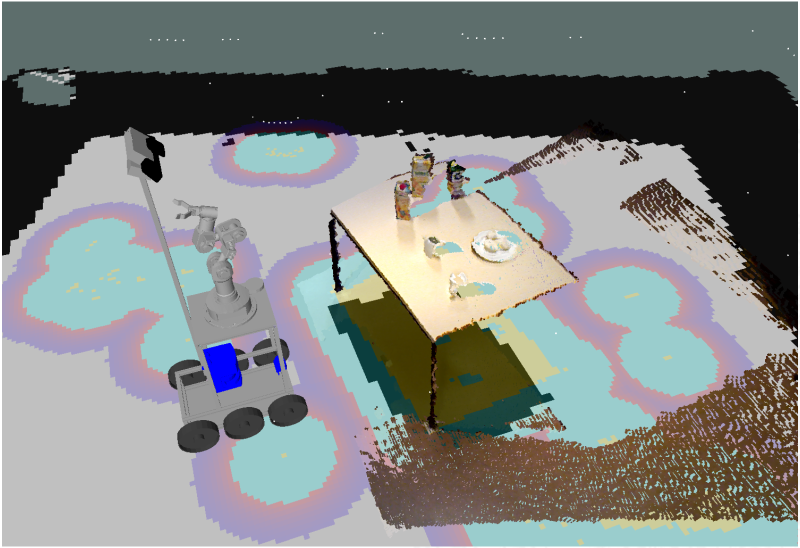
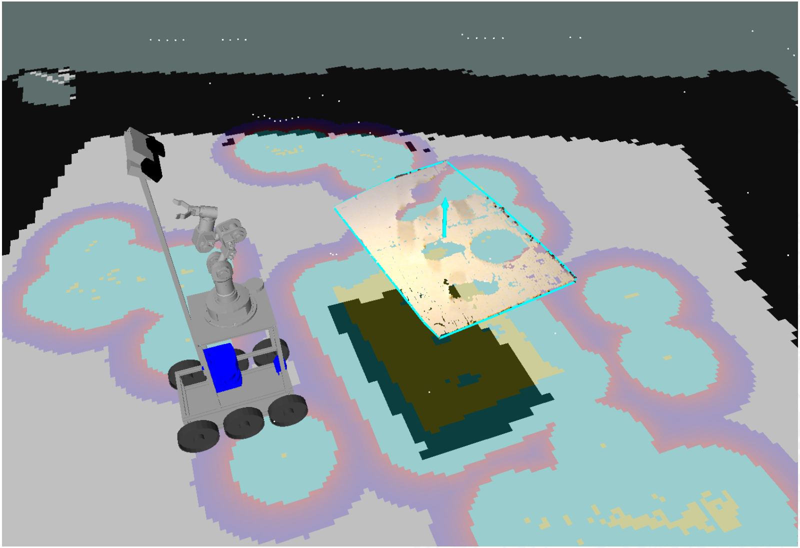
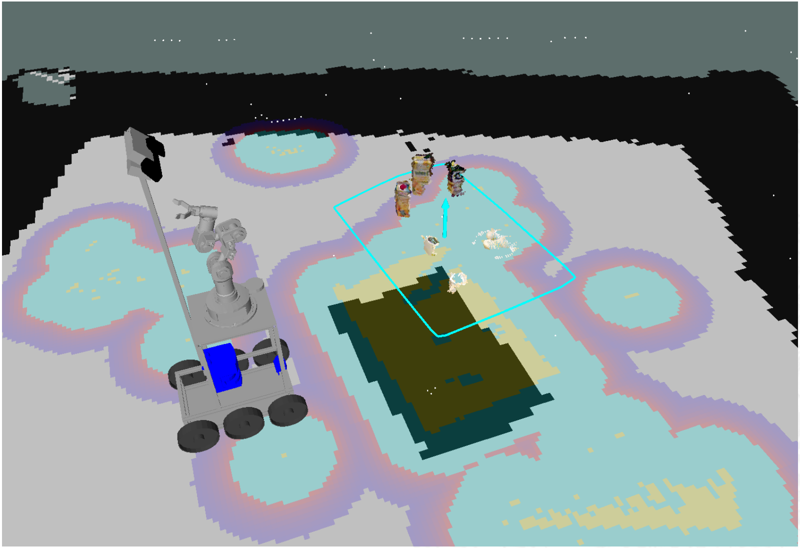
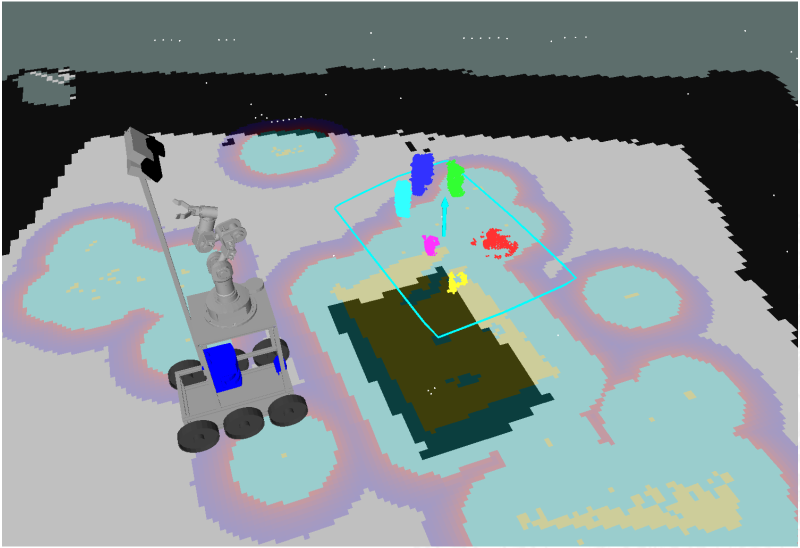
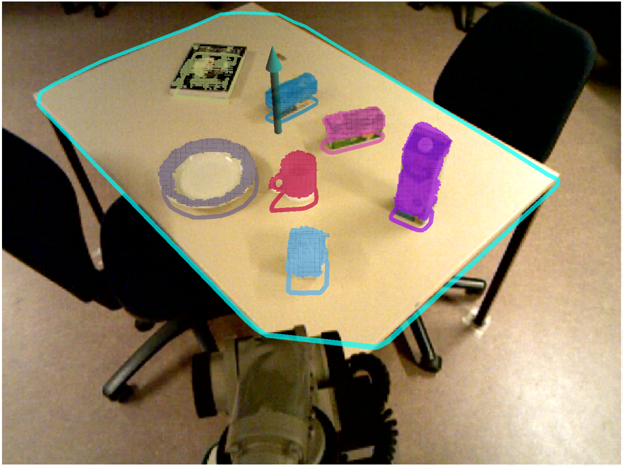




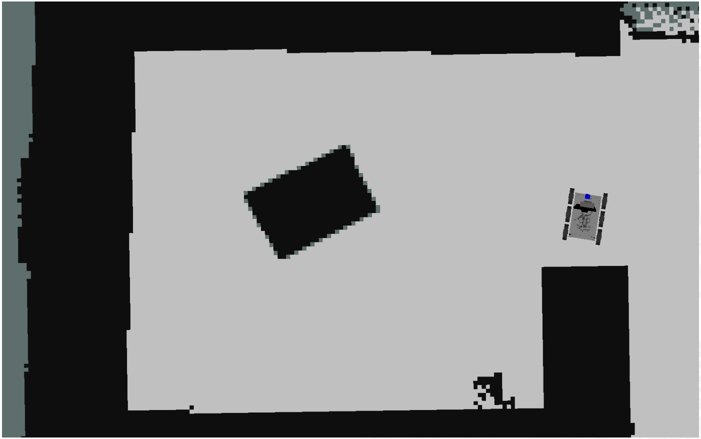




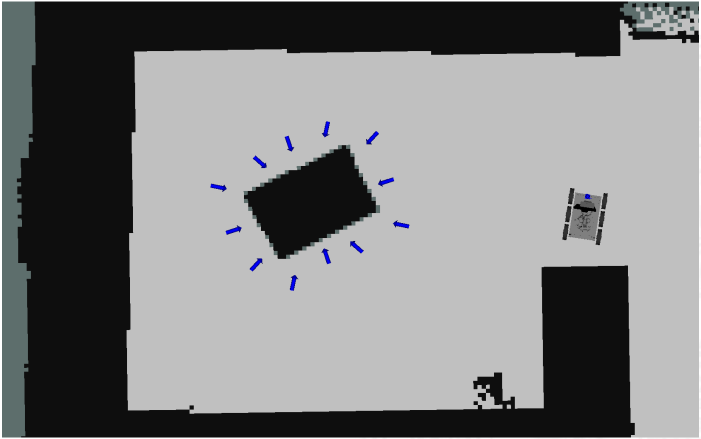
Tabletop Segmentation



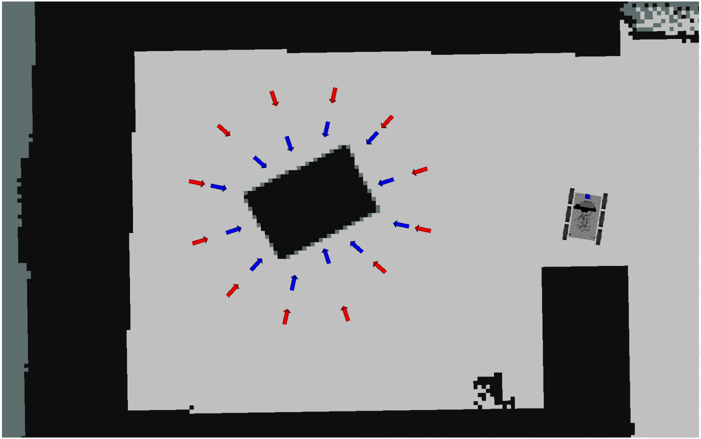
Exploration



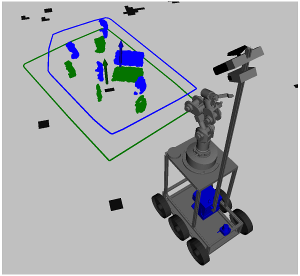
Exploration

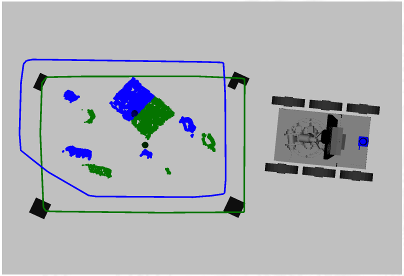


Exploration

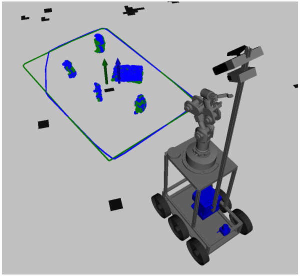


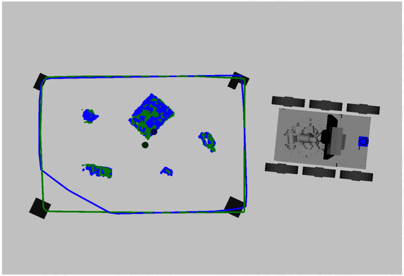
Noisy Localization





Aligned Views





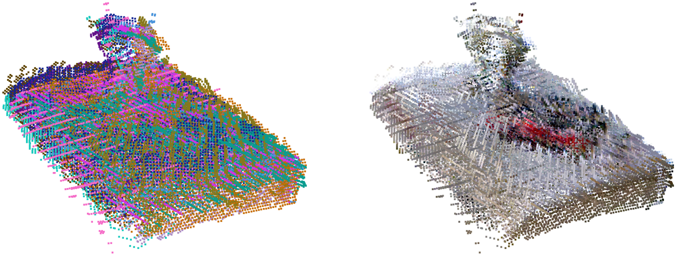
Incremental Plane ICP Registration

input: $\langle p_0, \lambda_{\text{map}}^{\mathtt{t_0}} \rangle, \langle p_1, \lambda_{\text{map}}^{\mathtt{t_1}} \rangle, \ldots$
yields: $\langle p_0^{\text{out}}, \Delta_0, \Lambda_0 \rangle,\ \langle p_1^{\text{out}}, \Delta_1, \Lambda_1 \rangle,\ \ldots$
procedure IncrementalPlaneICP($\langle p_0, \lambda_{\text{map}}^{\mathtt{t_0}} \rangle, \langle p_1, \lambda_{\text{map}}^{\mathtt{t_1}} \rangle, \ldots$)
  Incremental2.5D-ICP iicp
  $\Lambda_0 \leftarrow \lambda_{\text{map}}^{\mathtt{t_0}}$
  $\langle q_0, \Delta_0 \rangle \leftarrow \text{iicp}(p_0)$
  yield $\langle q_0, \Delta_0, \Lambda_0 \rangle$
  for $i \leftarrow 1, 2, \ldots$ **do**
    $\lambda_{\mathtt{t_0}}^{\mathtt{t}_i} \leftarrow (\Lambda_{i-1})^{-1} \circ \lambda_{\text{map}}^{\mathtt{t}_i}$
    $\xi_{\mathtt{t_0}}^{\mathtt{t}_i} \leftarrow \text{As2DTransform}(\lambda_{\mathtt{t_0}}^{\mathtt{t}_i})$
    $p_i^{\mathtt{t_0}} \leftarrow \xi_{\mathtt{t_0}}^{\mathtt{t}_i}(p_i)$
    $\langle q_i, \Delta_i \rangle \leftarrow \text{iicp}(p_i^{\mathtt{t_0}})$
    $\Lambda_i \leftarrow \lambda_{\text{map}}^{\mathtt{t}_i} \circ (\xi_{\mathtt{t_0}}^{\mathtt{t}_i})^{-1} \circ (\Delta_i)^{-1}$
    yield $\langle q_i, \Delta_i \circ \xi_{\mathtt{t_0}}^{\mathtt{t}_i}, \Lambda_i \rangle$

Incremental Plane ICP Registration

Exemplary table arrangement with the results of 6D ICP registration and Plane ICP

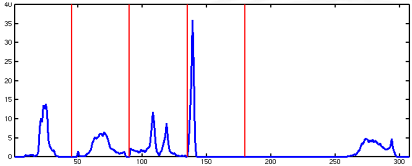
Multi-View Object Representation



The system yields sets of registered views of all detected objects, retaining the original viewpoint information of each percept.

Viewpoint Feature Histograms†

(a) A single view (point cloud) of an object



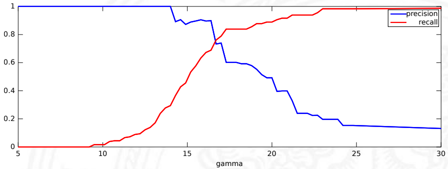
(b) The corresponding VFH with Shape Distribution Component

Views (and Sets of Views) can be clustered by 2−norm using a distance threshold γ.

† *CAD-model recognition and 6DOF pose estimation using 3D cues,* Aldoma et al., 2011

Evaluation

Test Set



Pair-Counted precision/recall depending on distance threshold γ

Evaluation

Example Classes at $\gamma = 16.4$

Evaluation

Example Classes at $\gamma = 16.4$

Evaluation

Example Classes at $\gamma = 16.4$

Evaluation

Example Classes at $\gamma = 16.4$

Summary

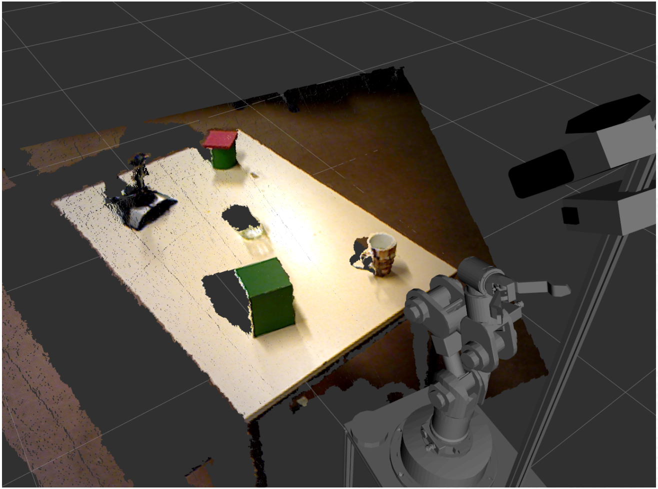
Outcome

A complete framework for autonomous tabletop exploration

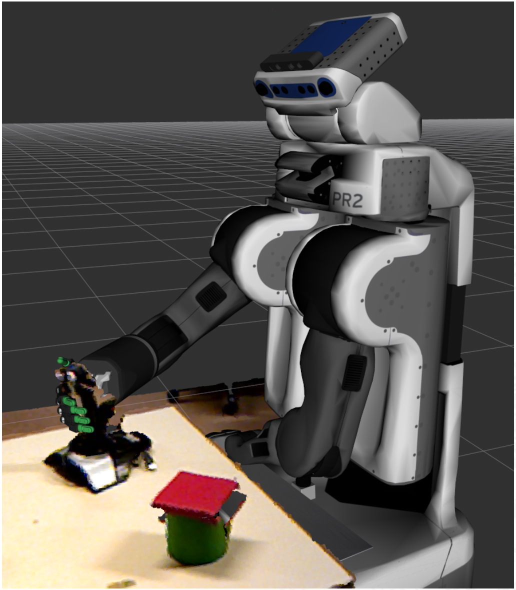
It ...

- yields object representations usable for unsupervised object learning
- demonstrates the feasibility of online exploration
- provides a basis for future work on individual components

Motivation



Video


PR2

Thank You for Listening. Questions?

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