Acquiring Semantic Maps for Household Tasks and More

Dejan Pangeric
Intelligent Autonomous Systems Group, Bosch Robotics
Technische Universität München, Bosch RTC

UPENN, October 2011
1. Introduction

2. Semantic Mapping 1

3. Opening of Cabinets

4. Semantic Mapping 2

5. Segmentation
1. Introduction

2. Semantic Mapping 1

3. Opening of Cabinets

4. Semantic Mapping 2

5. Segmentation
What are Semantic Maps?

Structures that enable the robot to answer the following categories of queries:

- “What do parts of the kitchen look like?”;
- “How can a container be opened and closed?”;
- “Where do objects of daily use belong?”;
- “What is inside of cupboards/drawers?”.
Acquiring Semantic Maps for Household Tasks and More

UPENN, October 2011

Dejan Pangercic
Earlier Work

Ref: Dejan Pangercic et al, IROS 2011

UPENN, October 2011

Acquiring Semantic Maps for Household Tasks and More

Dejan Pangercic
System Overview

DATA ACQUISITION and PROCESSING
- RGBD Point Clouds
- MLS Smoothing
- Point Cloud Registration

SURFACE AND TEXTURE RECONSTRUCTION
- Poisson-based Surface Generation
- Surface Segmentation and Unfolding
- Texture Reconstruction with Blending

POINT CLOUD DATA INTERPRETATION AND LEARNING OF ARTICULATION MODELS
- Recognition of Planes and Fixtures
- Cabinet Opening
- Segmentation of Cabinets through Interaction

GENERATION OF SEMANTIC MAP AND OBJECT ONTOLOGY
- Articulation Models
- Interface for Manual Object Annotation
- Rich Semantic Queries

APPLICATION LEVEL
- Inference of typical storage location places (showcased in right figure)
- Retrieval of objects of daily use
- Manipulation of cabinets
- Crowd-sourcing based object annotation

Acquiring Semantic Maps for Household Tasks and More

UPENN, October 2011
Dejan Pangeric
Registration, Reconstruction, Texture Re-projection

Testbed Kitchens

Poisson surface reconstruction

Blending-based texture reprojection

Ref: Benjamin Pitzer, Automatic Reconstruction of Textured 3D Models, PhD Thesis (Code coming soon!)

UPENN, October 2011

Acquiring Semantic Maps for Household Tasks and More
Final structure consists of 50K triangles, raw point cloud of 18M points
Suitable for crowd-sourcing-based annotation of objects
Triangulation of Depth Images (also in PCL) and Smoothing:

Generation of Artificial Data:
1. Introduction

2. Semantic Mapping 1

3. Opening of Cabinets

4. Semantic Mapping 2

5. Segmentation
PR2 Beta Sites Involved

**TUM**
3D Perception, Semantic Map, Coordinated Arm-Base Movement

**Freiburg**
Learning of Articulation Models, Impedance Control

**Bosch**
Main Testing Facility

UPENN, October 2011

Acquiring Semantic Maps for Household Tasks and More

Dejan Pangerlic
Two Handle Detectors

Non-reflective Handles (Rusu, ICAR2009):

Reflective Handles:
Using impedance controller from Willow Garage (pr2_cockpit stack)

Initialization: gently pull the handle backwards by moving the Cartesian equilibrium point towards the robot

Record the trajectory of robot’s gripper $y_{1:n}$ with $y_i \in SE(3)$

Ref: Sturm et al., JAIR 2011

VIDEO: *
Learning of Articulation Models - Model Fitting

Iteratively:
- (Re-)estimate the kinematic model $\mathcal{M} \in \{\text{rigid, prismatic, rotational}\}$
- Estimate model-specific parameter vector $\theta \in \mathbb{R}^d$ (encoding radius, rotation axis) of the articulated object: $\hat{\mathcal{M}}, \hat{\theta} = \arg \max_{\mathcal{M}, \theta} p(\mathcal{M}, \theta | y_{1:n})$
- Fit the parameter vector of all model candidates using an MLESAC estimator

Ref: Sturm et al., JAIR 2011

UPENN, October 2011
Acquiring Semantic Maps for Household Tasks and More

Dejan Pangercic
Learning of Articulation Models - Model Selection

- Select the best model according the Bayesian information criterion (BIC)
- Use the model to predict the continuation of the trajectory and to generate the next Cartesian equilibrium point $x_{n+1}^{CEP}$.
- Finally, determine opening angle / opening distance
- Output: Kinematic model

Ref: Sturm et al., JAIR 2011

UPENN, October 2011

Acquiring Semantic Maps for Household Tasks and More
Sample a noise-free trajectory $\bar{x}_{1:n}$ from the model over the configuration range.
Store and retrieve the trajectory from KnowRob DB (Tenorth, IROS 2009):

```prolog
?– rdf_triple (knowrob:’in–ContGeneric’, knowrob:’Cup67’, B),
 rdf_has (B, knowrob:openingTrajectory, Traj),
 findall (P, rdf_has (Traj, knowrob:pointOnTrajectory, P),
 Points).
```
Re-opening

- Check for robot’s workspace limit
- Use the inverse reachability map and search for base poses that allow for the full opening of the cabinet

VIDEO:
Segmentation of static and dynamic point cloud for observed cabinet:

Segmented model:

- Enables the robot to estimate and verify the configuration of the cabinet
- Allows the robot to plan collision-free opening of trajectories
- Allows to open and close cabinets in highly-constrained spaces (e.g., for cabinets located close to a wall)
Test Setup

29 cabinets, 5 kitchens of Bosch and TUM, PR2 Robot, 104 trials
2 handles, 9 different poses:

<table>
<thead>
<tr>
<th>positive</th>
<th>negative</th>
</tr>
</thead>
<tbody>
<tr>
<td>positive</td>
<td>45</td>
</tr>
<tr>
<td>negative</td>
<td>5</td>
</tr>
</tbody>
</table>
Evaluation of the opening distances and estimated opening radii:

<table>
<thead>
<tr>
<th>cabinet type</th>
<th>trials</th>
<th>translational err.</th>
<th>rotational err.</th>
</tr>
</thead>
<tbody>
<tr>
<td>drawers</td>
<td>18</td>
<td>0.664cm</td>
<td>4.96°</td>
</tr>
<tr>
<td>doors</td>
<td>35</td>
<td>0.516cm</td>
<td>36.2°</td>
</tr>
<tr>
<td>average</td>
<td>53</td>
<td>0.567cm</td>
<td>25.6°</td>
</tr>
</tbody>
</table>
## Results - Whole System

<table>
<thead>
<tr>
<th>activity</th>
<th>trials</th>
<th>successes</th>
<th>success rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>handle detection</td>
<td>104</td>
<td>97</td>
<td>93.3 %</td>
</tr>
<tr>
<td>operate cabinet and learn model</td>
<td>97</td>
<td>54</td>
<td>56.2 %</td>
</tr>
<tr>
<td>re-execute learned model</td>
<td>54</td>
<td>54</td>
<td>100 %</td>
</tr>
<tr>
<td>overall performance</td>
<td>104</td>
<td>54</td>
<td>51.9 %</td>
</tr>
</tbody>
</table>
## Results - Whole System - Failure Causes

<table>
<thead>
<tr>
<th>type of failure</th>
<th>trials</th>
<th>failed trials</th>
<th>rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a) handle detection</td>
<td>104</td>
<td>7</td>
<td>6.7%</td>
</tr>
<tr>
<td>(b) slippage of gripper</td>
<td>97</td>
<td>6</td>
<td>6.2%</td>
</tr>
<tr>
<td>(c) robot too weak at start</td>
<td>97</td>
<td>6</td>
<td>6.2%</td>
</tr>
<tr>
<td>(d) robot too weak during motion</td>
<td>97</td>
<td>23</td>
<td>23.7%</td>
</tr>
<tr>
<td>(f) overall failures in learning phase</td>
<td>97</td>
<td>43</td>
<td>44.3%</td>
</tr>
<tr>
<td>(g) sum (a)+(f)</td>
<td>104</td>
<td>50</td>
<td>48.1%</td>
</tr>
</tbody>
</table>
Discussion

Constrained Spaces:

Over-counter cabinets:

PR2 Weakness:

Floor:
Soft Carpets, etc.
All software (including documentation) is available on:
http://www.ros.org/wiki/pr2_cabinet_opening
1. Introduction
2. Semantic Mapping 1
3. Opening of Cabinets
4. Semantic Mapping 2
5. Segmentation
Segmentation of Cabinets

UPENN, October 2011

Acquiring Semantic Maps for Household Tasks and More

Dejan Pangeric
Annotation of Objects

- Acquire snapshots of cabinet insides
- Insert into KnowRob Ontology (OWL) which incorporates parts of OpenCyc
- Objects represented as instances of classes (e.g. PaperTowel)
Identification of Organizational Principles in Kitchen Scenario

Definition of Features:

- object type (e.g. food, dishes, cutlery, ...)
  → semantic distance in Ontology:

  \[
  \text{wupSimilarity}(C_1, C_2) = \frac{\text{depth}(\text{LCS}(C_1, C_2))}{\frac{1}{2}(\text{depth}(C_1) + \text{depth}(C_2))}
  \]

Ref: Schuster, ICRA2012
Learning Where Objects Are - Example

Observation

Ontology & Semantic Similarity

Inference Result: Fridge

UPENN, October 2011

Acquiring Semantic Maps for Household Tasks and More

Dejan Panceric
Coming in October/November 2011.

Stacks:

bosch_registration, bosch_surface_modelling, bosch_semantic_map
1. Introduction

2. Semantic Mapping 1

3. Opening of Cabinets

4. Semantic Mapping 2

5. Segmentation
Interactive Segmentation - System

Introduction
Semantic Mapping 1
Opening of Cabinets
Semantic Mapping 2
Segmentation

UPENN, October 2011
Acquiring Semantic Maps for Household Tasks and More
Dejan Pangeric
Contact Point and Push Direction

- Segmentation of cluttered scenes
- Contour estimation
- Finding concave corners
- Bisector gives a push direction
Features $u$ and $v$, depicted as red circles, are randomly selected.

From their trajectories $S_u$ and $S_v$, a rigid transformation $A_t$ is calculated.

If $u$ and $v$ are on the same object, all other features will move according the sequence of $A_t$.
Results
All software (including documentation) is available on:

http://www.ros.org/wiki/pr2_interactive_segmentation

This package is associated with the ICRA2012 submission titled: Segmentation of Cluttered Scenes through Interactive Perception.

This paper describes a novel object segmentation approach for autonomous service robots acting in human living environments. The proposed system allows a robot to effectively segment textured objects in cluttered scenes by leveraging its manipulation capabilities. In this interactive perception approach, 2D-features are tracked while the robot actively induces motions into a scene using its arm. Thus, the robot autonomously infers appropriate arm movements which can effectively separate objects. The resulting tracked feature trajectories are assigned to their corresponding object by using a novel randomized clumping algorithm, which samples rigid motion hypotheses for the a priori unknown number of scene objects. We evaluated the approach on challenging scenes which included occluded and reflective objects, as well as objects of varying shapes and sizes.
Summary

- End-to-end system for autonomous mapping and scene classification
- Sub-system for autonomous operating of cabinets
- Clustering algorithm for segmentation of textured objects
Thanks!

Collaborators: Ben Pitzer, Jürgen Sturm, Thomas Rühr, Kyle Maroney, Sarah Osentoski, Christian Bersch, Martin Schuster, Dominik Jain

Contact:
{pangercic}@cs.tum.edu

UPENN, October 2011

Acquiring Semantic Maps for Household Tasks and More