Acquiring Semantic Maps for Household Tasks and More

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October 2011
1. Introduction

2. Semantic Mapping 1

3. Opening of Cabinets

4. Semantic Mapping 2

5. Segmentation
Introduction

Semantic Mapping

End-to-end system to automatically reconstruct textured 3D models of kitchens and to equip them with the functional and semantic attributes

- Novel algorithm for the detection of the handles with surfaces with specular reflectivity
- Application of inference methods to identify organizational principles based on semantic similarities, powerful enough to reason about the typical storage places for objects of daily use
- Collaborator(s): Ben Pitzer, Dominik Jain, Martin Schuster
Segmentation of Cluttered Scenes through Interactive Perception

- A heuristic for finding a contact point and a push direction for the robot’s manipulator in order to induce distinct motions to effectively separate the objects.
- A novel randomized clustering algorithm for 2D-feature trajectories that is based on sampling rigid motion hypotheses for the \textit{a priori} unknown number of scene objects.
- Collaborator(s): Christian Bersch, Sarah Osentoski, Kyle Maroney.
We developed 4 modules:

- for detecting both Lambertian and non-Lambertian (i.e. specular) handles
- for opening and closing novel cabinets using impedance control and for learning their kinematic models
- for storing and retrieving information about these objects in the map
- for reliably operating cabinets (known kinematic model)

Collaborator(s): Thomas Rühr, Jürgen Sturm
IAS Group - Research Map

Planning & Reasoning

Knowledge & Learning

Perception

Action

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Goal: Acquire semantic maps such that they can 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?”.
Introduction

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Segmentation

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

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Registration, Reconstruction, Texture Re-projection

Testbed Kitchens

Poisson surface reconstruction

Blending-based texture re-projection

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

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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:
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PR2 Beta Sites Involved

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

Freiburg
Learning of Articulation Models, Impedance Control

Bosch
Main Testing Facility

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Two Handle Detectors

Non-reflective Handles (Rusu, ICAR2009):

Reflective Handles:

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Learning of Articulation Models - Arm Control

- 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 $y_i \in SE(3)$

Sturm et al., JAIR 2011
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: $\widehat{\mathcal{M}}, \widehat{\theta} = \arg\max_{\mathcal{M}, \theta} p(\mathcal{M}, \theta | y_{1:n})$
- Fit the parameter vector of all model candidates using an MLESAC estimator

Sturm et al., JAIR 2011

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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 $\mathbf{x}_{n+1}^{CEP}$.
- Finally, determine opening angle / opening distance
- Output: Kinematic model

Sturm et al., JAIR 2011
Sample a noise-free trajectory $\mathbf{x}_{1:n}$ from the model over the configuration range.

Store and retrieve the trajectory from KnowRob DB (Tenorth, IROS 2009):

\begin{verbatim}
?- rdf_triple (knowrob: 'in−ContGeneric', knowrob: 'Cup67', B),
rdf_has (B, knowrob: openingTrajectory, Traj),
findall (P, rdf_has (Traj, knowrob: pointOnTrajectory, P), Points).
\end{verbatim}
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, 104 trials
## Results - Detection of Specular Handles

2 handles, 9 different poses:

<table>
<thead>
<tr>
<th></th>
<th>positive</th>
<th>negative</th>
</tr>
</thead>
<tbody>
<tr>
<td>positive</td>
<td>45</td>
<td>4</td>
</tr>
<tr>
<td>negative</td>
<td>5</td>
<td>0</td>
</tr>
</tbody>
</table>

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### Results - Accuracy of Estimated Articulation Models

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>
Constrained Spaces:

PR2 Weakness:

Over-counter cabinets:

Floor:
Soft Carpets, etc.
All software (including documentation) is available on:

http://www.ros.org/wiki/pr2_cabinet_opening
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Segmentation of Cabinets

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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)
Learning Where Objects Are

Identification of Organizational Principles in Kitchen Scenario

Definition of Features:

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

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

Schuster, ICRA2012

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Learning Where Objects Are - Example

Observation

Ontology & Semantic Similarity

Inference Result: Fridge

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Coming in October/November 2011.

Stacks:

*bosch_registration*, *bosch_surface_modelling*, *bosch_semantic_map*
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Interactive Segmentation - System

INPUT DATA
- PR2 Robot
- Input Image
- Input Point Cloud

PUSH POINT/DIRECTION ESTIMATION
- Tabletop Depth Image
- Find Cluster of Objects
- Detection of Concave Corners, Push Point and Direction

FEATURE TRACKING
- Shi-Tomasi Feature Extraction
- Arm Navigation
- Optical Flow Feature Tracking

CLUSTERING
- Feature Trajectory Clustering

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Contact Point and Push Direction

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

From their trajectories $S_u$ and $S_\nu$, a rigid transformation $A_t$ is calculated.

If $u$ and $\nu$ are on the same object, all other features will move according the sequence of $A_t$. 

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Results

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All software (including documentation) is available on:
http://www.ros.org/wiki/pr2_interactive_segmentation
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!