A Comparison of Geometric and Energy-Based Point Cloud Semantic Segmentation Methods

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Context

Semantic navigation for indoor robots:

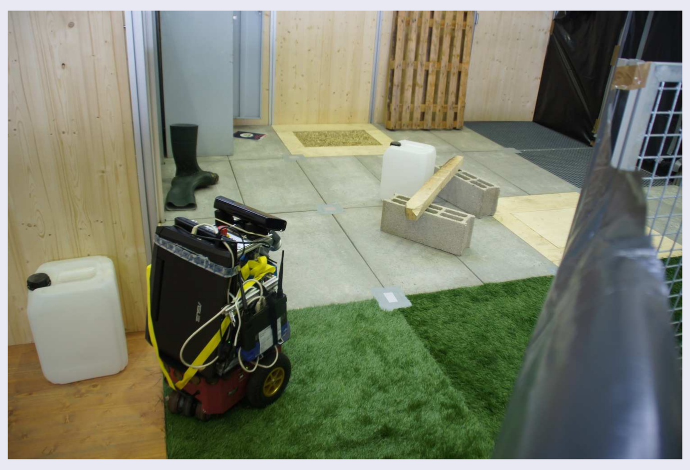
- mapping
- recognize objects, rooms, *etc.*

Low-cost RGB-D cameras:

- use depth information

CAROTTE competition

`http://www.defi-carotte.fr`



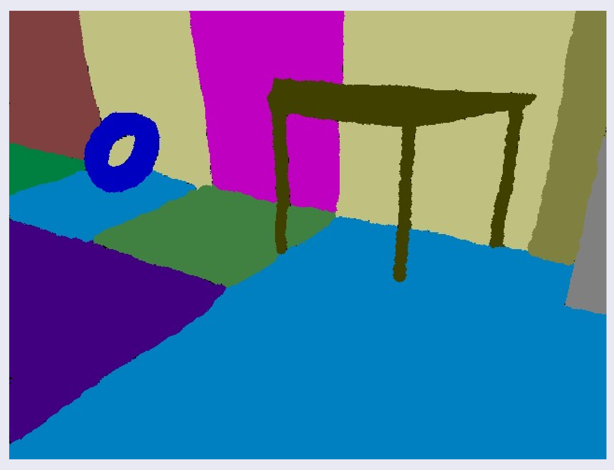
Problem

Object recognition at the category level is difficult:

⇒ focus on segmentation: try to recognize the structure of the environment (walls, ground) and the presence of objects

Multimodal segmentation:

$$\overset{\star}{\boldsymbol{x}} = \arg\max_{\boldsymbol{x}} \mathrm{P}(\boldsymbol{x}|\mathbf{A}, \mathbf{S}, \mathbf{G})$$

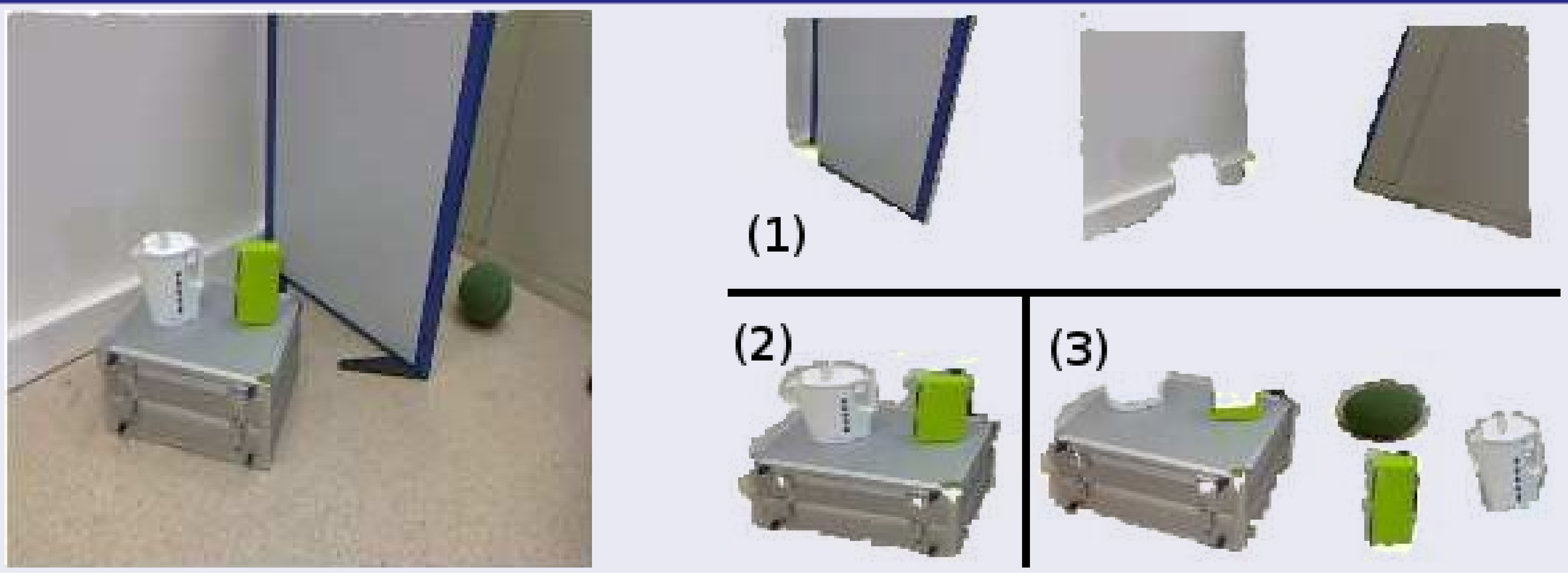


Baseline system

- Developed for the PACOM system (Filliat et al. 2012), inspired by Rusu et al. 2009
- Purely geometric
  - Detect the ground plane and remove the points
  - Detect walls *i.e.* planes perpendicular to ground and remove the points (1)
  - Project remaining points and group them: objects (2)
  - Decompose objects into planes and regroup them (3)

\+ No training, very good performance, decompose objects

\- Many parameters (including robot specific)

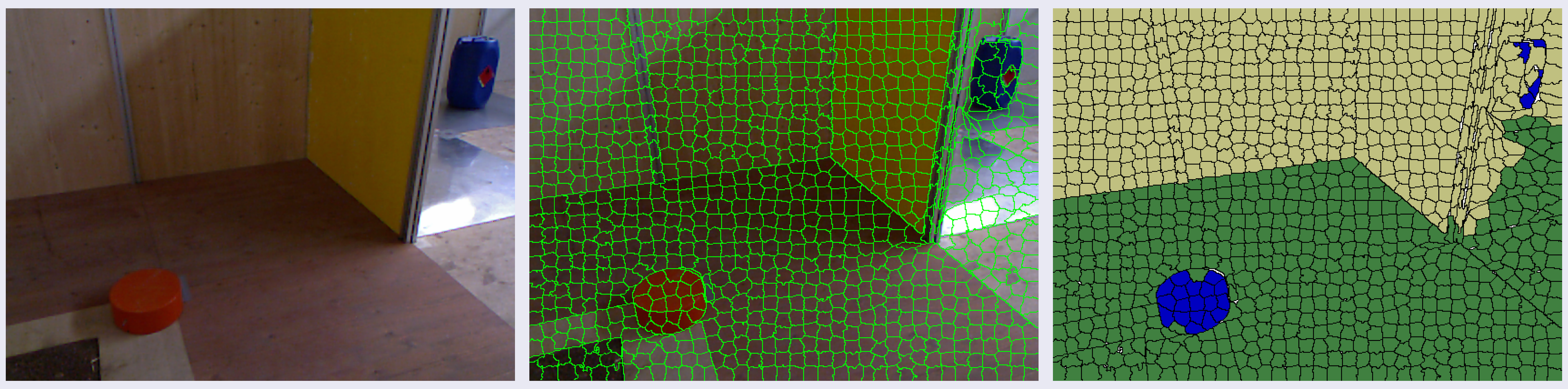


MRF-based system

1. Multimodal over-segmentation with an extension of SLIC (Achanta et al. 2012)
2. Labeling with a non-associative MRF:

$$E = \lambda_{color}\sum_{i=1}^{N} E^{A}(i) + \lambda_{shape}\sum_{i=1}^{N} E^{S}(i) + \lambda_{geom}\sum_{i=1}^{N} E^{G}(i)$$
$$+ \lambda_{prior}\sum_{i=1}^{N} E^{\text{prior}}(i) + \lambda_{normals}\sum_{(i,j)\in E} E^{\text{normals}}(i,j)$$
$$+ \lambda_{depth}\sum_{(i,j)\in E} E^{\text{depth}}(i,j)$$

Inference algorithm: Werner 2007



Input RGB-D image — Superpixels — Labeling

Multimodal SLIC Superpixels

- Adaptation of the k-means algorithm with local search (linear complexity)
- Distance function: given 2 pixels i and j:

$$D(i,j) = \sqrt{d_c(i,j)^2 + \frac{m^2}{S^2} d_s^2(i,j)}$$

where:

$$d_c(i,j) = \sqrt{(l_j - l_i)^2 + (a_j - a_i)^2 + (b_j - b_i)^2}$$
$$d_s(i,j) = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2 + (z_j - z_i)^2}$$

- Large m enforce compact superpixels, small m enforce adherence to image boundaries

Energies (green = learned parameter)

Unary:

- $E^{A}(\ell) = -\log \mathrm{P}\left(w^{A}|\ell\right)$ where w^{A} is the quantized SIFT descriptor
- $E^{S}(\ell) = -\log \mathrm{P}\left(w^{S}|\ell\right)$ where w^{S} is the quantized depth descriptor (Shotton et al. 2011)
- $E^{G}(\ell) = -\log \mathcal{N}(\boldsymbol{g}|\boldsymbol{\mu}_{\ell}, \boldsymbol{\Sigma}_{\ell})$ where $\boldsymbol{g} = [x, y]^{T}$ is 2D position
- $E^{\text{prior}}(\ell) = -\log \mathrm{P}(\ell)$

⇒ Necessary for unbalanced dataset

Binary:

- $E^{\text{normals}}(\ell_1, \ell_2) = -\log \mathrm{P}(\ell_1, \ell_2|\bar{\phi})$ where $\bar{\phi}$ is the quantized angle between normals

⇒ Enforce detection of different surfaces

- $E^{\text{depth}}(\ell_1, \ell_2) = \begin{cases} 1 - e & \text{if } \ell_1 = \ell_2 \\ \delta_{depth} + e & \text{else} \end{cases}$ where

$$e = \exp\left(-\frac{|\Delta z|^2}{2\sigma_{depth}^2}\right)$$

⇒ Enforce detection of edges

Easy to learn: discrete or Gaussian PDF

Database

- Acquired during competition
- Autonomous robot navigation
  - using the baseline method
- 100 manually labeled point clouds
  - 3 classes (wall, ground, object) decomposed into detailed classes (9 walls, 8 grounds, 16 objects)
  - Unbalanced

\+ Usable for segmentation and recognition

⇒ We use only 3 classes

`http://cogrob.ensta.fr/pacom`

Results: 5-fold cross-validation

Algorithm	Precision			Recall			Overall
	Walls	Ground	Objects	Walls	Ground	Objects	
Baseline	93.3	97.8	65.0	87.7	91.2	98.1	94.9
MRF strong regul. ($\lambda_{normal} = \lambda_{depth} = 1.0$)	96.4	89.5	46.8	77.6	79.5	41.6	76.0
MRF weak regul. ($\lambda_{normal} = \lambda_{depth} = 0.2$)	94.7	89.4	88.1	82.8	80.4	23.5	77.86
MRF no regul ($\lambda_{normal} = \lambda_{depth} = 0$)	94.7	88.8	64.8	81.1	78.5	32.1	76.8

- MRF is less good than domain-specific algorithm but gives interesting results
- MRF models have several advantages:
  - More generic
  - Less tuning
  - Use appearance
  - Probabilistic output

References

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