CSE-571 Probabilistic Robotics

Mapping

Problems in Mapping

- Sensor interpretation
 - How do we extract relevant information from raw sensor data?
 - How do we represent and integrate this information over time?
- Robot locations have to be known
 - How can we estimate them during mapping?

Types of SLAM-Problems

• Grid maps or scans







[Lu & Milios, 97; Gutmann, 98: Thrun 98; Burgard, 99; Konolige & Gutmann, 00; Thrun, 00; Arras, 99; Haehnel, 01;...]

Landmark-based







Fleonard et al., 98: Castelanos et al., 99: Dissanavake et al., 2001: Montemerlo et al., 2002:..

Occupancy Grid Maps

- Introduced by Moravec and Elfes in 1985
- Represent environment by a grid.
- Estimate the probability that a location is occupied by an obstacle.
- Key assumptions
 - Occupancy of individual cells is independent

$$Bel(m_t) = P(m_t | u_1, z_2 ..., u_{t-1}, z_t)$$

$$= \prod_{x,y} Bel(m_t^{[xy]})$$

• Robot positions are known!

Updating Occupancy Grid Maps

• Idea: Update each individual cell using a binary Bayes filter.

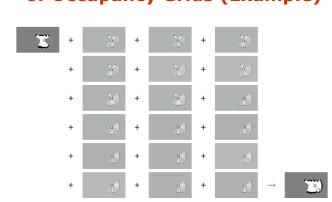
$$Bel(m_{t}^{[xy]}) = \eta \ p(z_{t} \mid m_{t}^{[xy]}) \sum_{m_{t-1}^{[xy]}} p(m_{t}^{[xy]} \mid m_{t-1}^{[xy]}, u_{t-1}) Bel(m_{t-1}^{[xy]})$$

• Additional assumption: Map is static.

$$Bel(m_t^{[xy]}) = \eta \ p(z_t \mid m_t^{[xy]}) Bel(m_{t-1}^{[xy]})$$

Inverse Sensor Model for Occupancy Grid Maps Combination of linear function and Gaussian: Occupancy probability Occupancy probability Occupancy probability $\overline{B}(m_t^{[xy]}) = \log odds(m_t^{[xy]} \mid z_t, x_t) - \log odds(m_t^{[xy]}) + \overline{B}(m_{t-1}^{[xy]})$

Incremental Updatingof Occupancy Grids (Example)



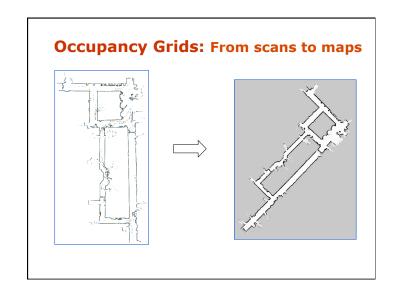
Alternative: Simple Counting

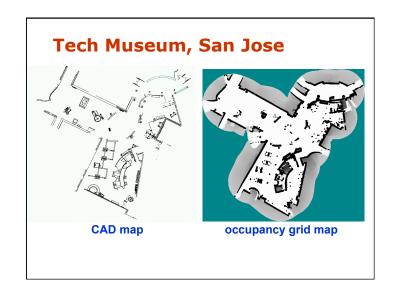
- For every cell count
 - hits(x,y): number of cases where a beam ended at <x,y>
 - misses(x,y): number of cases where a beam passed through <x,y>

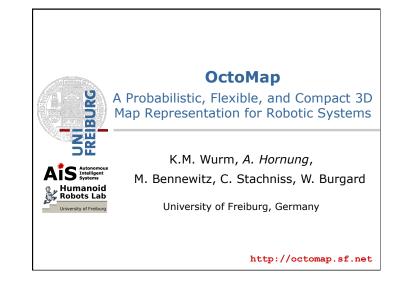
$$Bel(m^{[xy]}) = \frac{\text{hits}(x, y)}{\text{hits}(x, y) + \text{misses}(x, y)}$$

• Assumption: P(occupied(x,y)) = P(reflects(x,y))









Robots in 3D Environments



Mobile manipulation



Humanoid robots



Outdoor navigation



Flying robots

3D Map Requirements

- Full 3D Model
 - Volumetric representation
 - Free-space
 - Unknown areas (e.g. for exploration)
- Updatable
 - Probabilistic model (sensor noise, changes in the environment)
 - Update of previously recorded maps

3D Map Requirements

- Flexible
 - Map is dynamically expanded
 - Multi-resolution map queries
- Compact
 - Memory efficient
 - Map files for storage and exchange

Map Representations

Pointclouds

- Pro:
 - No discretization of data
 - Mapped area not limited



- Contra:
 - Unbounded memory usage
 - No direct representation of free or unknown space

Map Representations

3D voxel grids

- Pro:
 - Probabilistic update
 - Constant access time



- Contra:
 - Memory requirement
 - Extent of map has to be known
 - Complete map is allocated in memory

Map Representations

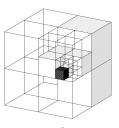
2.5D Maps

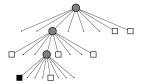
- 2D grid
- Height value(s) in each cell
- Pro:
 - Memory efficient
- Contra:
 - Not completely probabilistic
 - No distinction between free and unknown space

Map Representations

Octrees

- Tree-based data structure
- Recursive subdivision of space into octants
- Volumes allocated as needed
- Multi-resolution





Map Representations

Octrees

- Pro:
 - Full 3D model
 - Probabilistic
 - Flexible, multi-resolution
 - Memory efficient
- Contra:
 - Implementation can be tricky (memory, update, map files, ...)



OctoMap Framework

- Based on octrees
- Probabilistic representation of occupancy including unknown
- Supports multi-resolution map queries
- Lossless compression
- Compact map files
- Open source implementation as C++ library available at http://octomap.sf.net

Probabilistic Map Update

 Occupancy modeled as recursive binary Bayes filter [Moravec '85]

$$P(n \mid z_{1:t}) = \left[1 + \frac{1 - P(n \mid z_t)}{P(n \mid z_t)} \frac{1 - P(n \mid z_{1:t-1})}{P(n \mid z_{1:t-1})} \frac{P(n)}{1 - P(n)}\right]^{-1}$$

Efficient update using log-odds notation

$$L(n \mid z_{1:t}) = L(n \mid z_{1:t-1}) + L(n \mid z_t)$$

Probabilistic Map Update

- Clamping policy ensures updatability [Yguel '07] $L(n) \in [l_{min}, l_{max}]$
- Update of inner nodes enables multiresolution queries

$$L(n) = \max_{i=1..8} L(n_i)$$

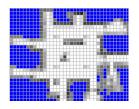






Lossless Map Compression

- Lossless pruning of nodes with identical children
- High compression ratios esp. in free space

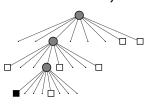




[Kraetzschmar 04]

Map Files

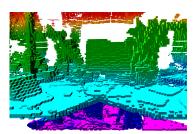
- Maximum-likelihood map stored as compact bitstream
- Occupied, free, and unknown areas
- Very moderate space requirements (usually less than 2 MB)



		0					
00	00	11	00	00	00	10	10
			0				
10	00	00	11	10	00	00	10
01	00	00	00	10	00	00	00

Examples

Cluttered office environment

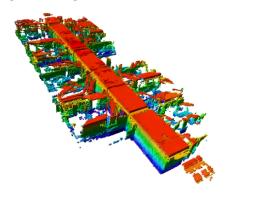




Map resolution: 2 cm

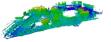
Examples: Office Building

• Freiburg, building 079

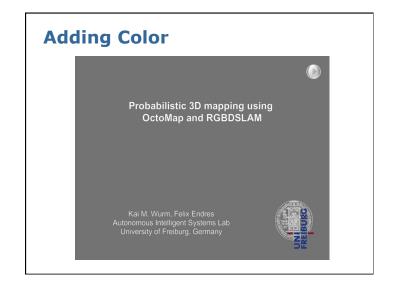


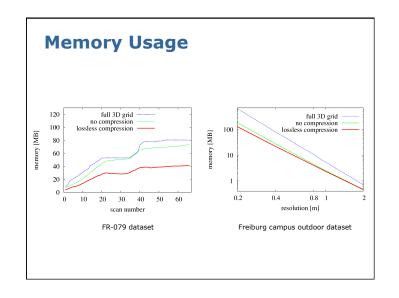
Examples: Large Outdoor Areas

■ Freiburg computer science campus (292 x 167 x 28 m³, 20 cm resolution)









Mapped Resolution Memory consumption [MB] File size [MB] Map dataset area [m³] [m] Full grid No compr. Lossless compr. All data Binary 0.05 80.54 73.64 41.70 15.80 0.67 FR-079 corridor 43.8 × 18.2 × 3.3 0.1 10.42 10.90 7.25 2.71 0.14 0.20 654.42 188.09 130.39 49.75 2.00 Freiburg outdoor 292 x 167 x 28 0.80 10.96 4.56 4.13 1.53 0.08

637.48

10.21

0.20

0.80

91.43

50.70

1.81

18.71 0.99

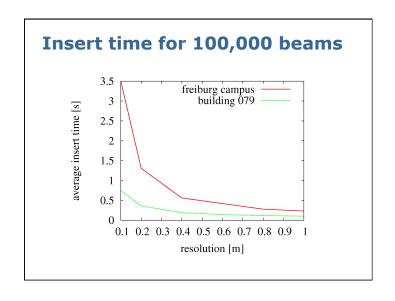
0.64 0.05

Memory Usage

 $250 \times 161 \times 33$

New College

(Epoch C)



OctoMap Implementation

- Open source C++ library
- Fully documented
- Can be easily adapted to your projects
- ROS integration
- Includes OpenGL viewer
- Already used by several other researchers

http://octomap.sf.net

