Terrain Classification with Markov Random Fields on fused Camera and 3D Laser Range Data

Marcel Häselich, Marc Arends, Dagmar Lang, Dietrich Paulus

mhaeselich@uni-koblenz.de

Active Vision Group, AGAS Robotics
University of Koblenz-Landau
robots.uni-koblenz.de

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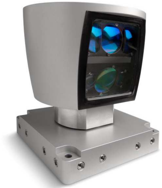
Platform and Deployed Sensors

Mustang MK IA



Velodyne HDL-64E S2

Cameras

- GOAL: Create an efficient environment representation for path planning in unstructured environments
  - Sensor calibration and fusion
  - Data reduction
  - Obstacle avoidance
  - Environment interpretation
  - Surface negotiability

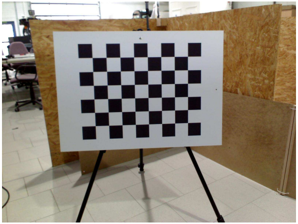
Terrain Classification with Markov Random Fields

Advantages:

- context-sensitive classification
  - varying density of the data
- robustness against sensor noise
  - ego-motion or percussions on rough terrain
- integration of multiple sensor data
- similarity to image processing
- regard the context-sensitivity of neighboring cells and also the acquired features simultaneously

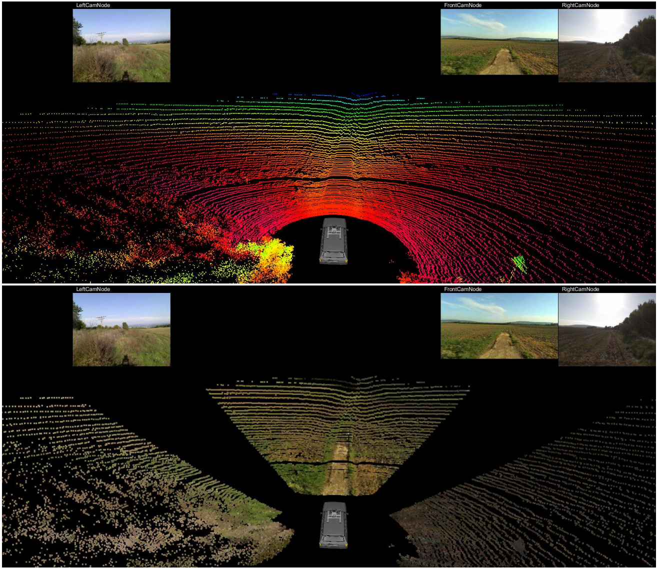
Calibration

- Calibration as described by Unnikrishnan and Herbert [Unnikrishnan 2005]
- Semi-automatic process
- 20 camera/ laser data pairs required
- Pattern needs to be visible for both sensors

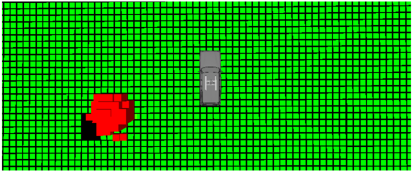


calibration pattern

FUSED CAMERA AND LASER DATA



GRID STRUCTURE



- Subdivide the 3D point cloud into an 2D grid
  - 40 m×40 m grid, each cell is 50 cm×50 cm
  - centered around the origin of the sensor

Laser-based features:

roughness f_r	Unevenness of a terrain cell [Neuhaus 2009]
height difference f_h	Distance between the lowest and the highest laser point

Camera-based features:

texture	*second angular moment* f_{sam}, *variance* f_v and *inverse difference moment* f_{idm} [Haralick 1973]
homogeneity	texture homogeneity f_{fh} [Knauer 2010]
color	Interpolated colors f_c

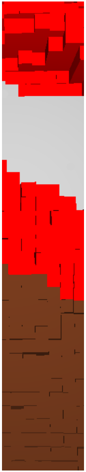
$\Rightarrow$ combination yields the vector $\mathbf{f} = (f_r, f_h, f_{sam}, f_v, f_{idm}, f_{fh}, f_c)$

Features are learned by annotated terrain cells by hand.

Classes

road	flat cells, perfectly drivable
rough	less flat cells with a rough surface, but still drivable
obstacle	cell with positive obstacle impossible to navigate
unknown	cells without any information

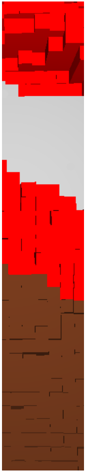
The neighborhood component



$$E_{\mathcal{N}_{ij}} = \sum_{\omega \in \Omega_{ij}} (\beta \cdot \delta(c_{ij}, c_\lambda))$$

- 8 neighbors, β can be used to weight the influence according to the distance
- ω is a class $\in \Omega = \{street, rough, obstacle, unknown\}$
- $\delta(c_{ij}, c_\lambda) = \begin{cases} -1, & \text{if } c_{ij} = c_\lambda, \\ +1, & \text{else.} \end{cases}$

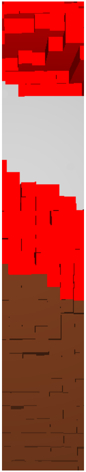
The feature component



$$E_{f_{ij}} = \sum_k \left(\frac{(f_{ij_k} - \mu_{ij_k})^2}{2\sigma_{ij_k}^2} + \log\left(\sqrt{2\pi}\sigma_{ij_k}\right) \right)$$

- f_{ij_k} is the k-th feature of cell C_{ij}
- μ_{ij_k} mean f the k-th feature
- σ_{ij_k} standard deviation of the k-th feature

Complete energy



The energy E_{ij} of a cell C_{ij} at position (i, j) within the grid

$$E_{ij} = E_{\mathcal{N}_{ij}} + \alpha \cdot E_{f_{ij}}$$

is defined by the neighborhood component $E_{\mathcal{N}_{ij}}$ and the feature component $E_{f_{ij}}$. α is a weighting constant used to control the influence of the different energy types.

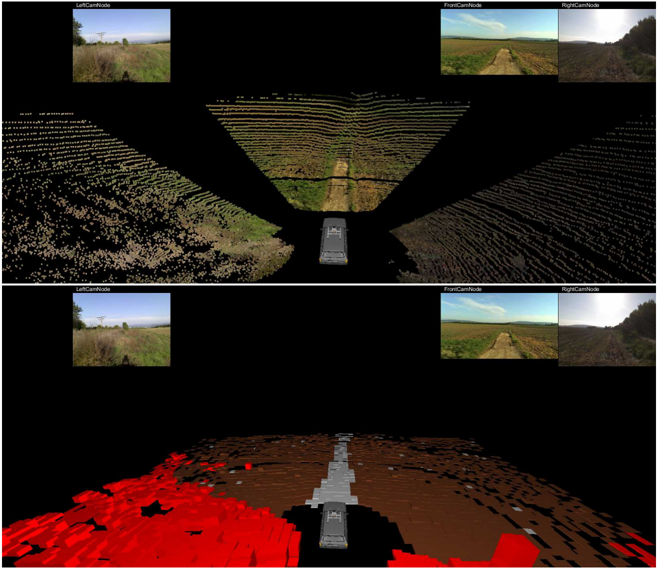
$$\text{Goal: minimize } \sum_{i,j} E_{i,j}$$

$\Rightarrow$ maximize a posteriori probability of the labeling of the terrain

$\Rightarrow$ apply Gibbs Sampling (Geman and Geman [Geman 1984]):

Find a label for each cell which fits best for the computed features and the labels of the neighbor cells

MRF CLASSIFICATION RESULT



TRUE POSITIVE RATE (TPR) AND FALSE POSITIVE RATE (FPR)

Class/value	L	L + H	L + FH	L + C
Road/TPR	91.049 %	91.914 %	90.432 %	91.049 %
Road/FPR	1.523 %	1.146 %	1.158 %	1.372 %
Rough/TPR	74.618 %	73.828 %	75.158 %	75.293 %
Rough/FPR	1.190 %	1.103 %	1.306 %	1.422 %
Obstacle/TPR	92.826 %	91.785 %	92.881 %	92.552 %
Obstacle/FPR	3.565 %	4.426 %	3.221 %	3.118 %

Table: Field scenario.

Class/value	L	L + H	L + FH	L + C
Road/TPR	95.197 %	91.747 %	95.021 %	94.981 %
Road/FPR	4.336 %	5.571 %	4.312 %	4.499 %
Rough/TPR	5.680 %	0.406 %	2.840 %	3.854 %
Rough/FPR	0.292 %	0.101 %	0.259 %	0.281 %
Obstacle/TPR	96.234 %	95.365 %	96.076 %	96.339 %
Obstacle/FPR	6.900 %	6.686 %	7.276 %	6.793 %

Table: Forest scenario.

Runtime measurements

Mode	Mean	Std. dev.	Max	Min
L (MRF)	62.667 ms	7.357 ms	82.240 ms	48.787 ms
L+H (MRF)	744.917 ms	131.507 ms	993.987 ms	421.465 ms
L+FH (MRF)	141.379 ms	11.233 ms	188.420 ms	121.733 ms
L+C (MRF)	144.439 ms	12.566 ms	187.013 ms	117.326 ms

Table: Runtime results of the algorithm on recorded sensor data in real-time. No data reduction or pre-processing was applied.

$\alpha = 0.4$ and $\beta = 0.8$ are fixed for all experiments.

Achievements:

- Markov Random Field can be used on data of a modern 3D laser reange finder
- integration of context sensitivity and different features from both laser and image data
- returns classified 2D grid with terrain negotiability information for each cell
- recall ratio of about 90% for detecting streets and obstacles

Limitations/future work:

- sensor calibration needs to concern the instant of time where the data was recorded
  - precise time stamps
- computation time of the image features
- integration of time / access previous classifications

Demonstration

Thank you for your attention!

Questions?

Sources

- R. Unnikrishnan and M. Hebert.: Fast Extrinsic Calibration of a Laser Rangefinder to a Camera, Pittsburgh, USA, 2005.
- F. Neuhaus, D. Dillenberger, J. Pellenz and D. Paulus: Terrain Drivability Analysis in 3D Laser Range Data for Autonomous Robot Navigation in Unstructured Environments, 14th IEEE International Conference on Emerging Technologies and Factory Automation, 2009
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