## **Probabilistic Techniques for Robot Navigation**

#### **A Key Technology for Our Future Society**

Wolfram Burgard





# **Key Challenges in Navigation**

Highly accurate localization Robust mapping Long-term autonomy









#### **Nature of Data**





#### **Odometry Data**

**Range Data** 

#### **Probabilistic Robotics**

Explicit representation and utilization of uncertainty

Perception = state estimation

Action = utility optimization

#### **Probabilistic Robotics**

Explicit representation and utilization of uncertainty

- Perception = state estimation  $Bel(x \mid z, u) = \alpha p(z \mid x) \int_{x'} p(x \mid u, x') Bel(x') dx'$
- Action = utility optimization

$$\pi^*(x) = \operatorname{argmax}_{u} \sum_{x'} p(x' \mid u, x) V^*(x')$$

# MCL: Global Localization (Sonar)



## **Precise Localization and Positioning for Mobile Robots**



# **Accurate Localization**

- KUKA omniMove (11t)
- Safety scanners
- Error in the area of millimeters
- Even in dynamic environments





# **26 Units installed at Boeing**

- Fuselage assembly
- 20 vehicles to transport industrial robots for drilling and filling of 60,000 fasteners in
- 6 vehicles for logistics of parts, work stands and fuselages





#### Accurate Indoor RGB-D Localization with a Google Tango Device based on 2D Floor Plans

Wera Winterhalter, Freya Fleckenstein, Bastian Steder, Wolfram Burgard, Luciano Spinello







#### How to Learn a Map: SLAM



- Problem described as a graph
  - Every node corresponds to a robot position and to a laser measurement
  - An edge between two nodes represents a datadependent spatial constraint between the nodes



 Once we have the graph, we determine the most likely map by "moving" the nodes



- Once we have the graph, we determine the most likely map by "moving" the nodes
- … like this.



- Once we have the graph, we determine the most likely map by "moving" the nodes
- ... like this.
- Then we render a map based on the known poses



#### **Freiburg Campus Octomap**



# **3D Map of the Stanford Parking Garage**



approx. 260MB

# **Autonomous Parking**

![](_page_17_Picture_1.jpeg)

# **Autonomous Navigation in Urban Areas**

Can we build a robot that is able to navigate autonomously through city centers?

![](_page_18_Picture_2.jpeg)

![](_page_18_Picture_3.jpeg)

![](_page_18_Picture_4.jpeg)

# **Challenge: Canals**

![](_page_19_Picture_1.jpeg)

#### **Challenge: Kids**

![](_page_20_Picture_1.jpeg)

## **The Tagesthemen-Report**

![](_page_21_Picture_1.jpeg)

# **Learning Driving Styles**

- Users have different expectations
- Many parameters such as accelerations, distances, velocities, etc.

![](_page_22_Picture_3.jpeg)

 Difficult to tune parameters for non-technical users

![](_page_22_Picture_5.jpeg)

#### **Learning Driving Behavior**

![](_page_23_Picture_1.jpeg)

# **Online Prediction of User Preferences**

![](_page_24_Picture_1.jpeg)

#### Neurobots

![](_page_25_Picture_1.jpeg)

![](_page_25_Picture_2.jpeg)

# And what's next?

![](_page_26_Figure_1.jpeg)

#### **Deep Learning**

#### **Applications in Robotics ...**

RGB-D

Images

Sound

![](_page_27_Picture_4.jpeg)

- 🖛 🌍 🎆

object

## **Terrain Classification using a Late Fusion DCNN Architecture**

![](_page_28_Picture_1.jpeg)

Glare

![](_page_28_Picture_3.jpeg)

![](_page_28_Picture_4.jpeg)

![](_page_28_Picture_5.jpeg)

![](_page_28_Picture_6.jpeg)

![](_page_28_Picture_7.jpeg)

![](_page_28_Picture_8.jpeg)

#### **Autonomous Navigation in Outdoor Areas**

![](_page_29_Picture_1.jpeg)

#### ... and End to End Navigation

![](_page_30_Picture_1.jpeg)

### Outlook

- With deep learning a new massively parallel and data intensive paradigm has come up that outperforms classical approaches
- Deep learning will play a major role in robotics through the concept of end-to-end learning where no programming is needed.

#### **Summary**

- Probabilistic methods are a powerful tool for realizing autonomous systems
- The corresponding state estimation procedures provide the means for robust navigation systems