

Introduction to Mobile Robotics

Welcome

Wolfram Burgard



Today

- This course
- Robotics in the past and today

Organization

- **Self Study**
lecture recordings, no on-site lectures
- **Thursday 13:00 – 14:00**
homework, practical exercises (Python), discussions
- **Web page:**
www.informatik.uni-freiburg.de/~ais/
- **Exam: Oral or written**

People

Teaching:

- Wolfram Burgard

Teaching assistants:

- Daniel Büscher
- Marina Kollmitz
- Lukas Luft

Goal of this course

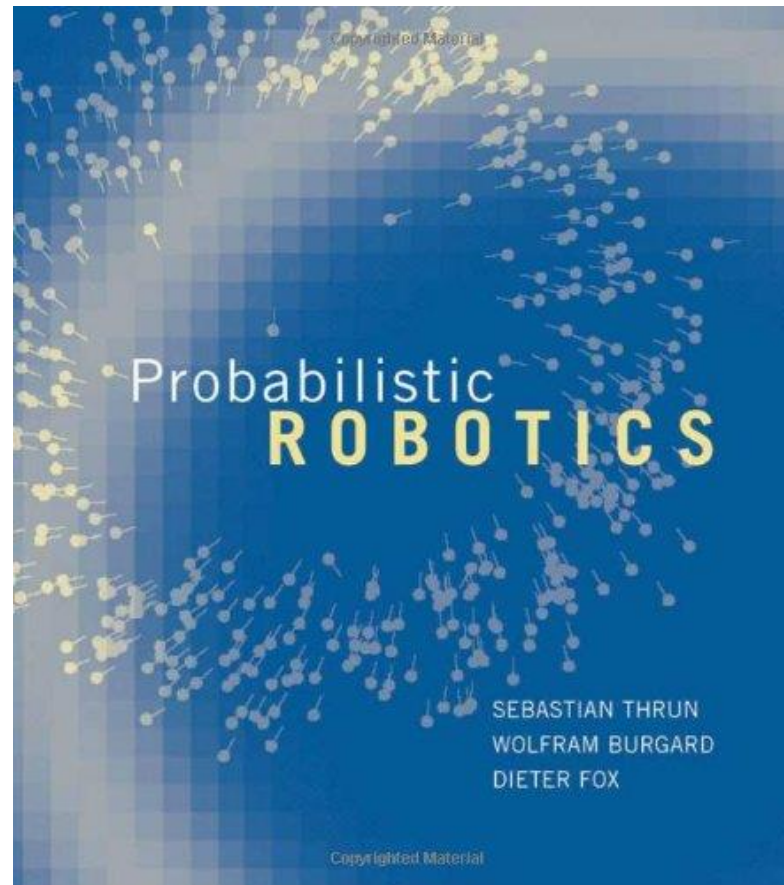
- Provide an overview of problems and approaches in mobile robotics
- Probabilistic reasoning: Dealing with noisy data
- Hands-on experience

Content of this Course

1. Linear Algebra
2. Wheeled Locomotion
3. Sensors
4. Probabilities and Bayes
5. Probabilistic Motion Models
6. Probabilistic Sensor Models
7. Mapping with Known Poses
8. The Kalman Filter
9. The Extended Kalman Filter
10. Discrete Filters
11. The Particle Filter, MCL
12. SLAM: Simultaneous Localization and Mapping
13. SLAM: Landmark-based FastSLAM
14. SLAM: Grid-based FastSLAM
15. SLAM: Graph-based SLAM
16. Techniques for 3D Mapping
17. Iterative Closest Points Algorithm
18. Path Planning and Collision Avoidance
19. Multi-Robot Exploration
20. Information-Driven Exploration
21. Summary

Reference Book

Thrun, Burgard, and Fox:
“Probabilistic Robotics”



Relevant other Courses

- Foundations of Artificial Intelligence
- Computer Vision
- Machine Learning

- and many others from the area of cognitive technical systems.

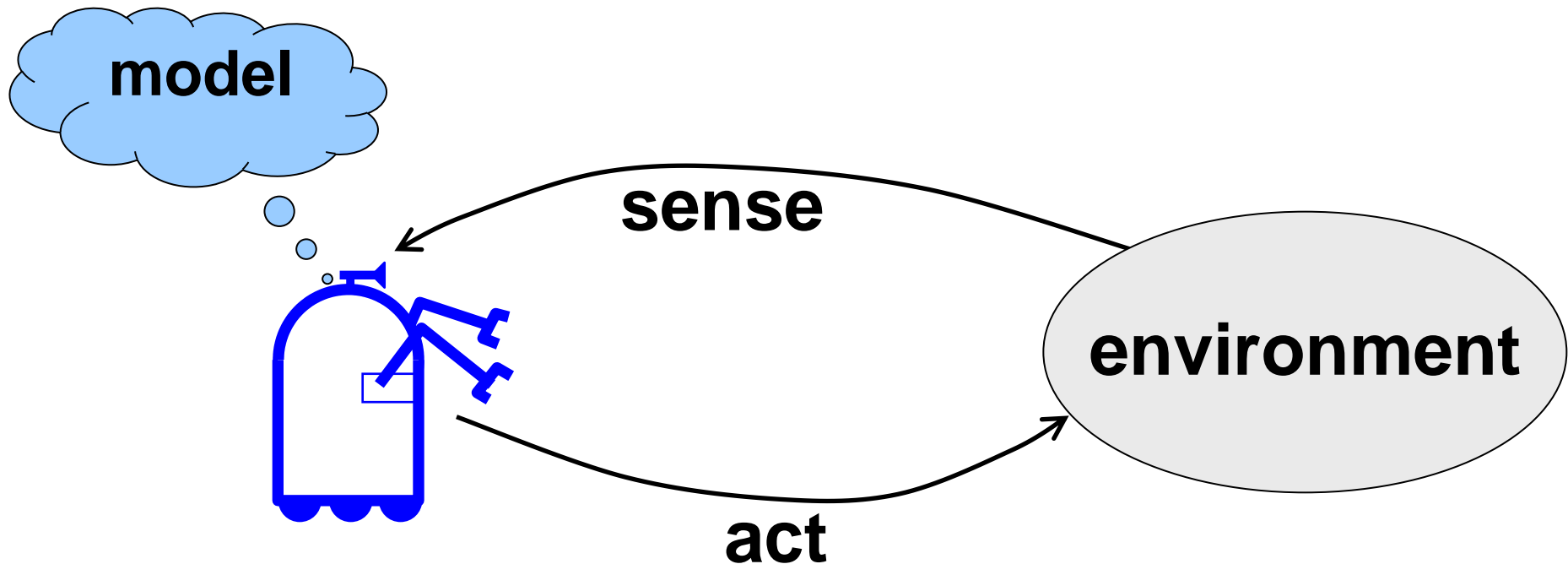
Opportunities

- Projects
- Practicals
- Seminars
- Thesis

- ... your future!

Autonomous Robot Systems

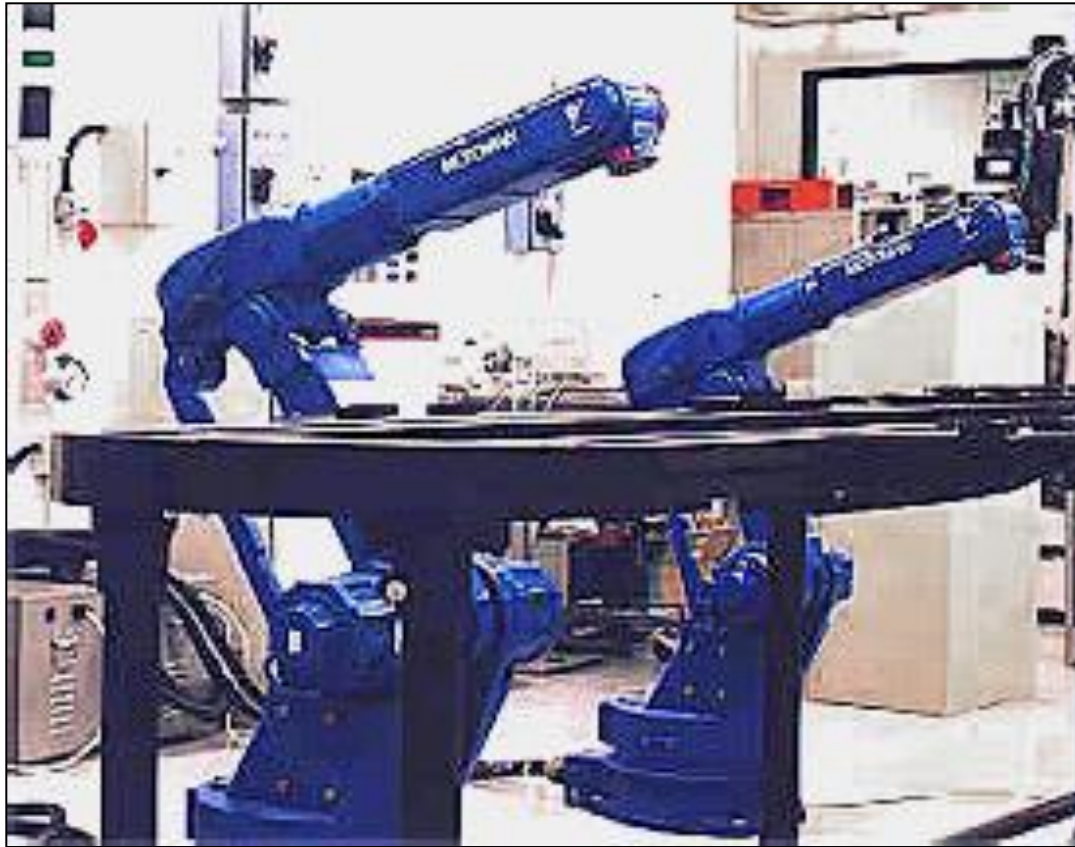
- perceive their environment and
- generate actions to achieve their goals.



Tasks Addressed that Need to be Solved by Robots

- Navigation
- Perception
- Learning
- Cooperation
- Acting
- Interaction
- Robot development
- Manipulation
- Grasping
- Planning
- Reasoning
- ...

Robotics Yesterday

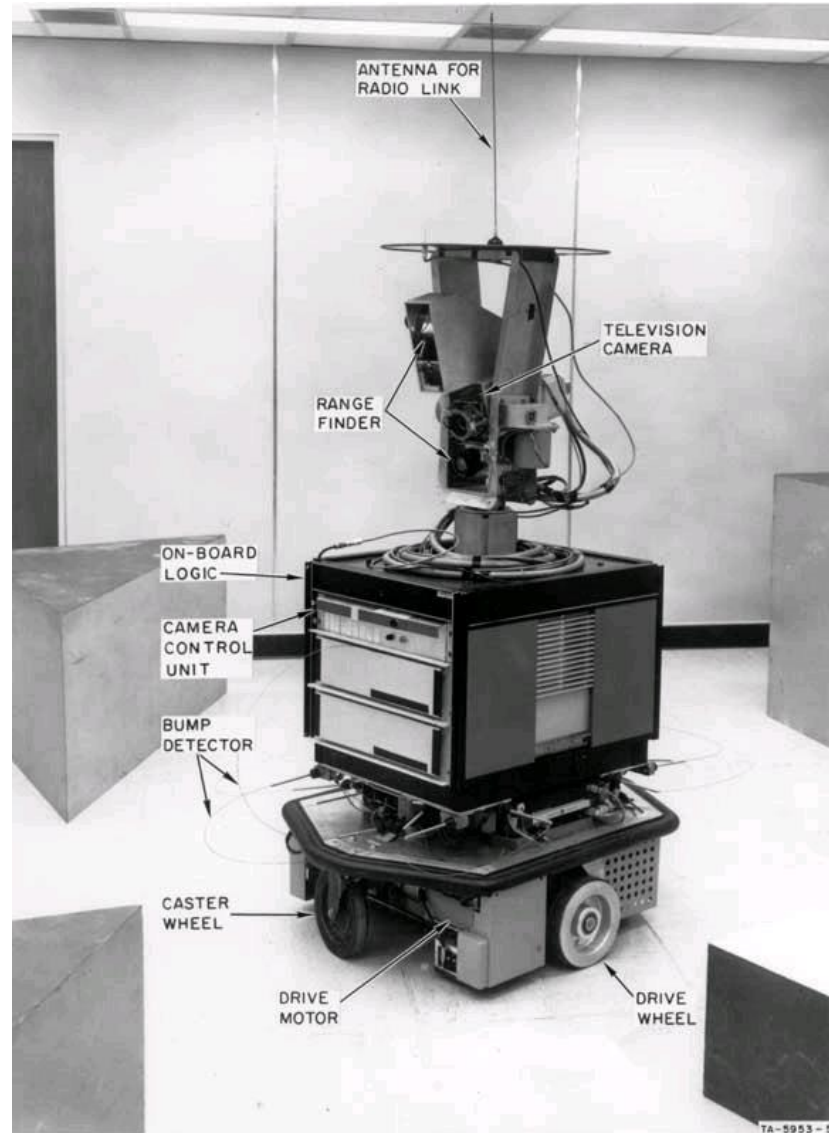


Current Trends in Robotics

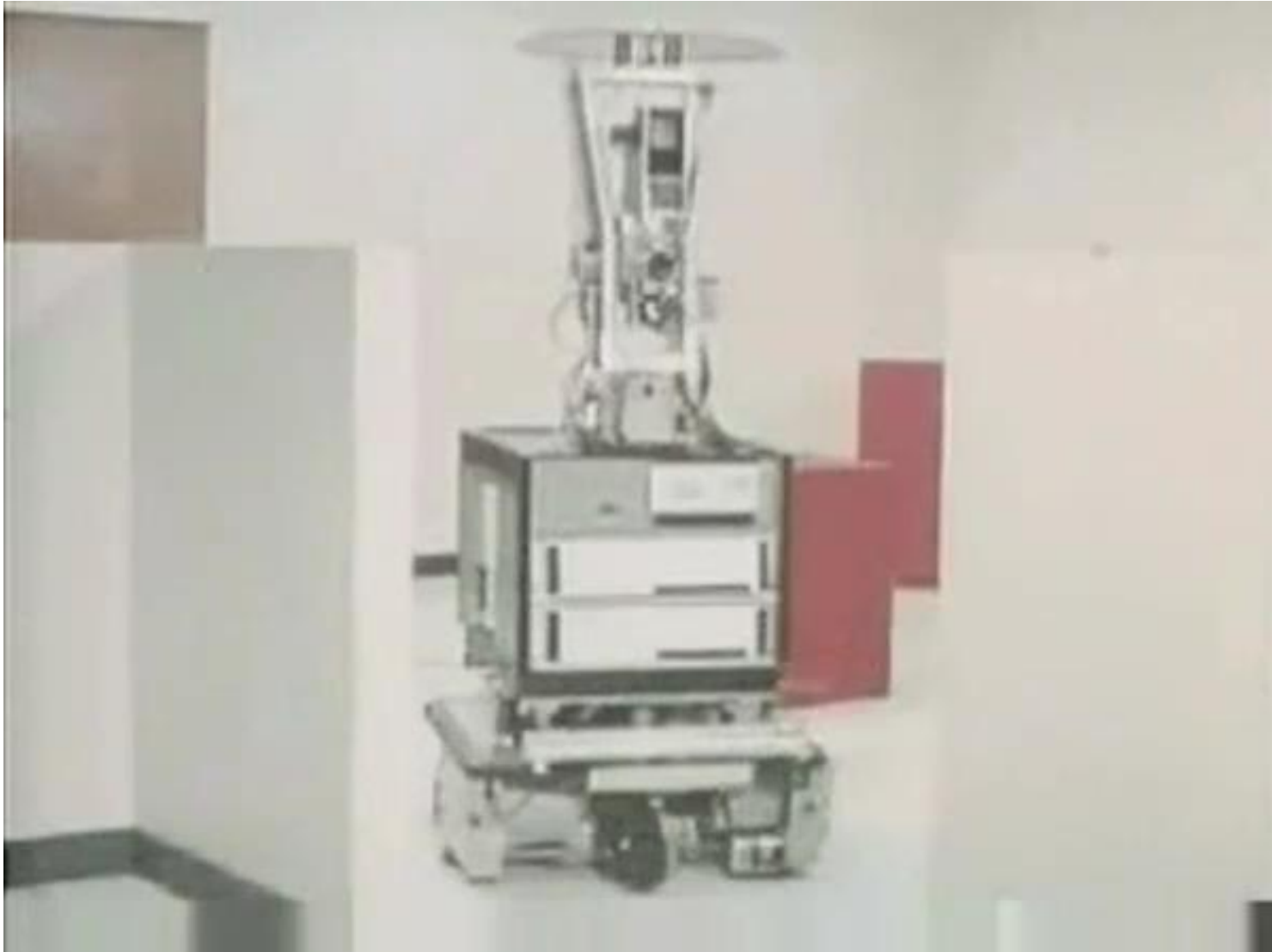
Robots are moving away from factory floors to

- Entertainment, toys
- Personal services
- Medical, surgery
- Industrial automation
(mining, harvesting, ...)
- Hazardous environments
(space, underwater)

Shakey the Robot (1966)



Shakey the Robot (1966)



Robotics Today

- Lawn mowers
- Vacuum cleaners
- Self-driving cars
- Logistics
- ...

The Helpmate System



Autonomous Vacuum Cleaners



Autonomous Lawn Mowers



DARPA Grand Challenge



[Courtesy by Sebastian Thrun]

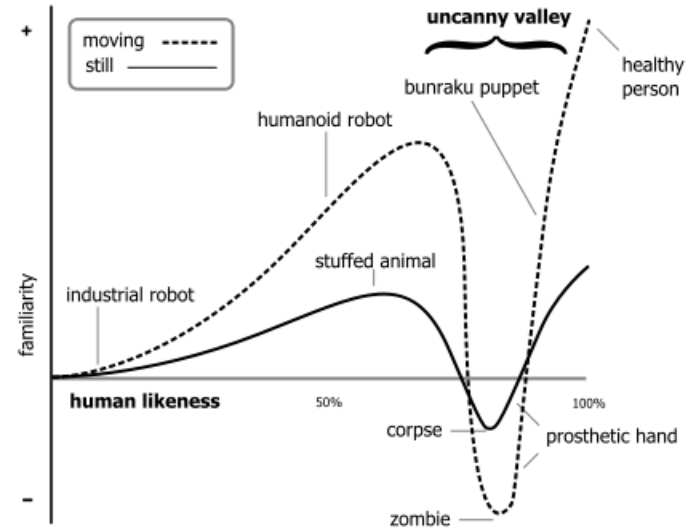
Walking Robots



[Courtesy by Boston Dynamics]

Androids

Overcoming the uncanny valley



[Courtesy by Hiroshi Ishiguro]

Driving in the Google Car



Autonomous Motorcycles



[Courtesy by Anthony Levandowski]

The Google Self Driving Car



Folding Towels

Cloth Grasp Point Detection
based on Multiple-View Geometric Cues
with Application to Robotic Towel Folding

Jeremy Maitin-Shepard
Marco Cusumano-Towner
Jinna Lei
Pieter Abbeel

Department of Electrical Engineering and Computer Science
University of California, Berkeley

International Conference on Robotics and Automation, 2010

Rhino

(Univ. Bonn + CMU, 1997)

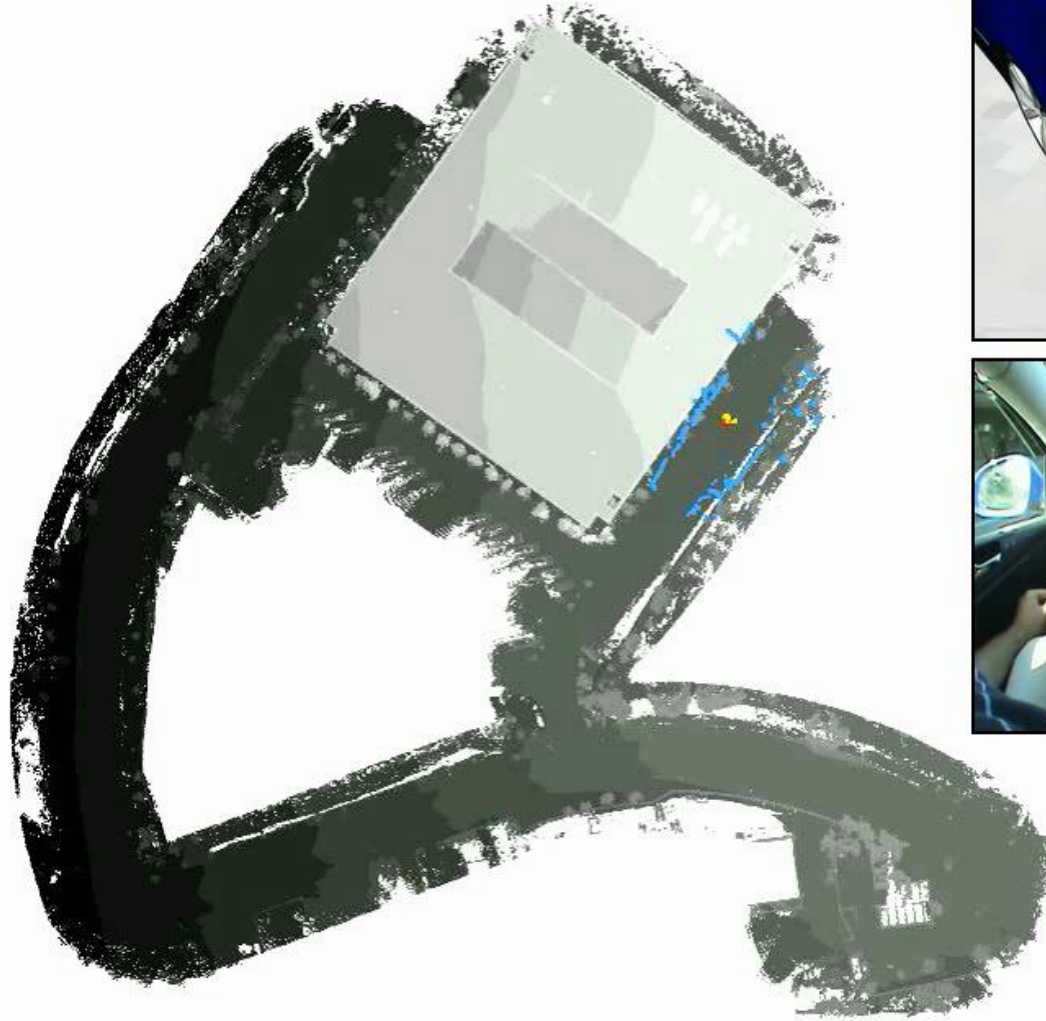


Minerva (CMU + Univ. Bonn, 1998)



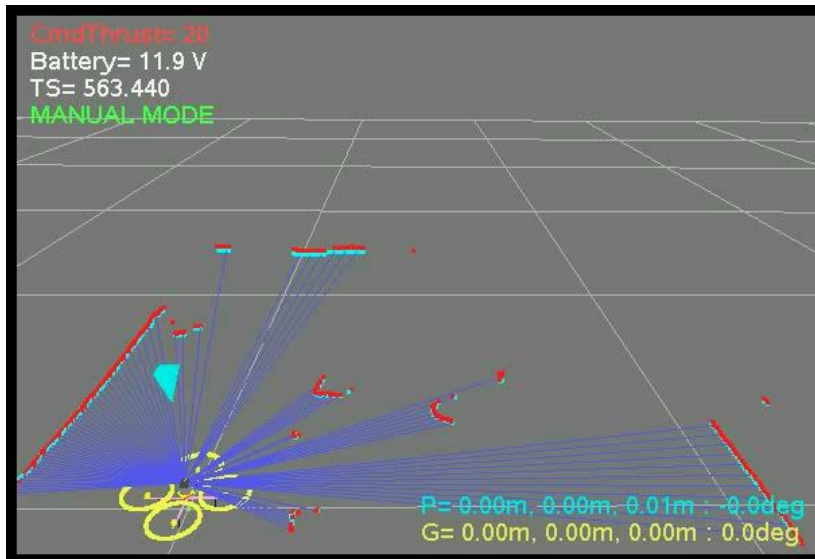
Robotics in Freiburg

Autonomous Parking



Autonomous Quadrotor Navigation

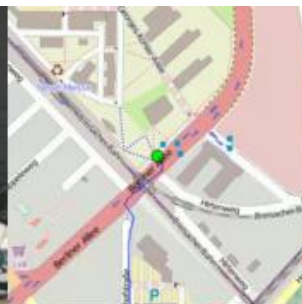
Custom-built system:
laser range finder
inertial measurement unit
embedded CPU
laser mirror



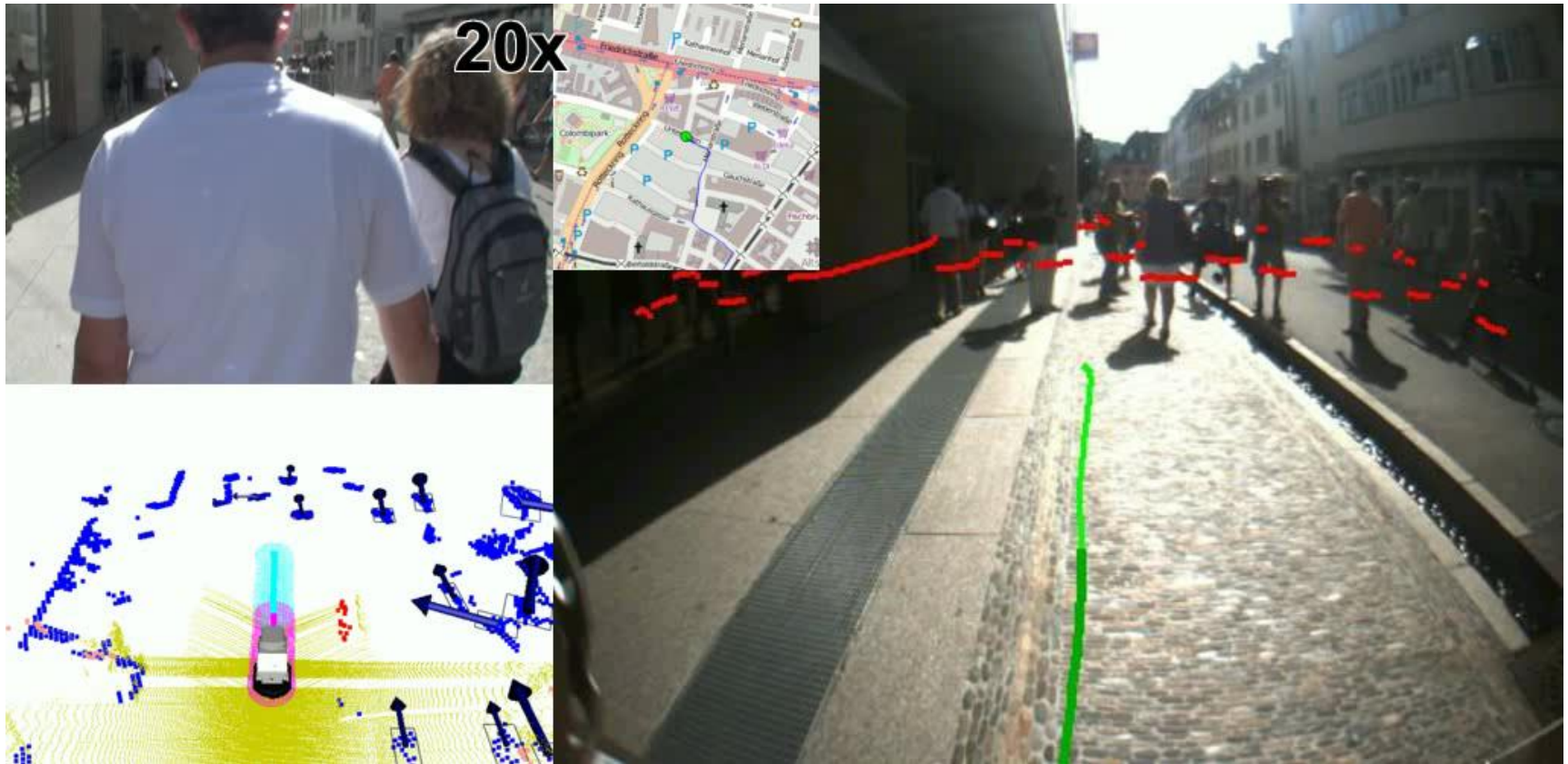
Precise Localization and Positioning for Mobile Robots



Obelix – A Robot Traveling to Downtown Freiburg



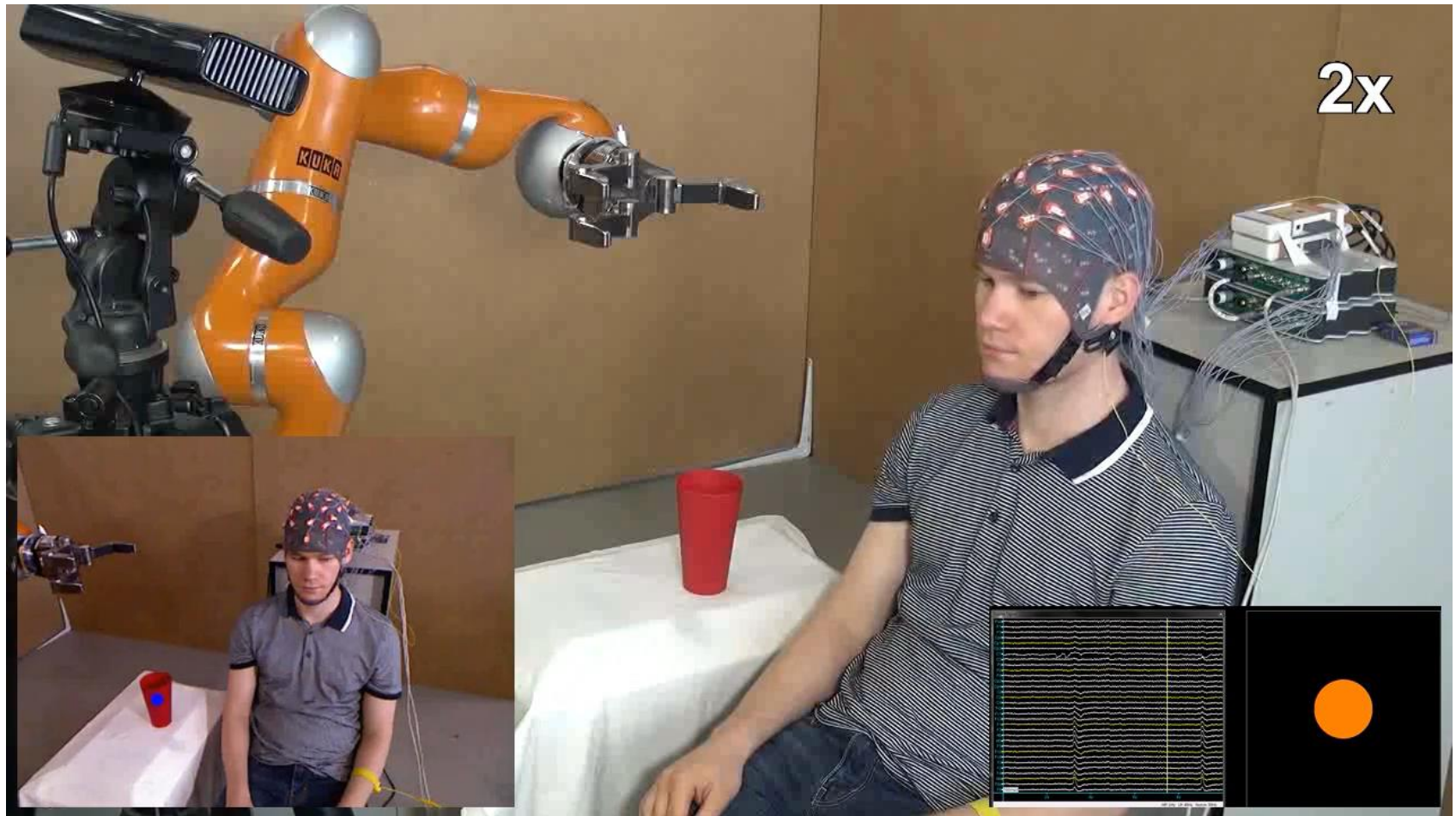
The Obelix Challenge (Aug 21, 2012)



The Tagesthemen-Report



Brain-controlled Robots



Teaching: Student Project on the Autonomous Portrait Robot



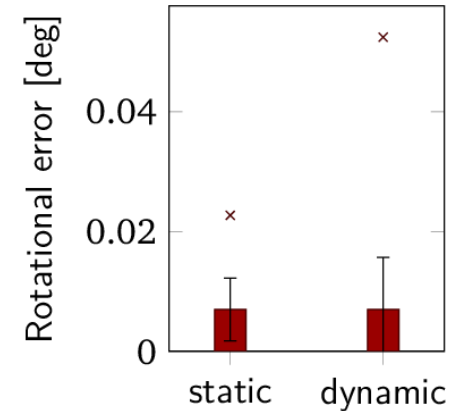
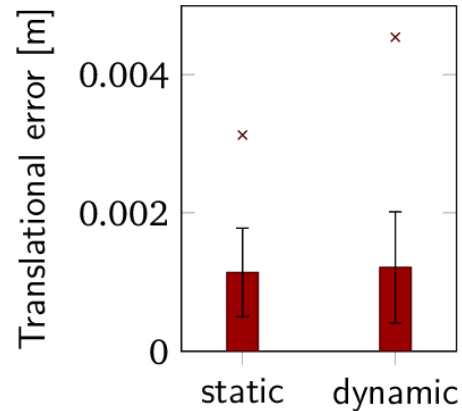
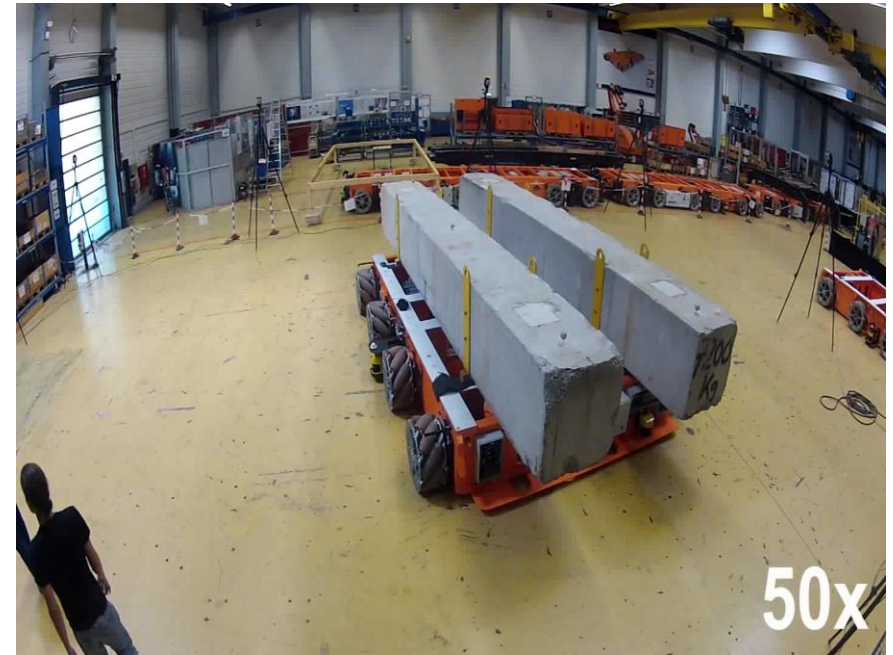
Final Result



Other Cool Stuff from AIS

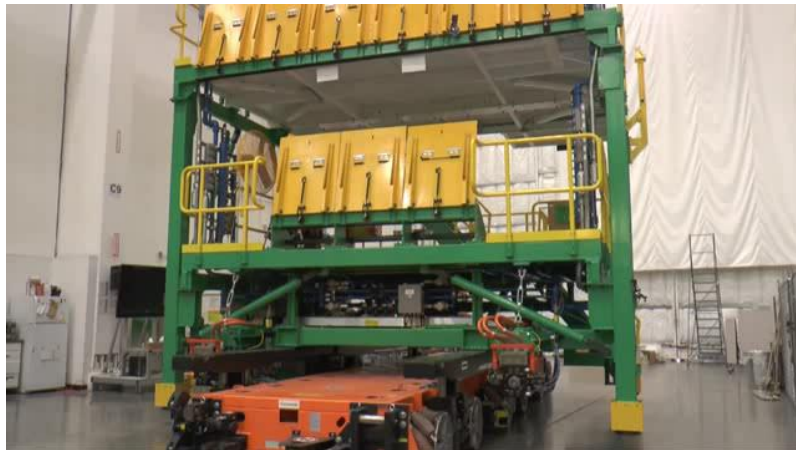
Accurate Localization

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



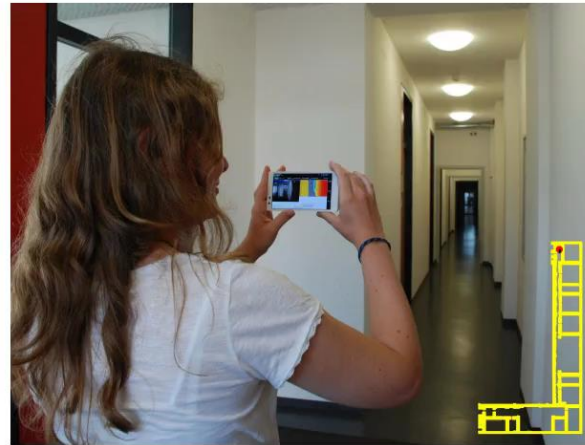
26 Units installed at Boeing

- 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



Deep Learning to Manipulate from Parallel Interaction



Source: Google Research Blog

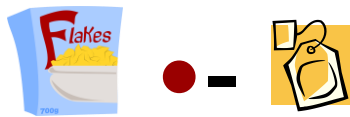
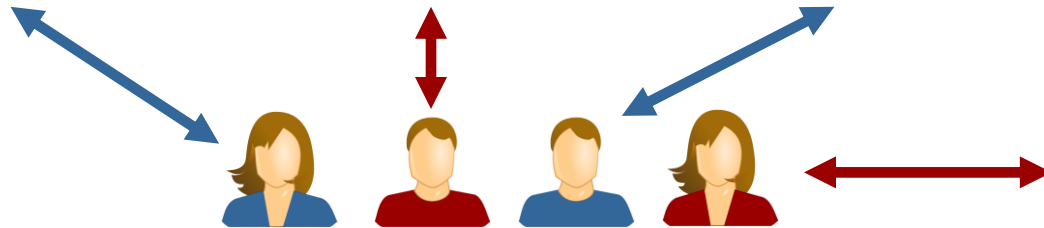
Learning User Preferences

- Task preferences are **subjective**
- Fixed rules do not match all users
- Constantly querying humans is suboptimal
- How to handle new objects?

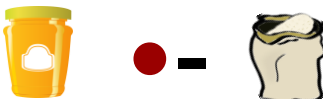
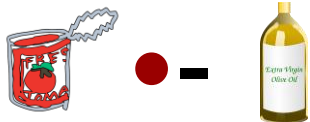
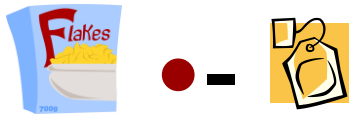
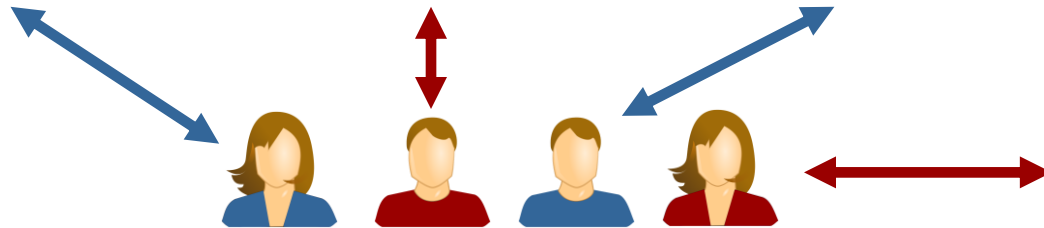













Where
does this
go?

Collaborative Filtering



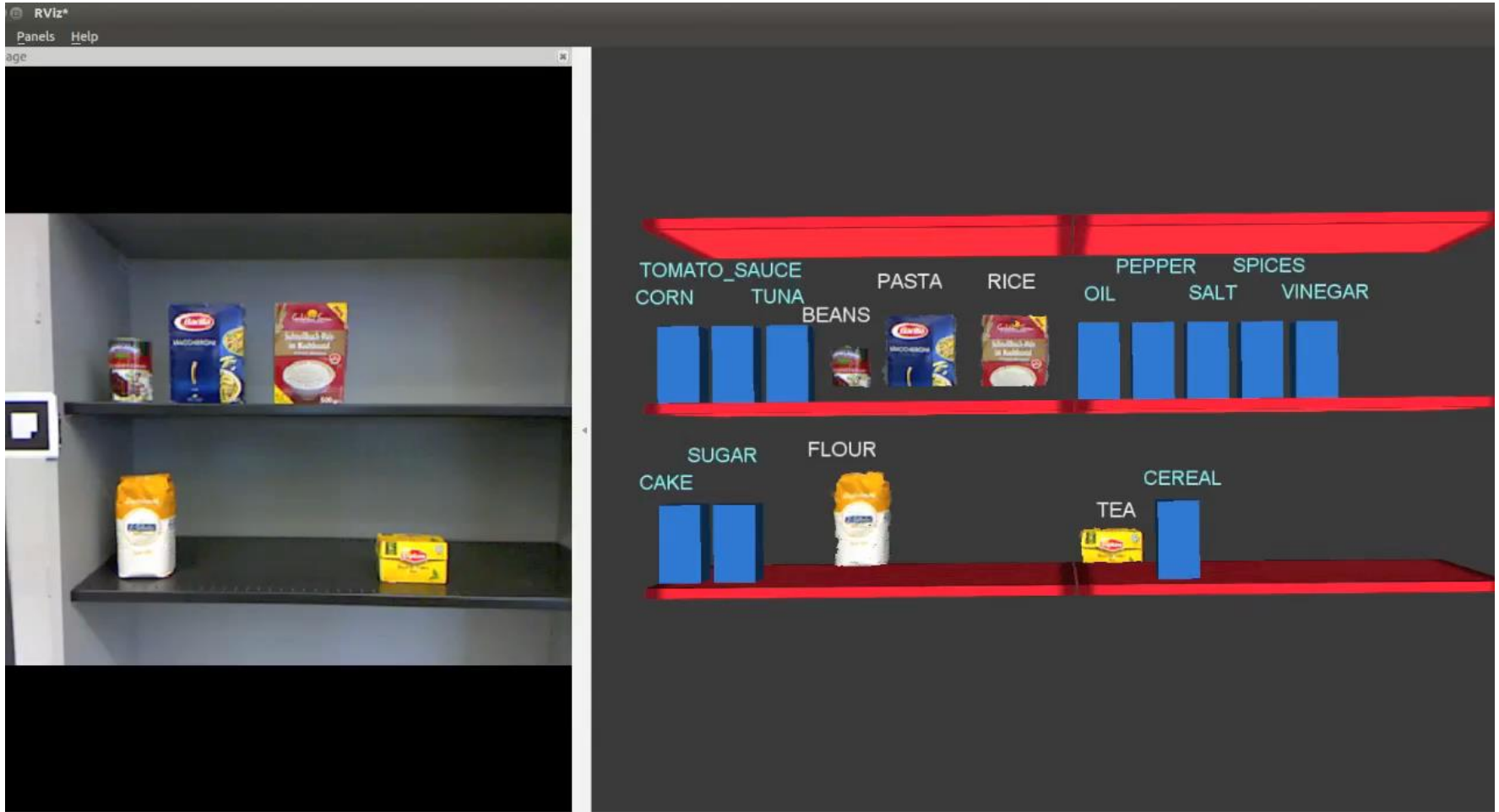
Collaborative Filtering





Online Prediction of Preferences



Localization in Urban Environments

- Inaccurate (if even available) GPS signal
- No map
- Limited Internet

Motivation



Example



Example contin.



Text: irpostbankfinanzcenter tllgi

Matched Landmarks:

- Postbank finanzcenter



Text: melange

Matched Landmarks:

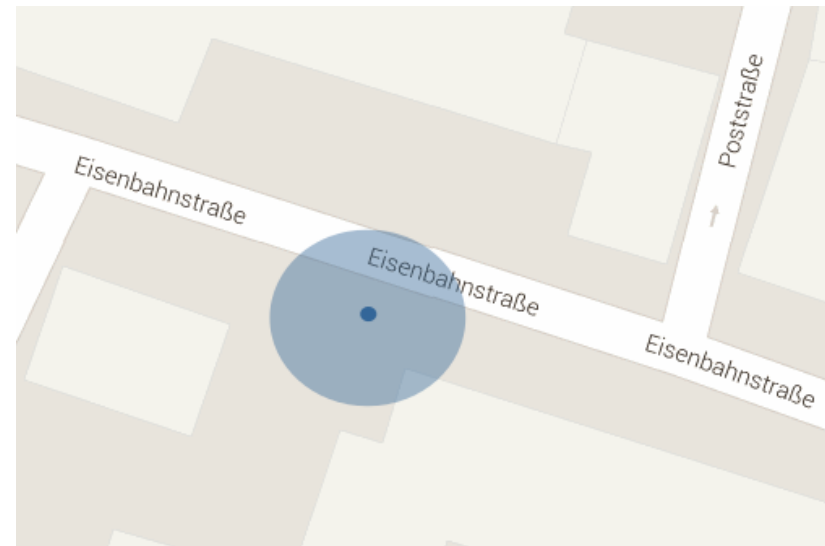
- Melange
- Melange



Text: casanova

Matched Landmarks:

- Casanova



Example



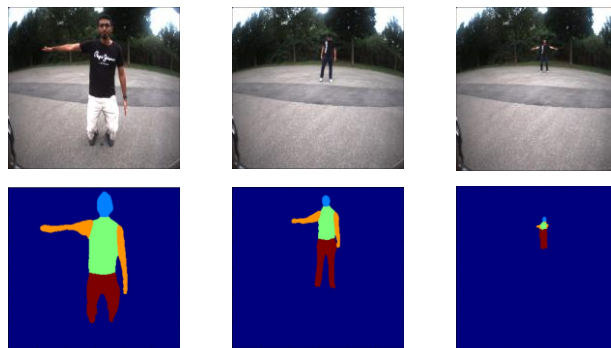
Deep Learning Applications

- RGB-D



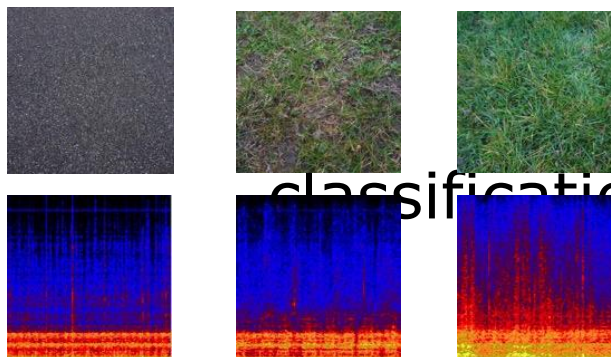
object
recognition

- Images



human part
segmentation

- Sound

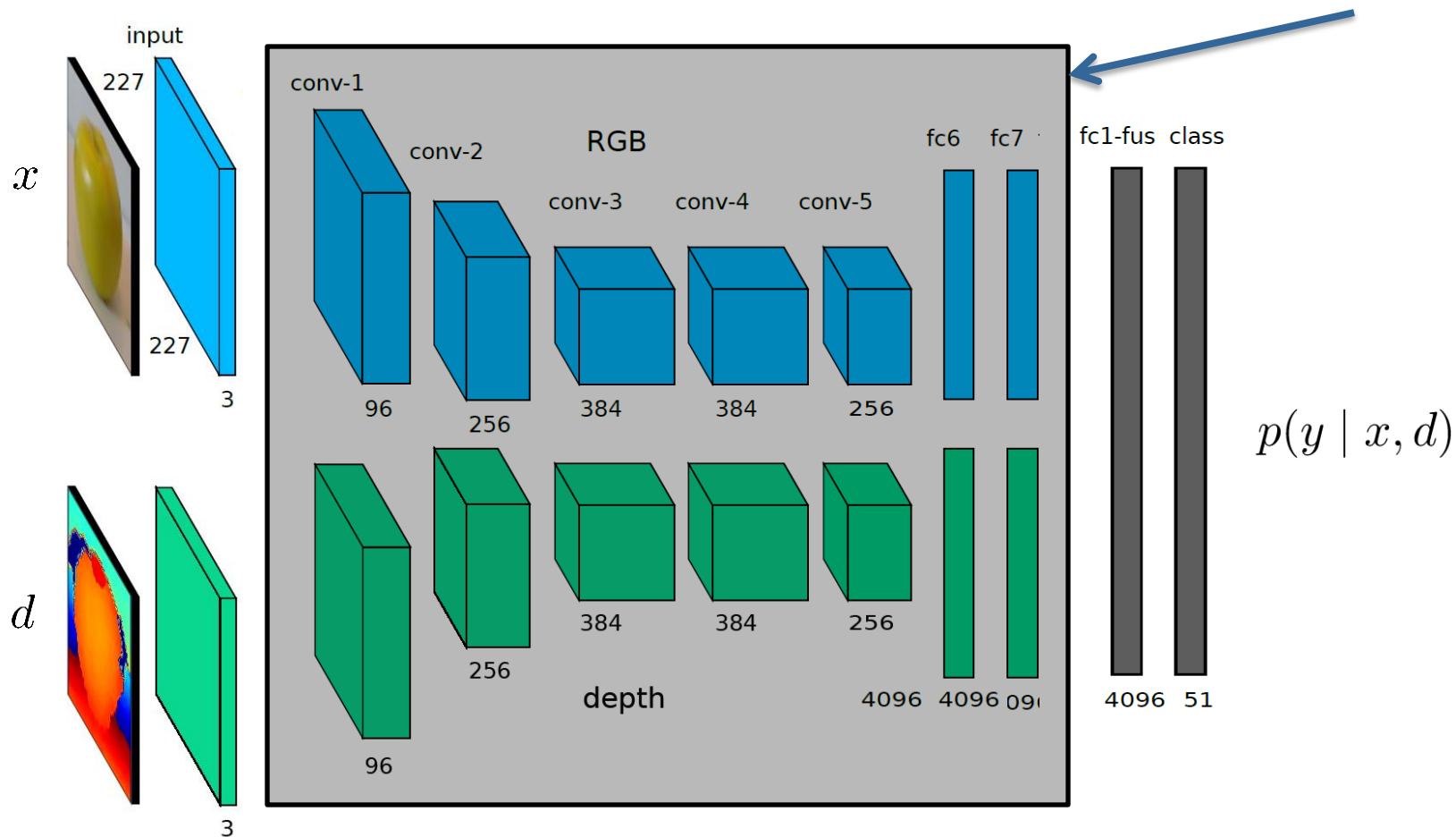


terrain

classification

DCN for Object Recognition

- Fusion layers automatically learn to combine feature responses of the two network streams
- During training, weights in first layers stay fixed



Learning Results



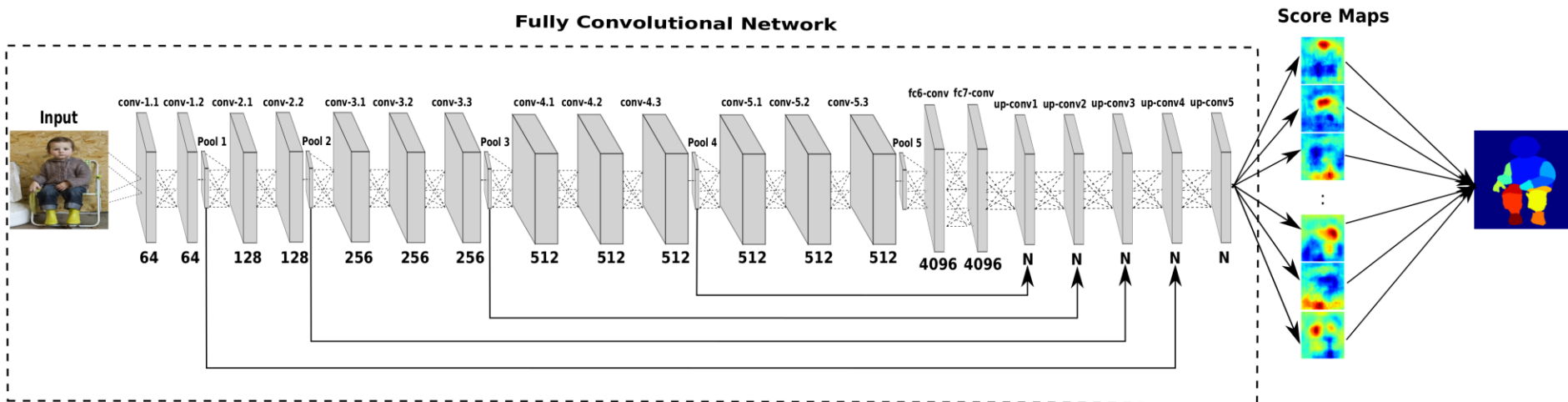
•[Lai et. al, 2011]

•Category-Level Recognition [%] (51 categories)

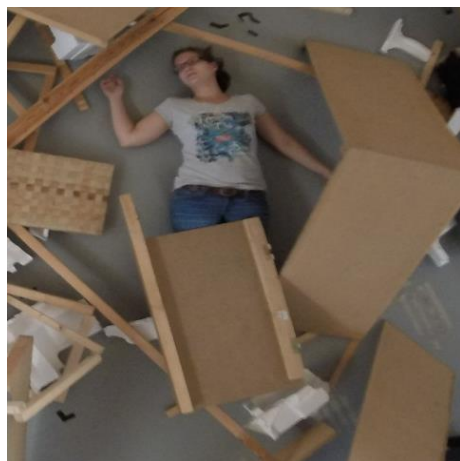
Method	RGB	Depth	RGB-D
CNN-RNN	80.8	78.9	86.8
HMP	82.4	81.2	87.5
CaRFs	N/A	N/A	88.1
CNN Features	83.1	N/A	89.4
This work, Fus-CNN	84.1	83.8	91.3

Network Architecture

- Fully convolutional network
 - Contraction and expansion of network input
 - Up-convolution operation for expansion
- Pixel input, pixel output



Deep Learning for Body Part Segmentation



• **Input Image**



• **Ground Truth**



• **Segmentation mask**

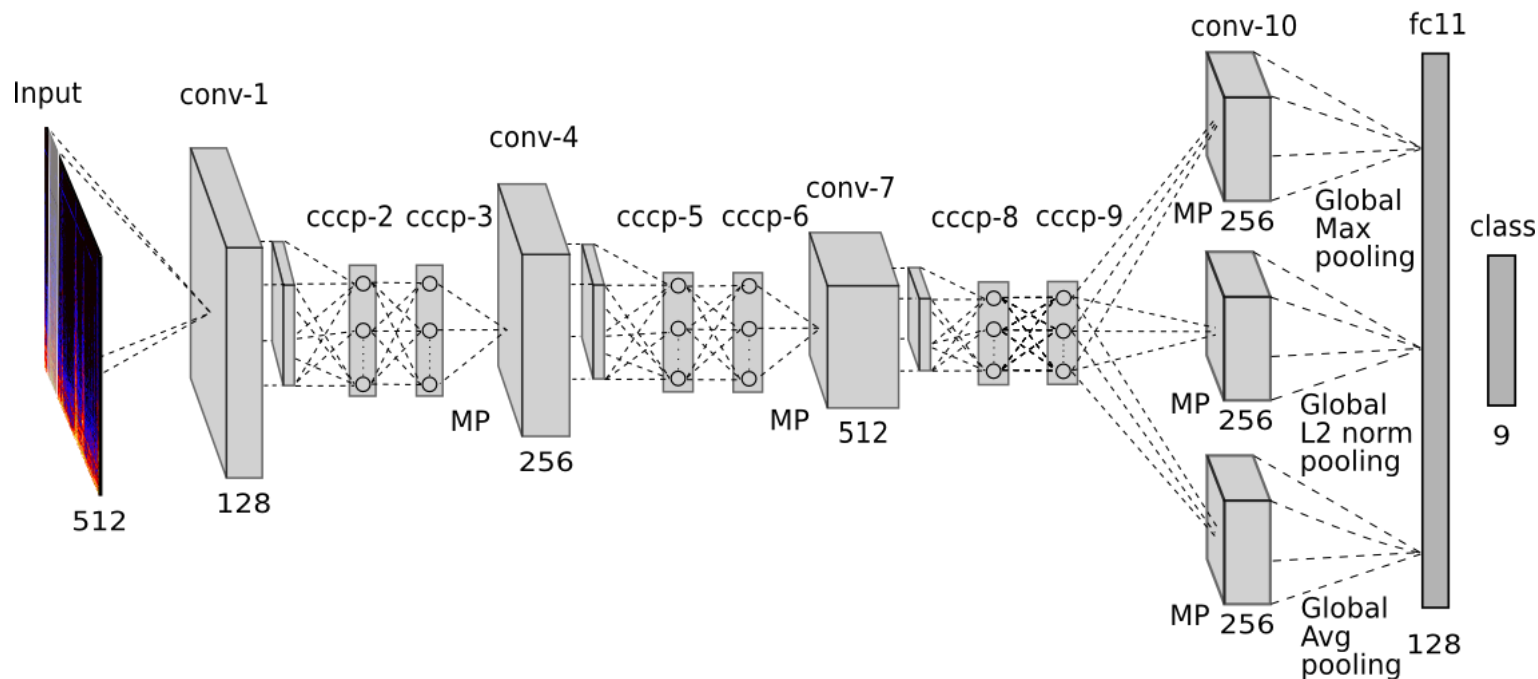
Method	Head	Torso	Arms	Legs	IOU
FCN	52.71	62.49	35.04	43.25	43.20
Ours	80.56	79.45	63.93	64.91	71.99

Deep Learning for Terrain Classification using Sound

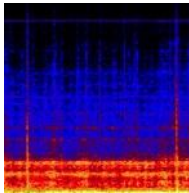


Network Architecture

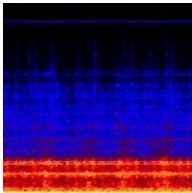
- Novel architecture designed for unstructured sound data
- Global pooling gathers statistics of learned features across time



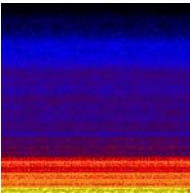
Data Collection



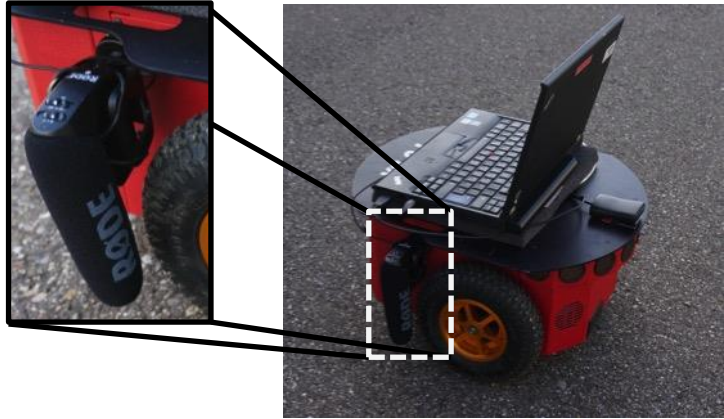
Wood



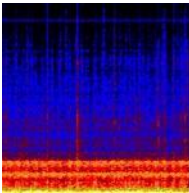
Linoleum



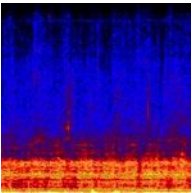
Carpet



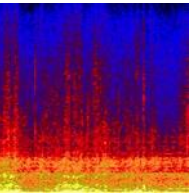
P3-DX



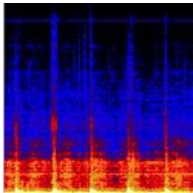
Asphalt



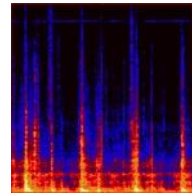
**Mowed
Grass**



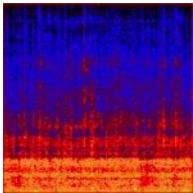
Grass



Paving



**Cobble
Stone**



Offroad

Results - Baseline Comparison

Features	SVM Linear	SVM RBF	(300ms window) k-NN
Ginna [1]	44.87 ± 0.70	37.51 ± 0.74	57.26 ± 0.60
Spectral [2]	84.48 ± 0.36	78.65 ± 0.45	76.02 ± 0.43
Ginna & Shape [3]	85.50 ± 0.34	80.37 ± 0.55	78.17 ± 0.37
MFCC & Chroma [4]	88.95 ± 0.21	88.55 ± 0.20	88.43 ± 0.15
Trimbral [5]	89.07 ± 0.12	86.74 ± 0.25	84.82 ± 0.54
Cepstral [6]	89.93 ± 0.21	78.93 ± 0.62	88.63 ± 0.06

~~90.9%~~ improvement in 500ms window with previous state of the art

[1] T. Giannakopoulos, K. Dimitrios, A. Andreas, and T. Sergios, SETN 2006

[2] M. C. Wellman, N. Srour, and D. B. Hillis, SPIE 1997.

[3] J. Libby and A. Stentz, ICRA 2012

[4] D. Ellis, ISMIR 2007

[5] G. Tzanetakis and P. Cook, IEEE TASLP 2002

[6] V. Brijesh, and M. Blumenstein, Pattern Recognition Technologies and Applications 2008

Thank you

... and enjoy the course!