Introduction to Mobile Robotics

Welcome

Lukas Luft, Wolfram Burgard

Today

- This course
- Robotics in the past and today

Organization

- Wed 14:00 – 16:00
  Fr 16:00 – 17:00
  lectures, discussions

- Fr 17:00 – 18:00
  homework, practical exercises (Python)

- Web page:
  www.informatik.uni-freiburg.de/~ais/

- Exam: Oral or written

People

Teaching:

- Wolfram Burgard

Teaching assistants:

- Marina Kollmitz
- Johannes Meyer
- Iman Nematollahi
- Lukas Luft
- Daniel Büscher

Goal of this course

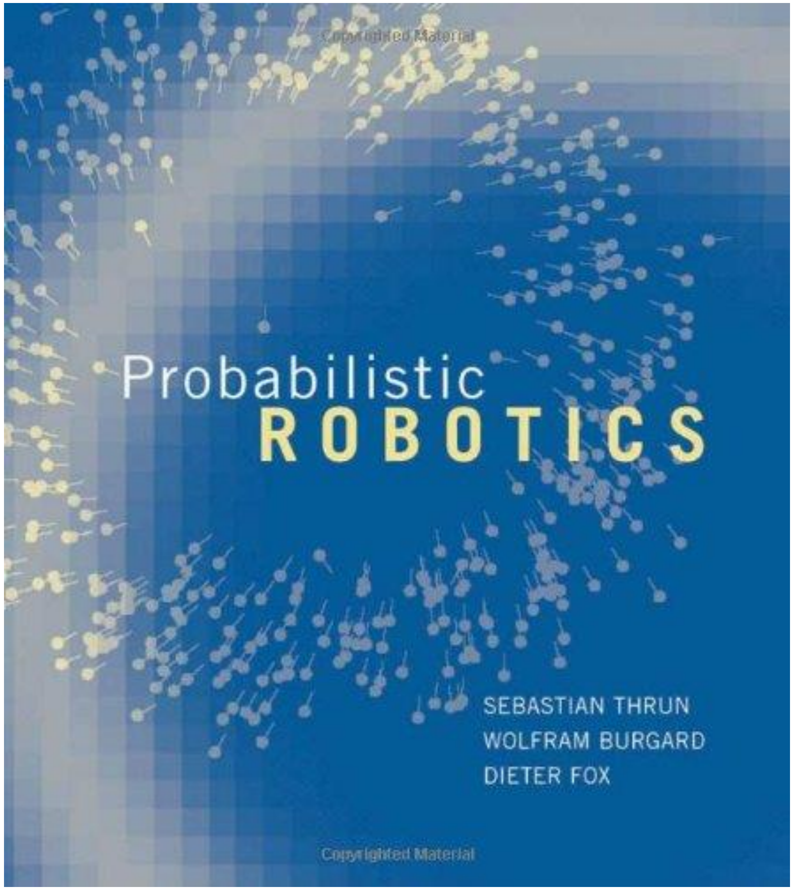
- Provide an overview of problems and approaches in mobile robotics
- Probabilistic reasoning: Dealing with noisy data
- Hands-on experience

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!

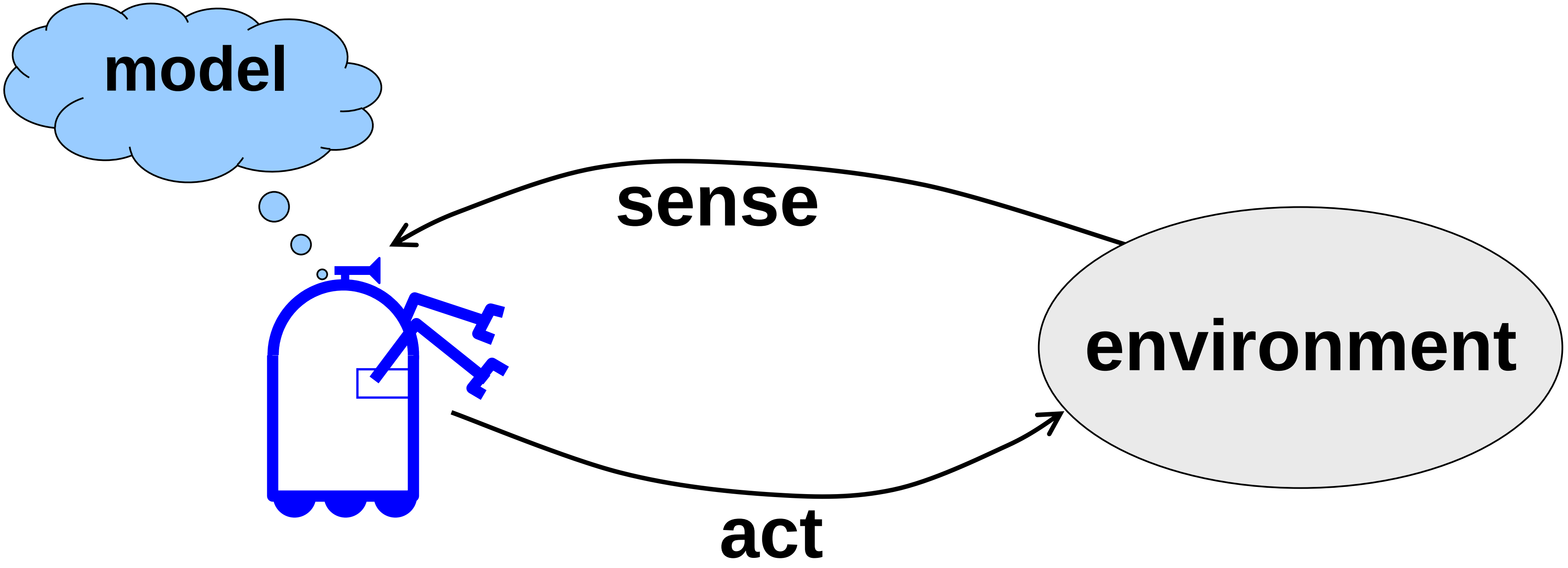
Tasks Addressed that Need to be Solved by Robots

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

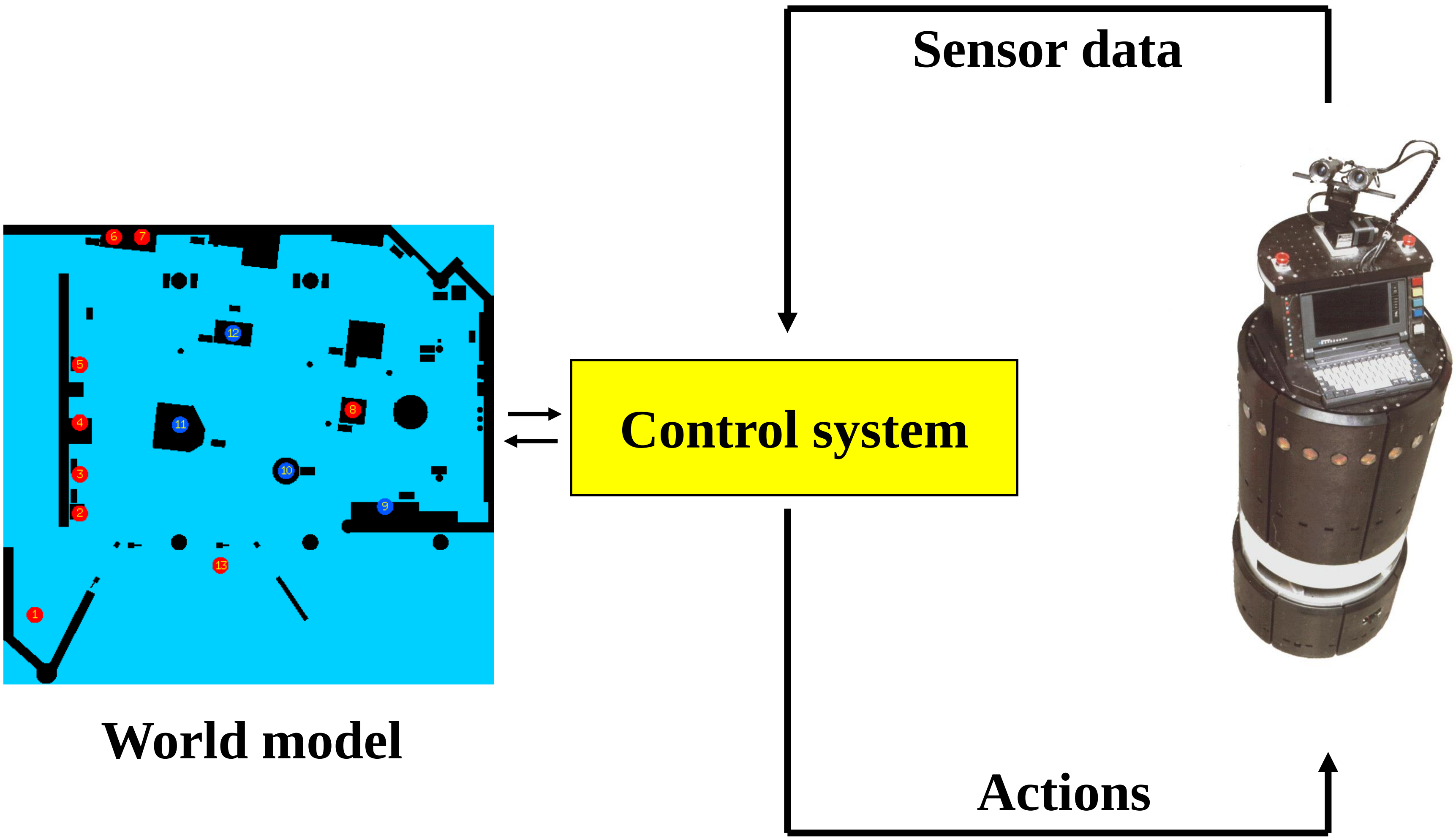
…

Autonomous Robot Systems

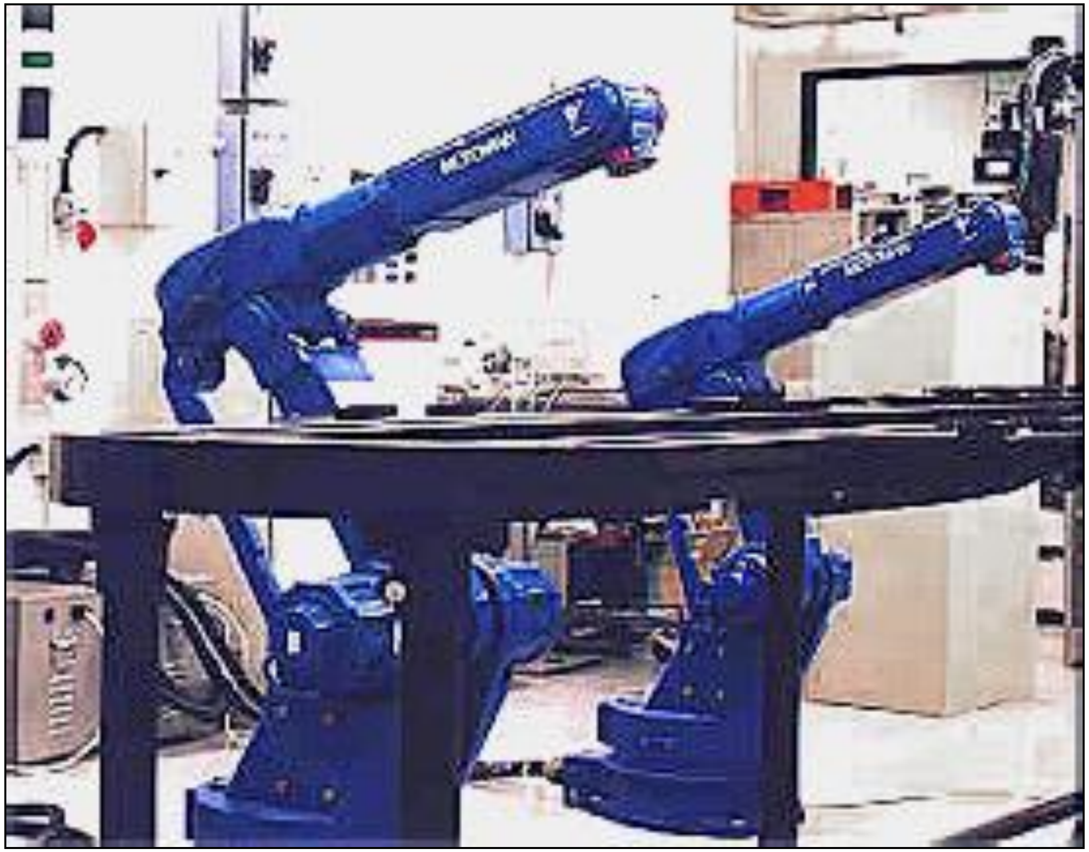
- perceive their environment and
- generate actions to achieve their goals.



Autonomous Robot Systems



Robotics Yesterday

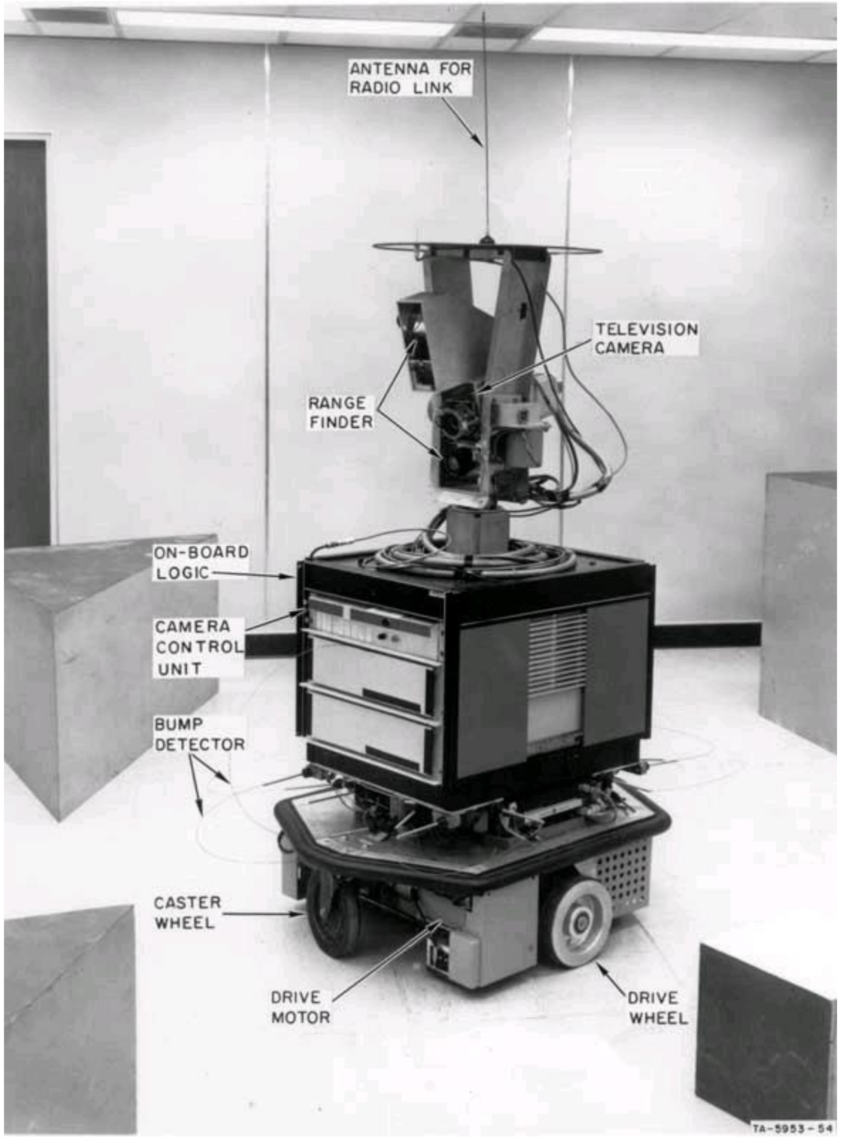


Current Trends in Robotics

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

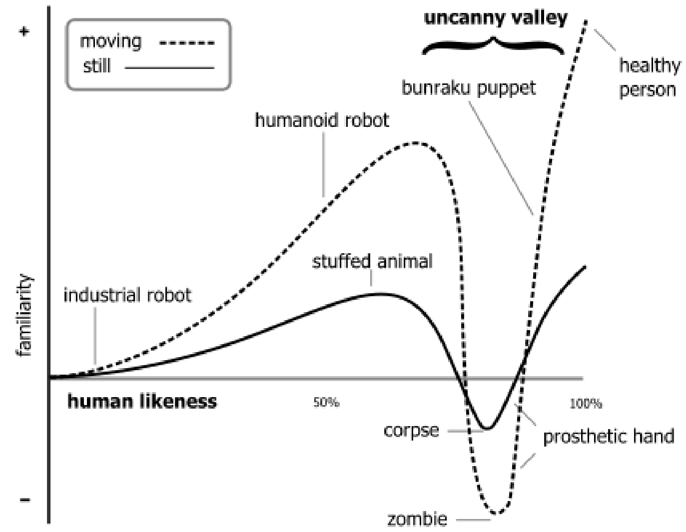
[Courtesy by Sebastian Thrun]

Walking Robots

[Courtesy by Boston Dynamics]

Androids

Overcoming the uncanny valley



[Courtesy by Hiroshi Ishiguro]

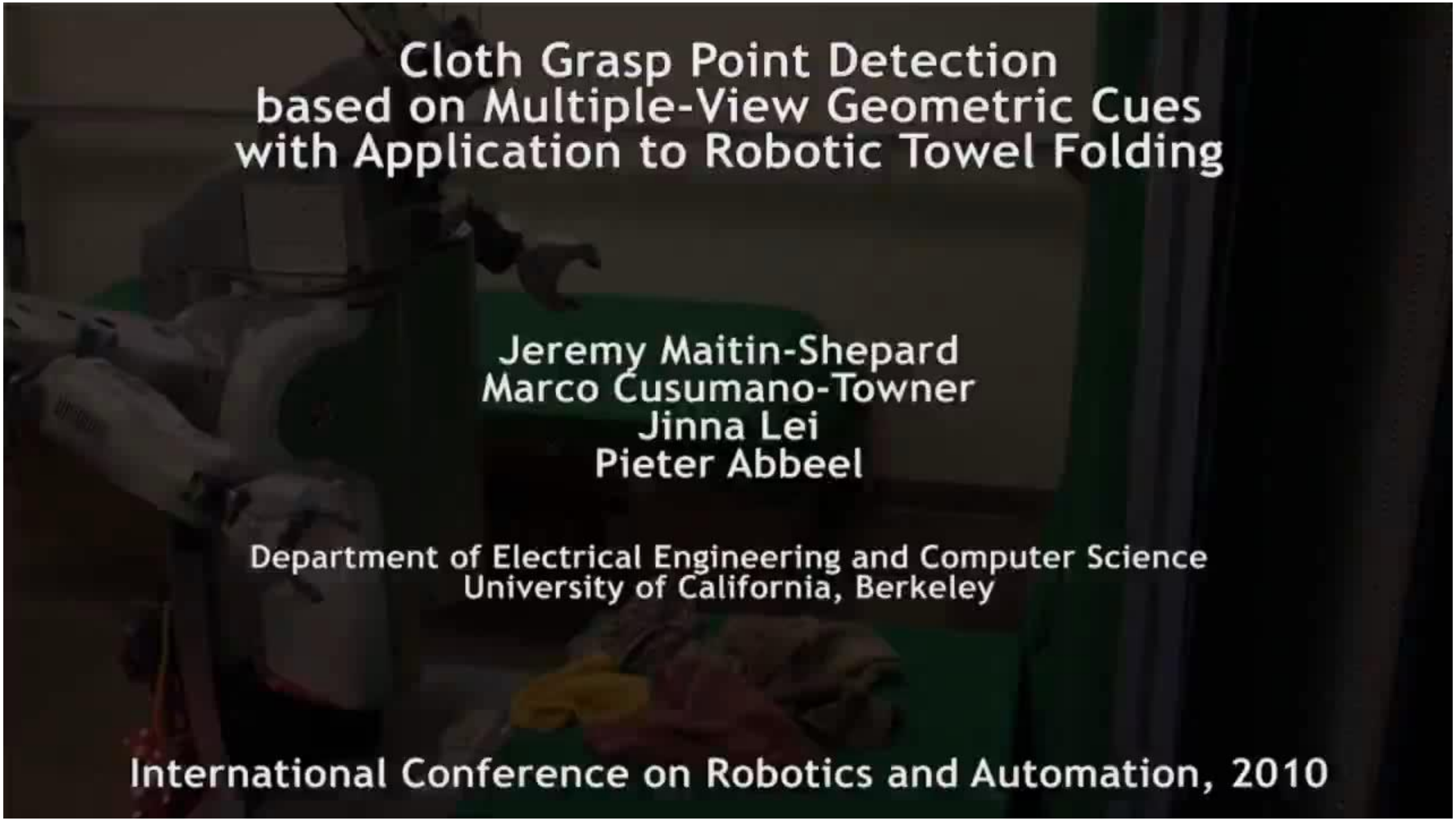
Driving in the Google Car

Autonomous Motorcycles

[Courtesy by Anthony Levandowski]

The Google Self Driving Car

Folding Towels

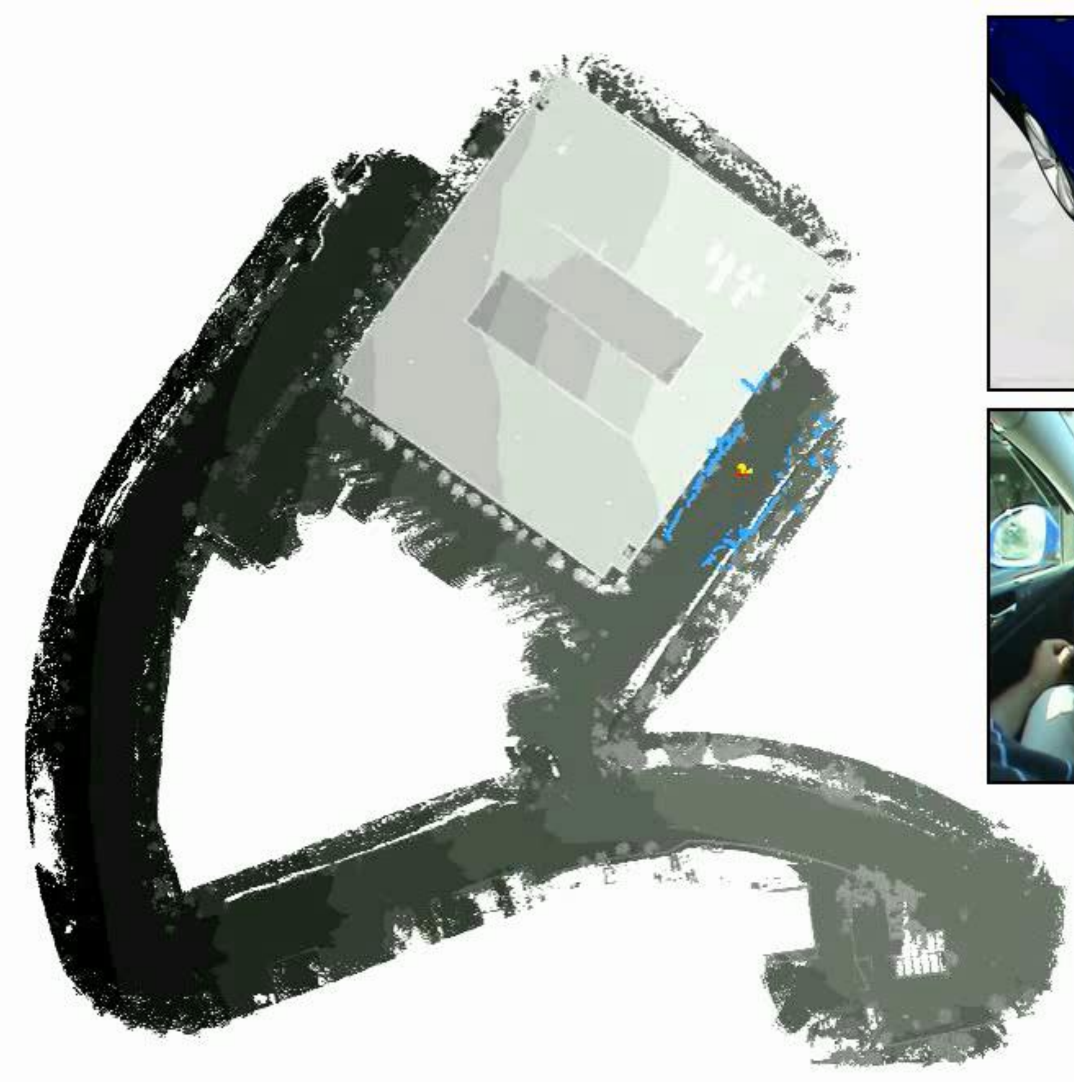


Rhino (Univ. Bonn + CMU, 1997)

Minerva (CMU + Univ. Bonn, 1998)

Robotics in Freiburg

Autonomous Parking



Autonomous Quadrotor Navigation

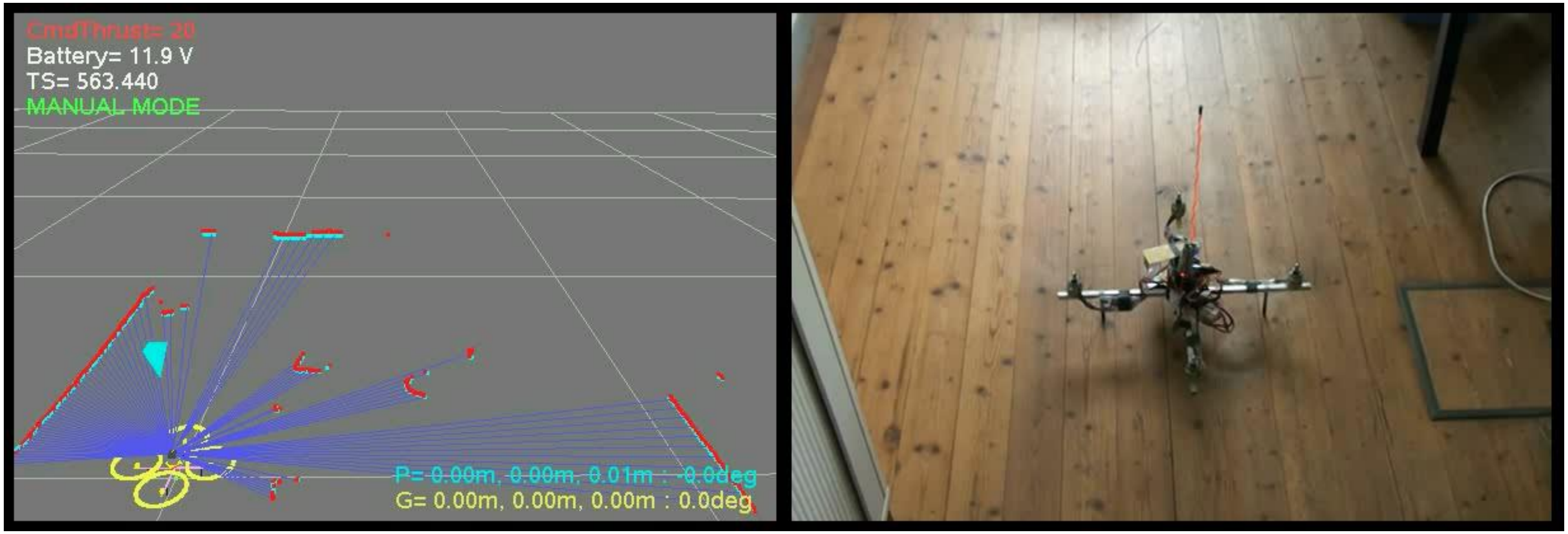
Custom-built system:

laser range finder

inertial measurement unit

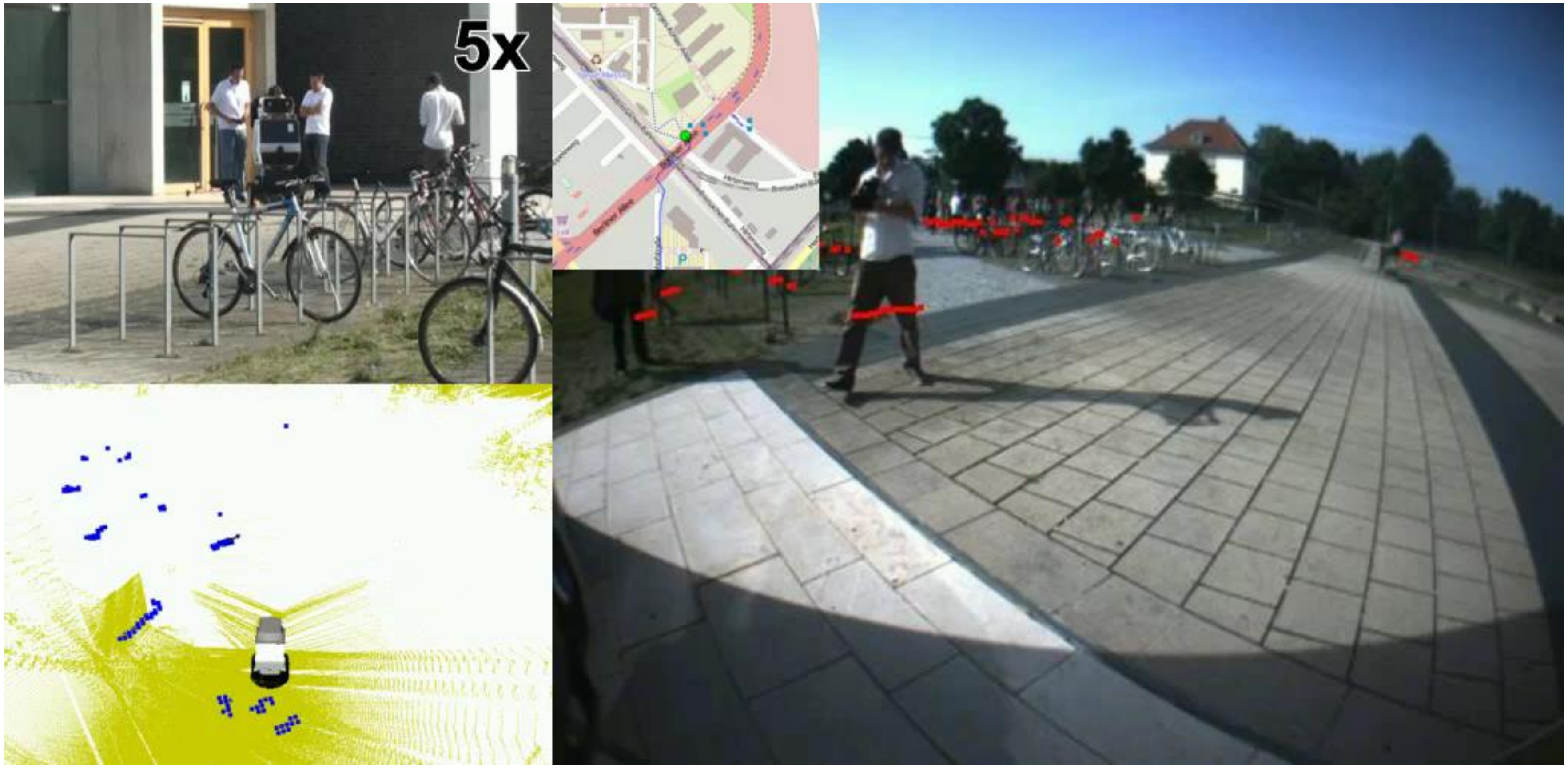
embedded CPU

laser mirror

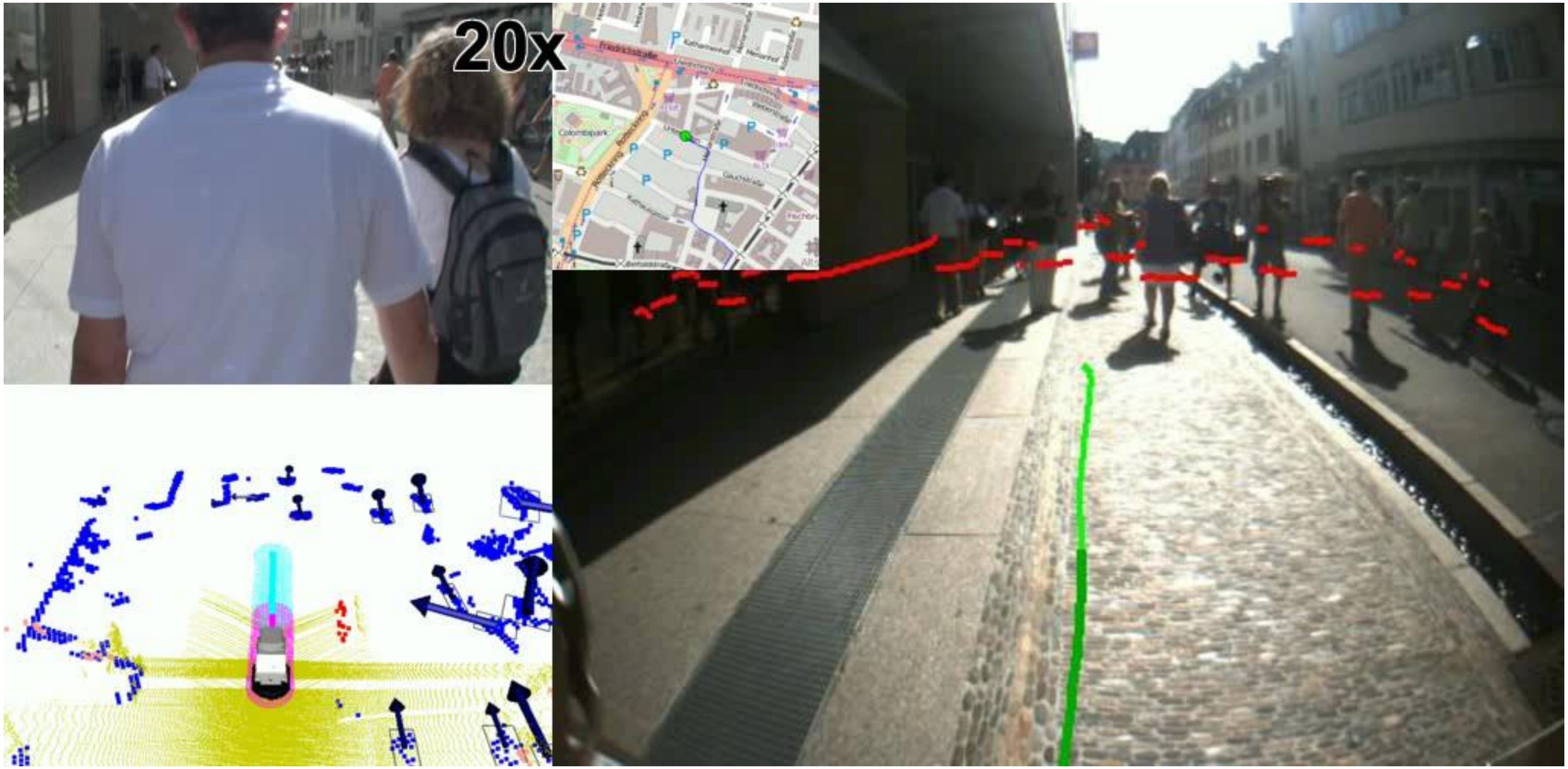


Precise Localization and Positioning for Mobile Robots

Obelix – A Robot Traveling to Downtown Freiburg

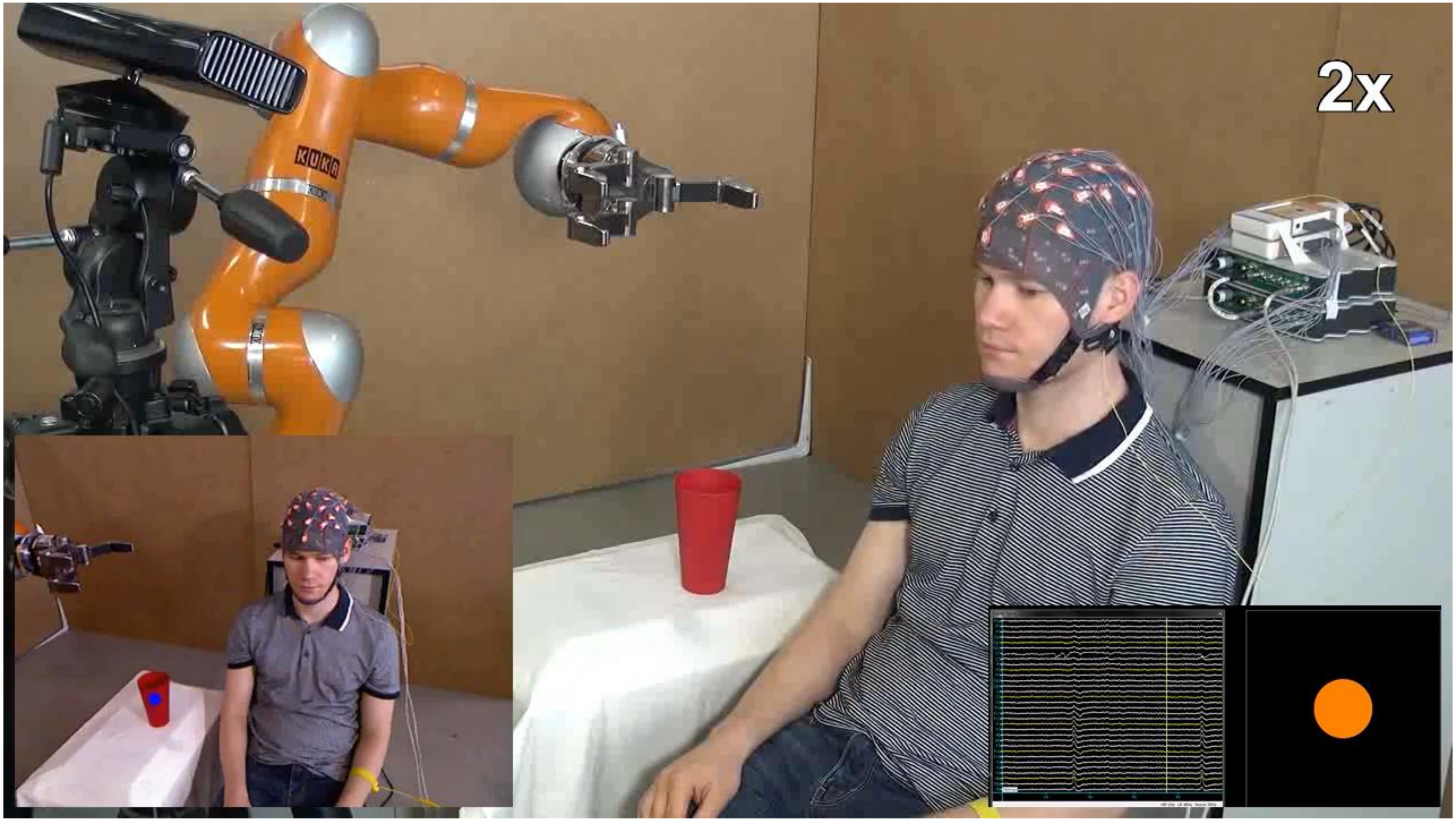


The Obelix Challenge (Aug 21, 2012)



The Tagesthemen-Report

Brain-controlled Robots



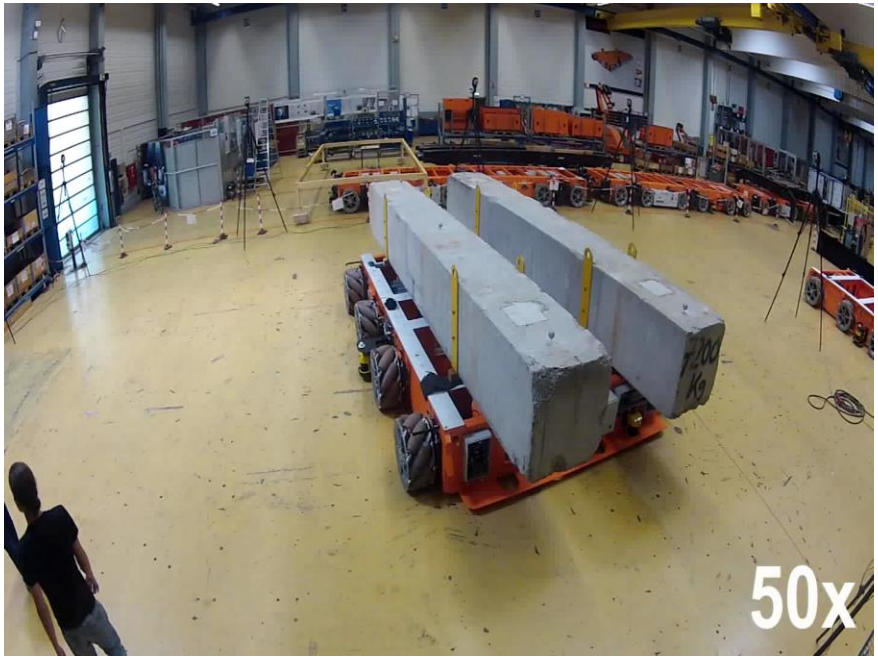
Teaching: Student Project on the Autonomous Portrait Robot

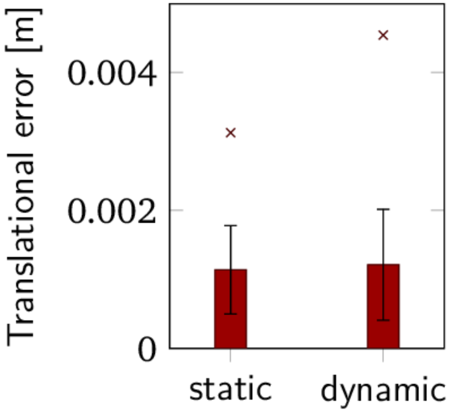
Final Result

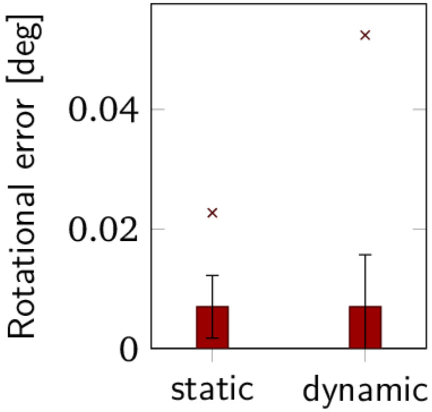
Other Cool Stuff from AIS

Accurate Localization

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

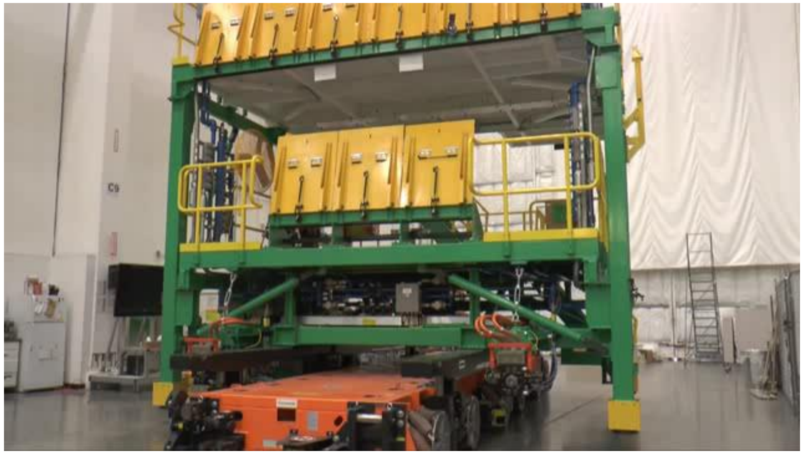






26 Units installed at Boeing

- 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

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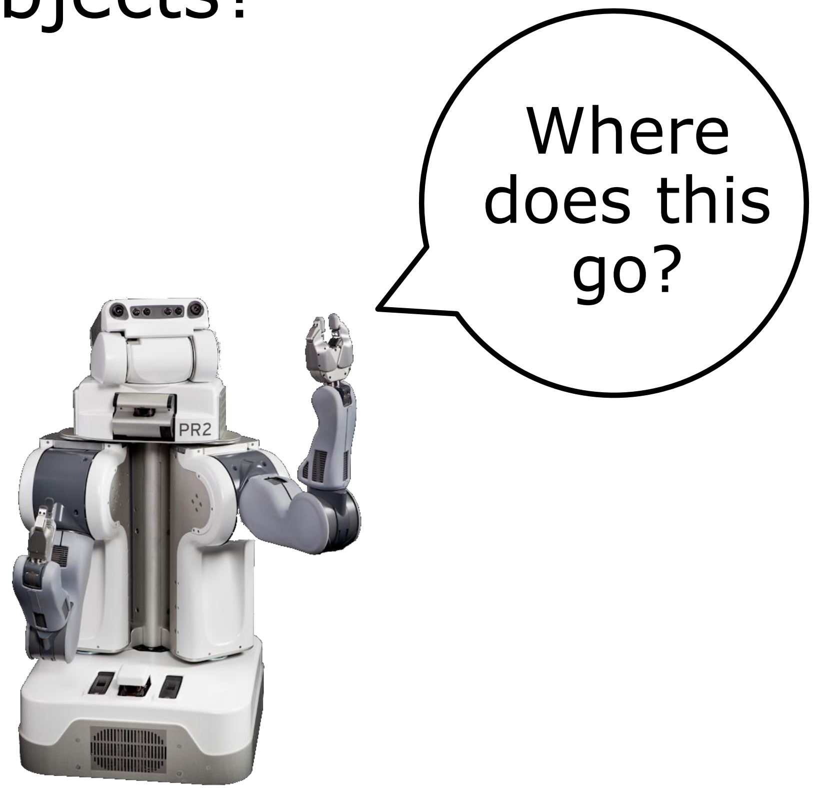
Autonomous Intelligent Systems

Deep Learning to Manipulate from Parallel Interaction

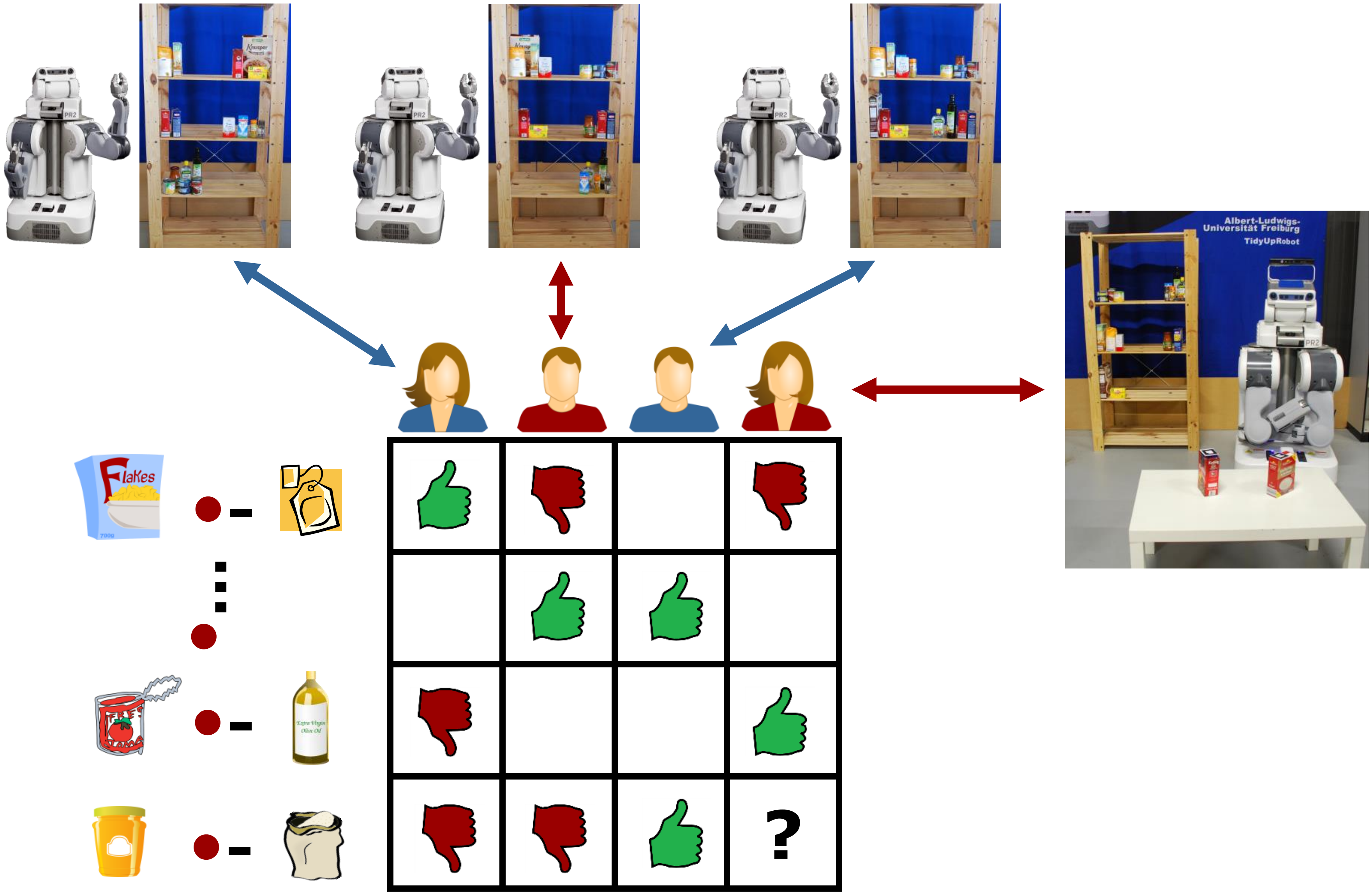
Source: Google Research Blog

Learning User Preferences

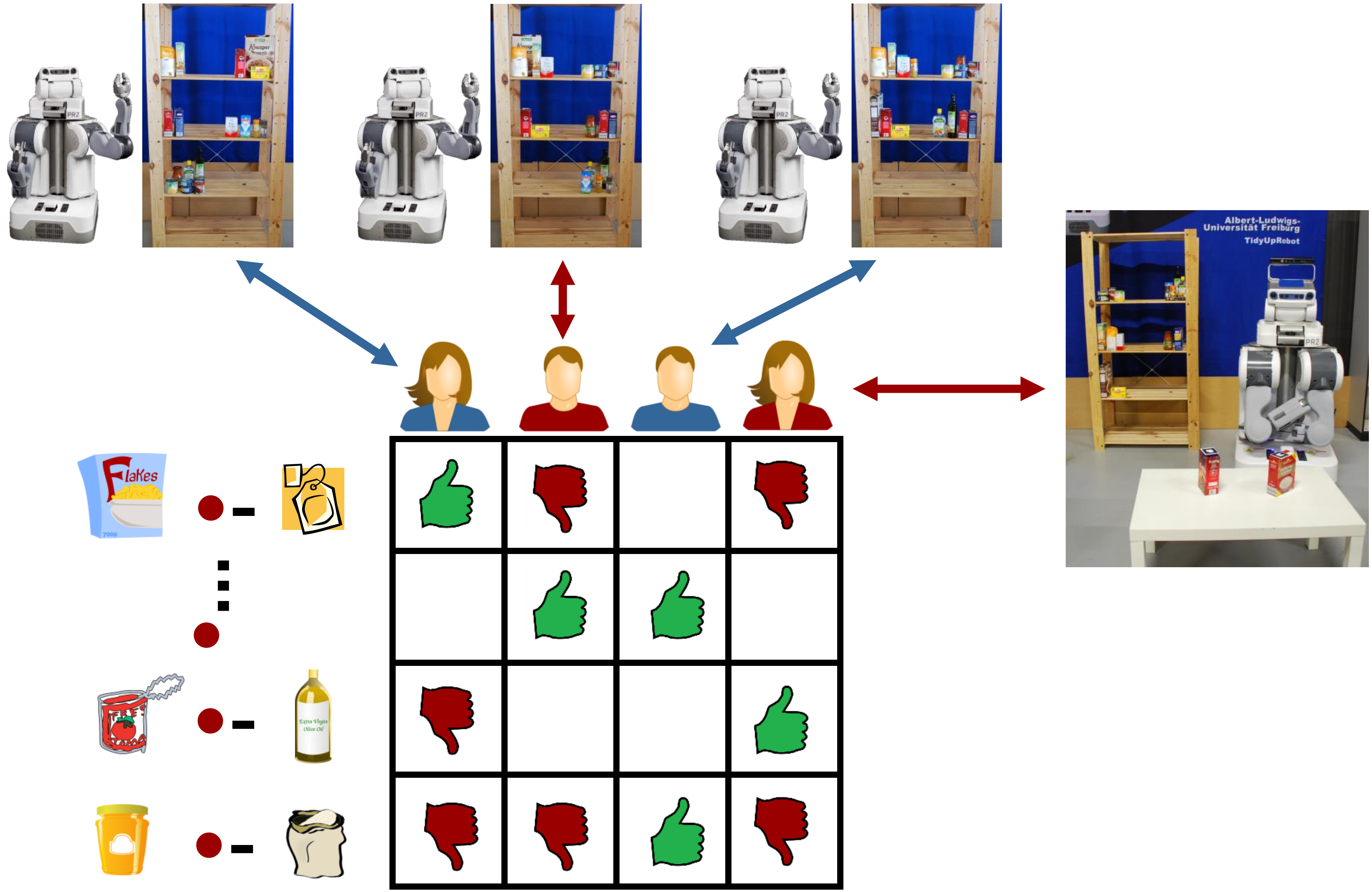
- Task preferences are subjective
- Fixed rules do not match all users
- Constantly querying humans is suboptimal
- How to handle new objects?



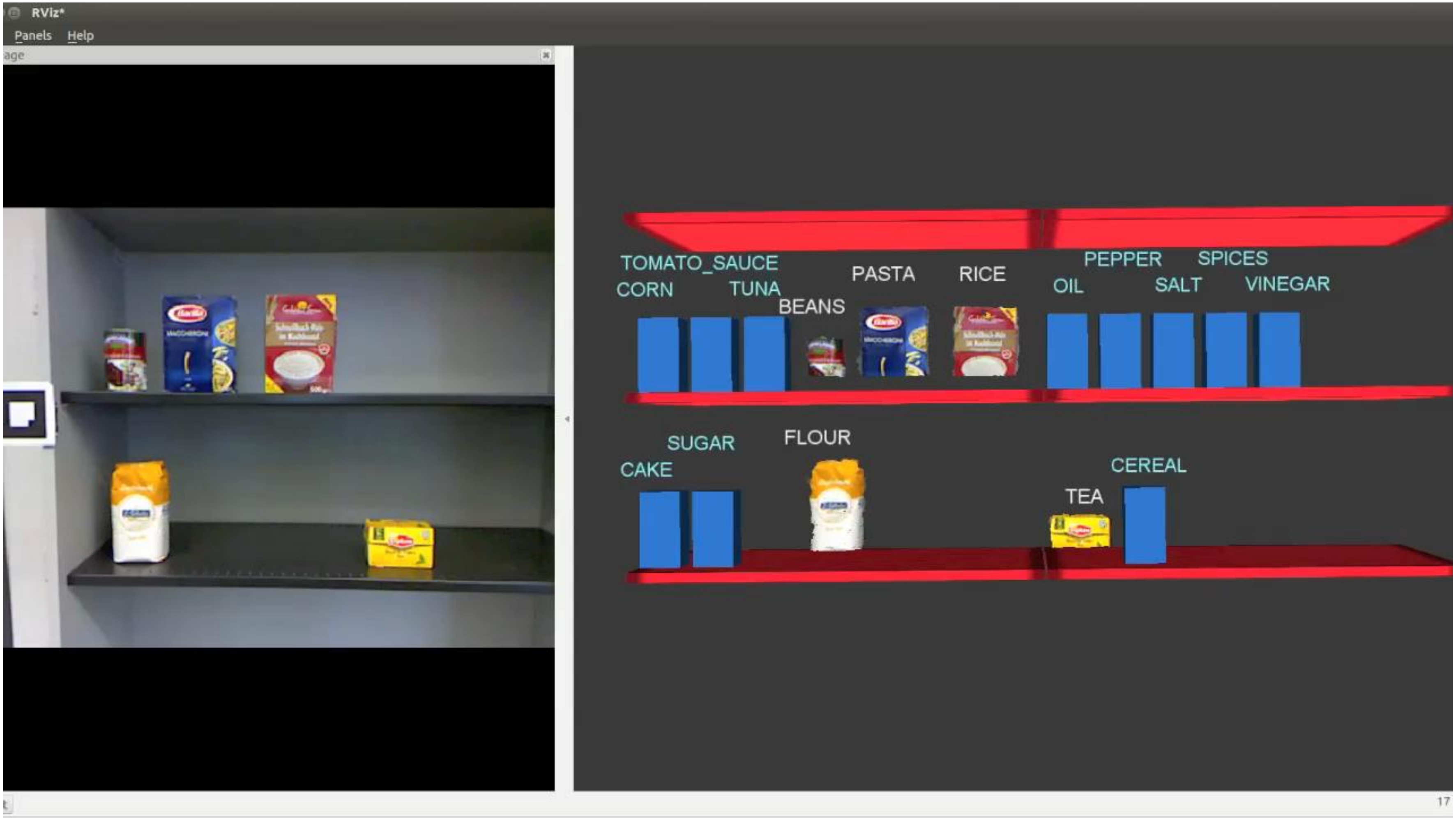
Collaborative Filtering



Collaborative Filtering



Online Prediction of Preferences



Localization in Urban Environments

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

Motivation


LONDON STREET
ARTILLERY STREET


KITCHEN
THE CAMDEN HEAD
Google
© 2014 Google


La bottega del Caffè
246
245
IBM
ICE CREAM
PIZZA
Google
© 2014 Google


CAMDEN TOWN STATION
HSBC
Google
© 2014 Google

Example

Casanova
FREIBURGER MELANGE
Eisenbahnstraße
Postbank Finanzcenter
VWA Freiburg

Example contin.

Text: irpostbankfmarzcenter tllgi
Matched Landmarks:
- Postbank finanzcenter

Text: melange
Matched Landmarks:
- Melange
- Melange

Text: casanova
Matched Landmarks:
- Casanova

Example

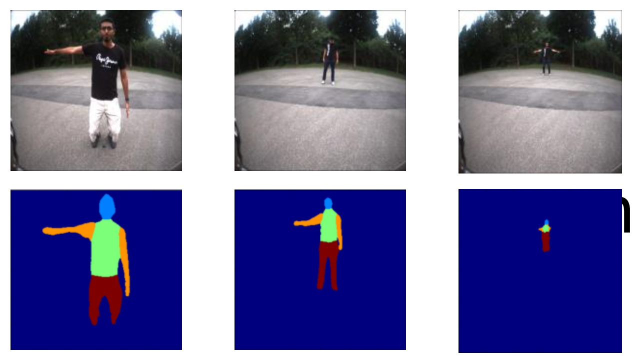

T M Lewin
T.M.LEWIN
437
Strand
A4
Strand
Strand
A4
Strand
A4
Bain & Comp
Charles I Statue
Buckingham Arcade
NatWest
Sainsbury's Local
McDonald's
Sainsbury's Local
Westminster The Strand - WC2N 5HY
Buckingham Arcade
NatWest
Open every day
Google

Deep Learning Applications

- RGB-D

object recognition

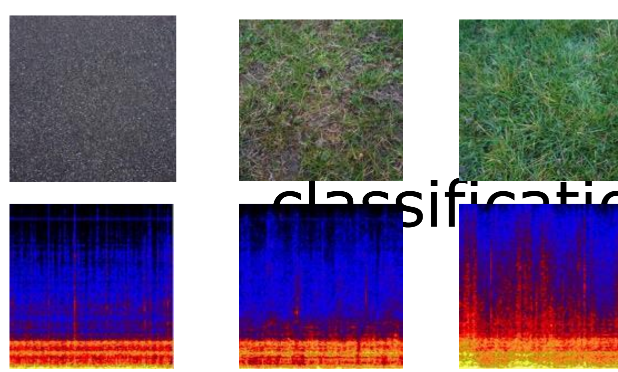
- Images



human part

entation

- Sound

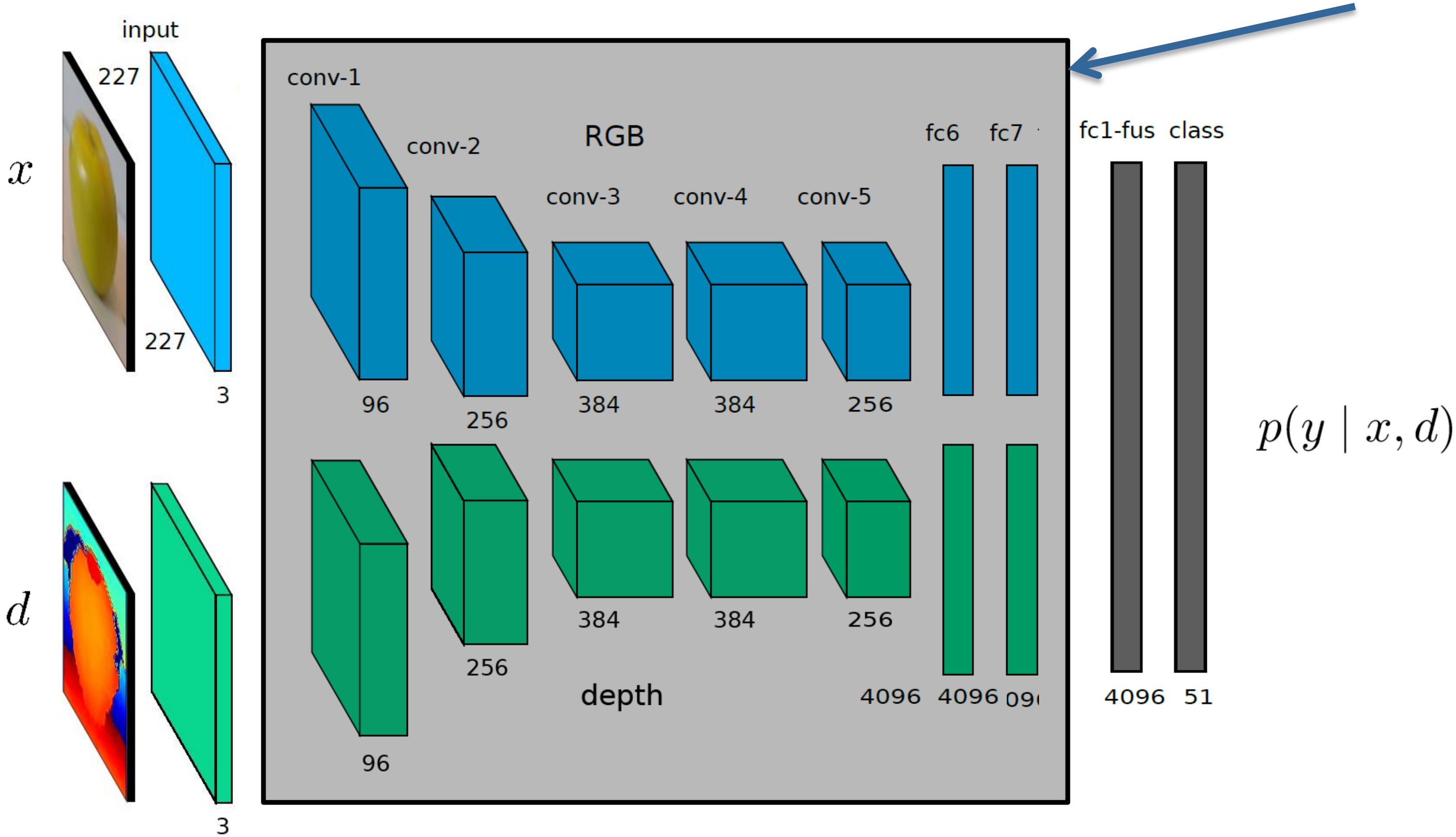


terrain

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

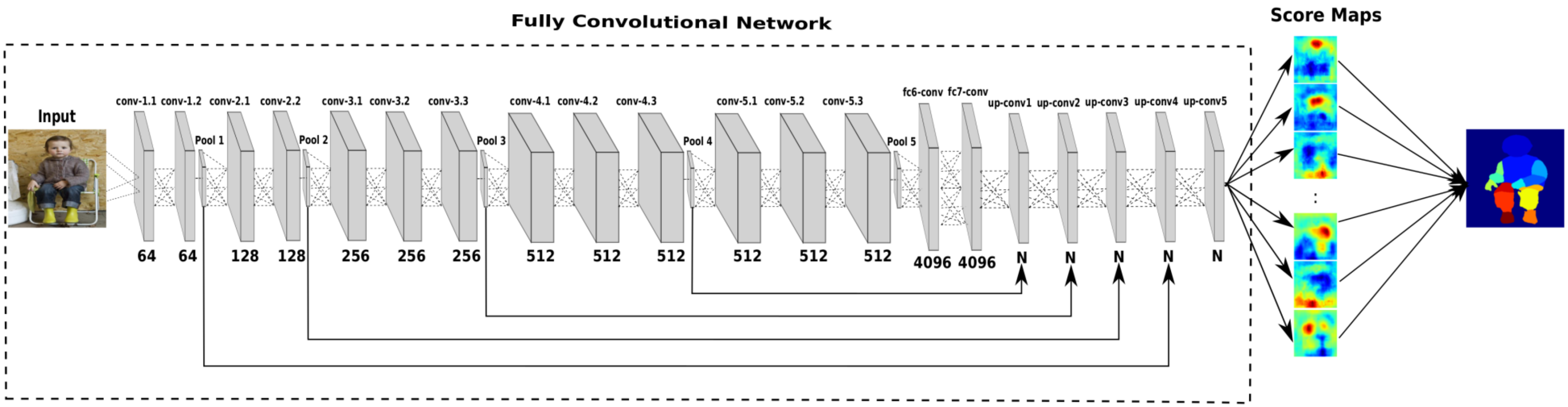
• [Lai et. al, 2011]

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

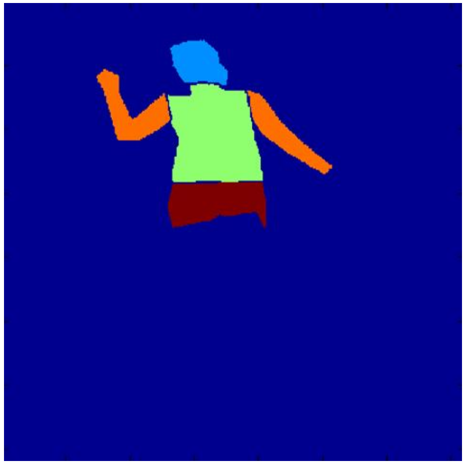
Method	RGB	Depth	RGB-D
CNN-RNN	80.8	78.9	86.8
HMP	82.4	81.2	87.5
CaRFs	N/A	N/A	88.1
CNN Features	83.1	N/A	89.4
This work, Fus-CNN	**84.1**	**83.8**	**91.3**

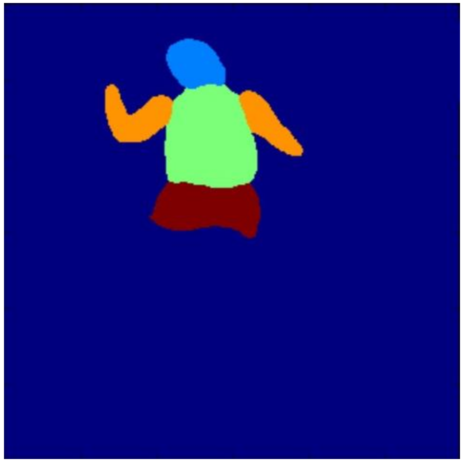
Network Architecture

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



Deep Learning for Body Part Segmentation





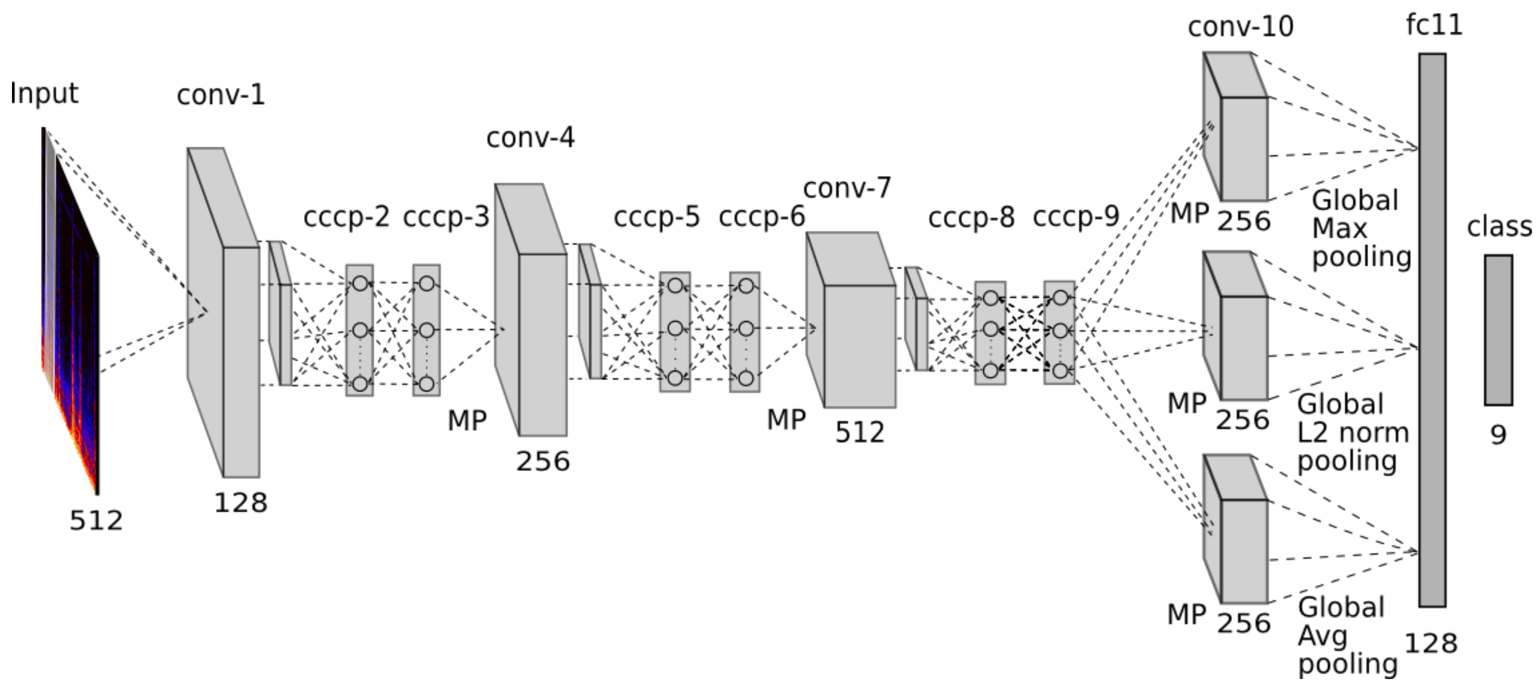
- **Input Image**
- **Ground Truth**
- **Segmentation mask**

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



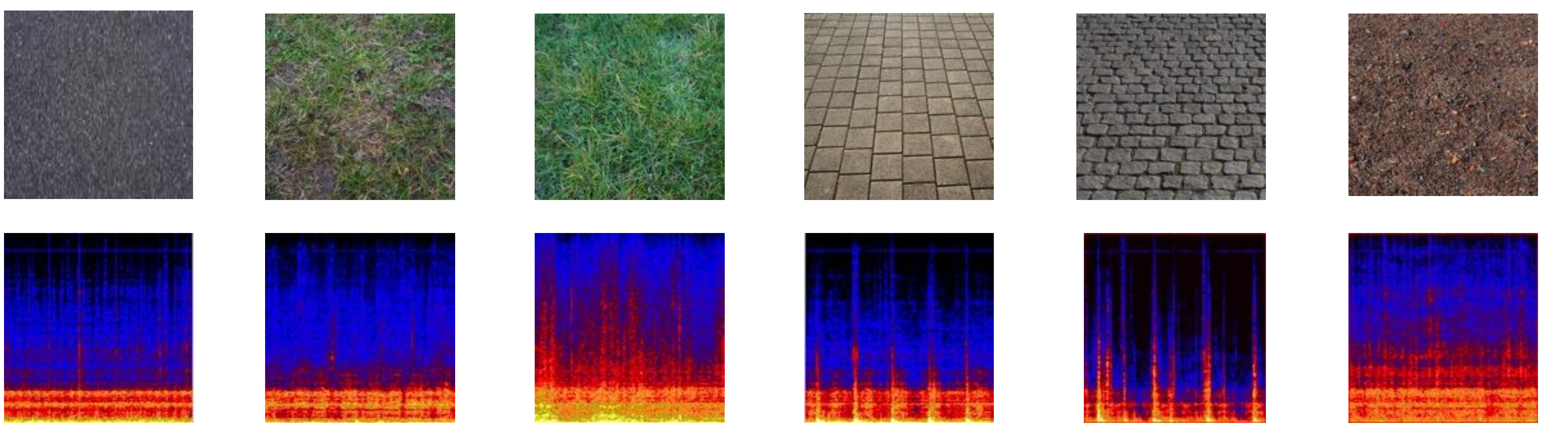
Data Collection

Wood

Linoleu
m

Carpet

P3-DX



Asphal
t

Mowe
d
Grass

Grass

Paving

Cobble
Stone

Offroa
d

Results - Baseline Comparison

(300ms window)

Features	SVM Linear	SVM RBF	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**

96.41% using a 500ms window

10.9% improvement over the 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!