

# Perception and Planning for Autonomous Mobile Robots

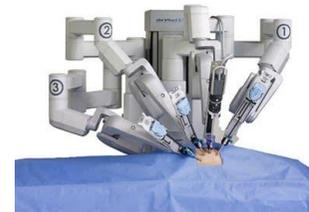
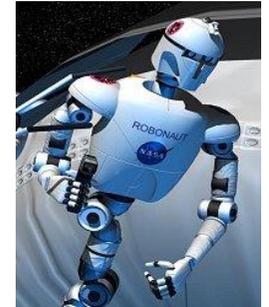
**Sven Behnke**

University of Bonn  
Computer Science Institute VI  
Autonomous Intelligent Systems



# Many New Application Areas for Robots

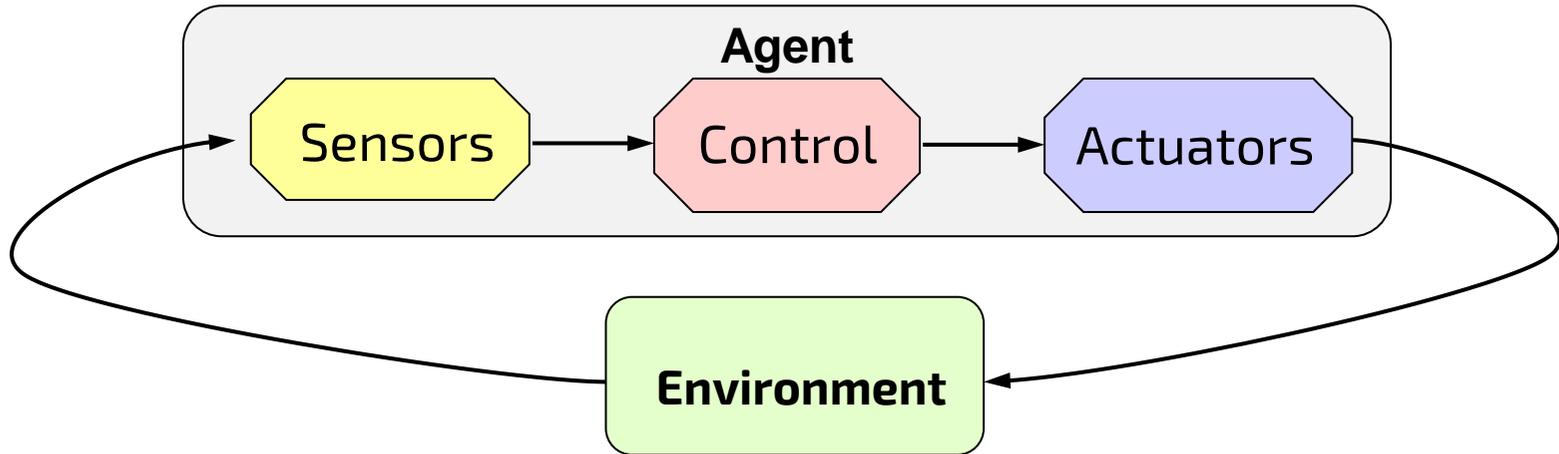
- Self-driving cars
- Logistics
- Agriculture, mining
- Collaborative automation
- Personal assistance
- Space, search & rescue
- Healthcare
- Toys



**Need more cognitive abilities!**

# Sub-problems

- Environment perception
- Behavior planning
- Action generation



# Some of our Cognitive Robots

- Equipped with numerous sensors and actuators
- Complex demonstration scenarios



Soccer



Domestic service



Mobile manipulation



Bin picking



Aerial inspection

# Our Domestic Service Robots



Dynamaid

- Size: 100-180 cm, weight: 30-35 kg
- 36 articulated joints
- PC, laser scanners, Kinect, microphone, ...



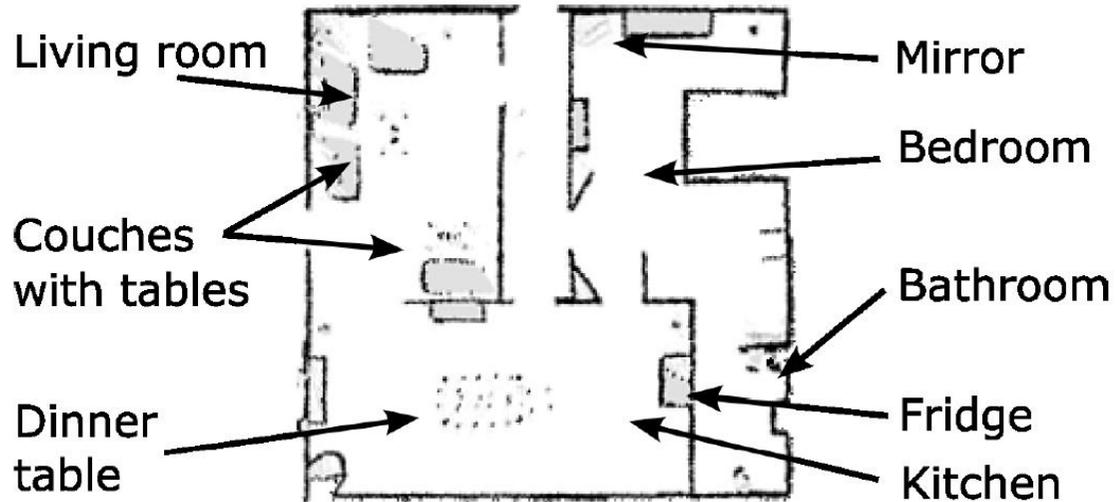
Cosero

[Stückler et al.:  
Frontiers in Robotics  
and AI 2016]

# Cognitive Service Robot Cosero

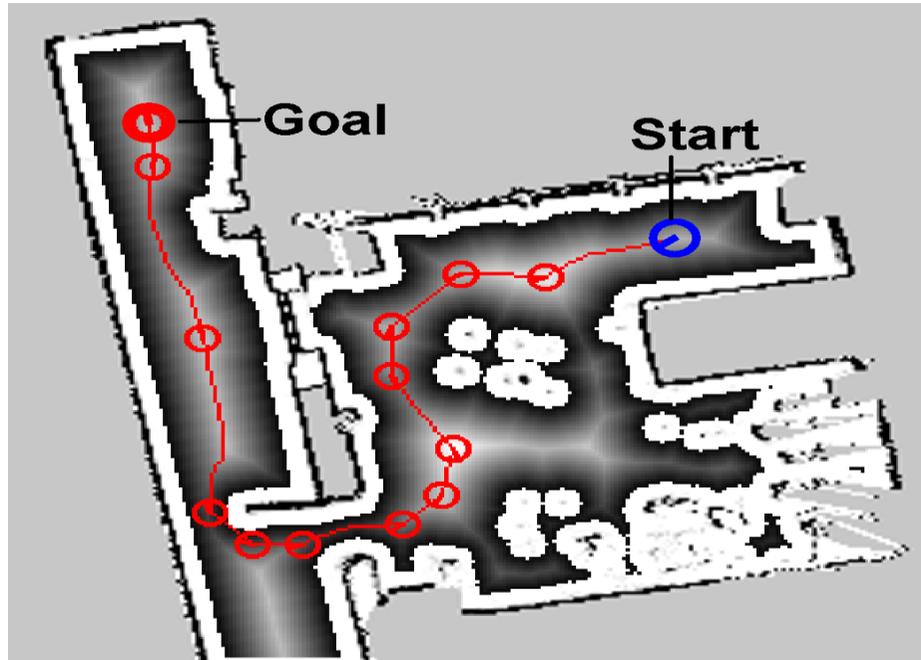


# Mapping the Environment



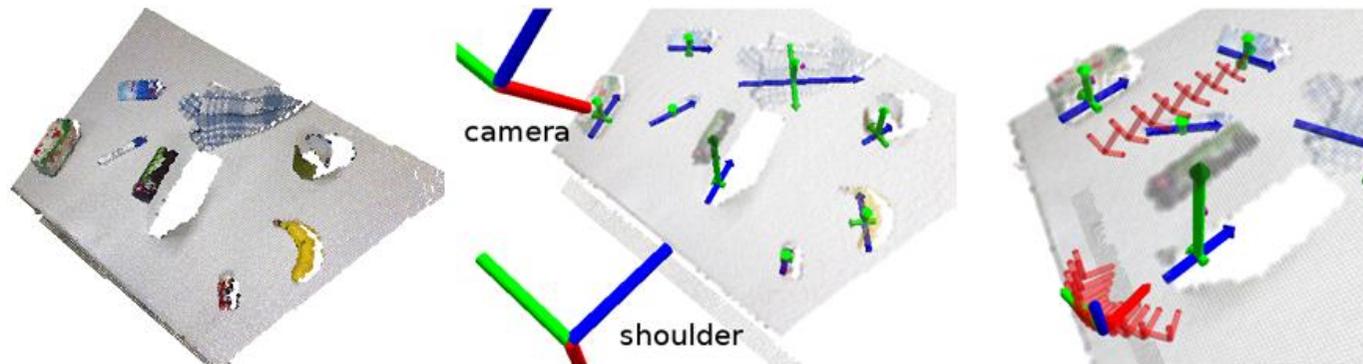
# Path Planning

- Global planning tries to keep away from obstacles
- Obstacle avoidance using two lasers
- Robot alignment in narrow passages
- Plan revision when path blocked

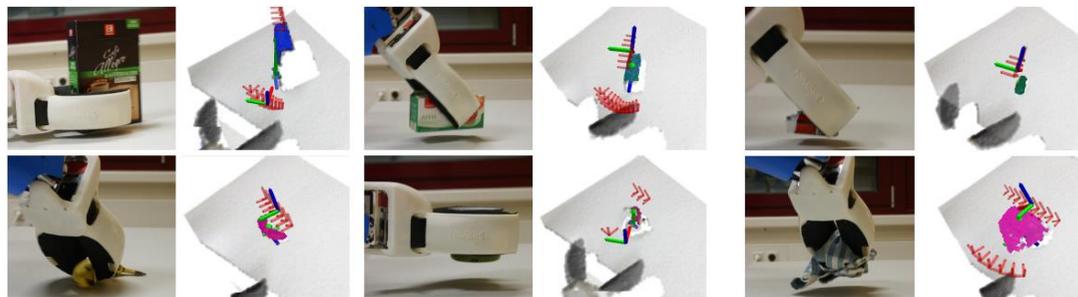


# Object Perception and Grasp Planning

- Detection of clusters above horizontal plane
- Two grasps (top, side)

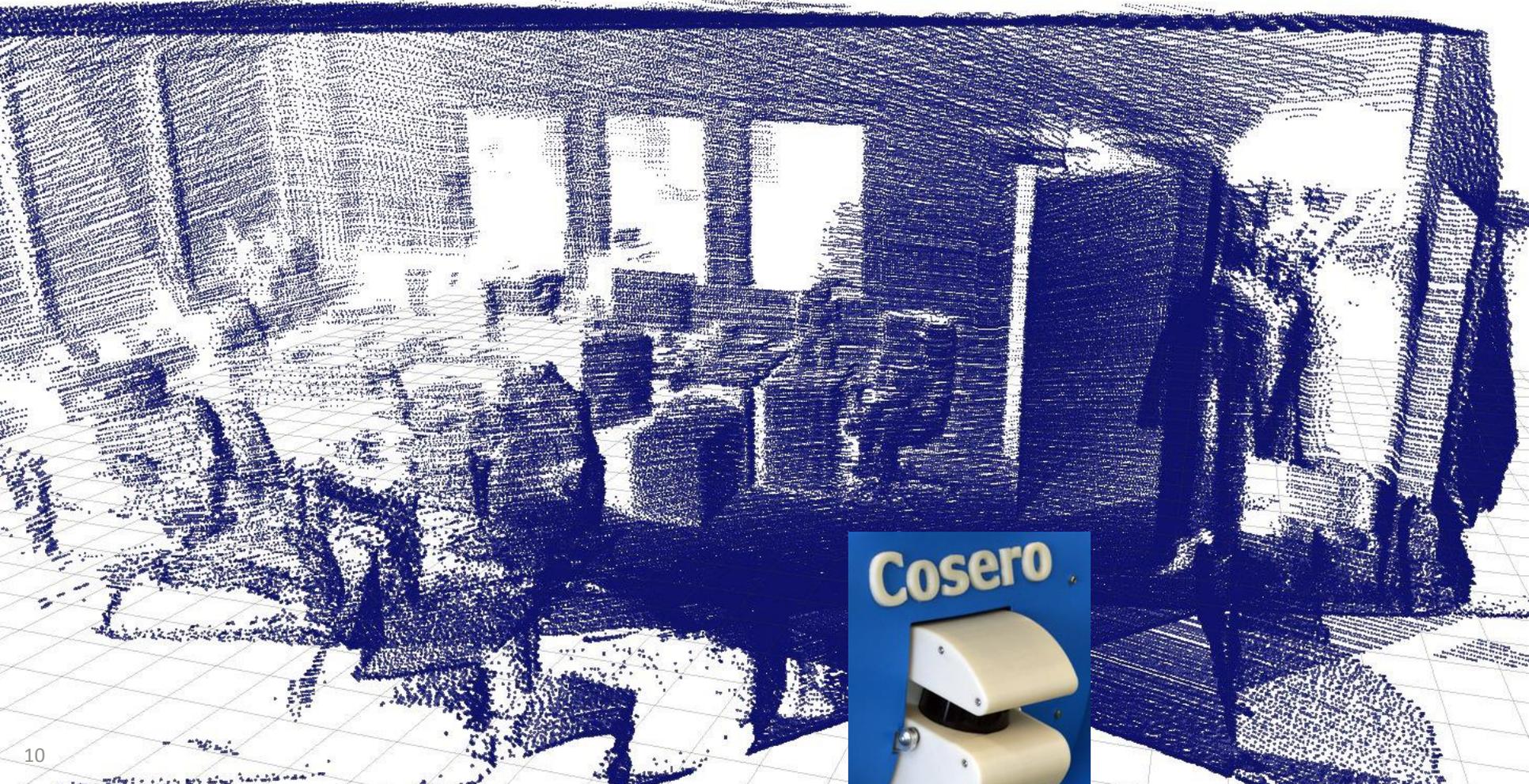


- Flexible grasping of many unknown objects

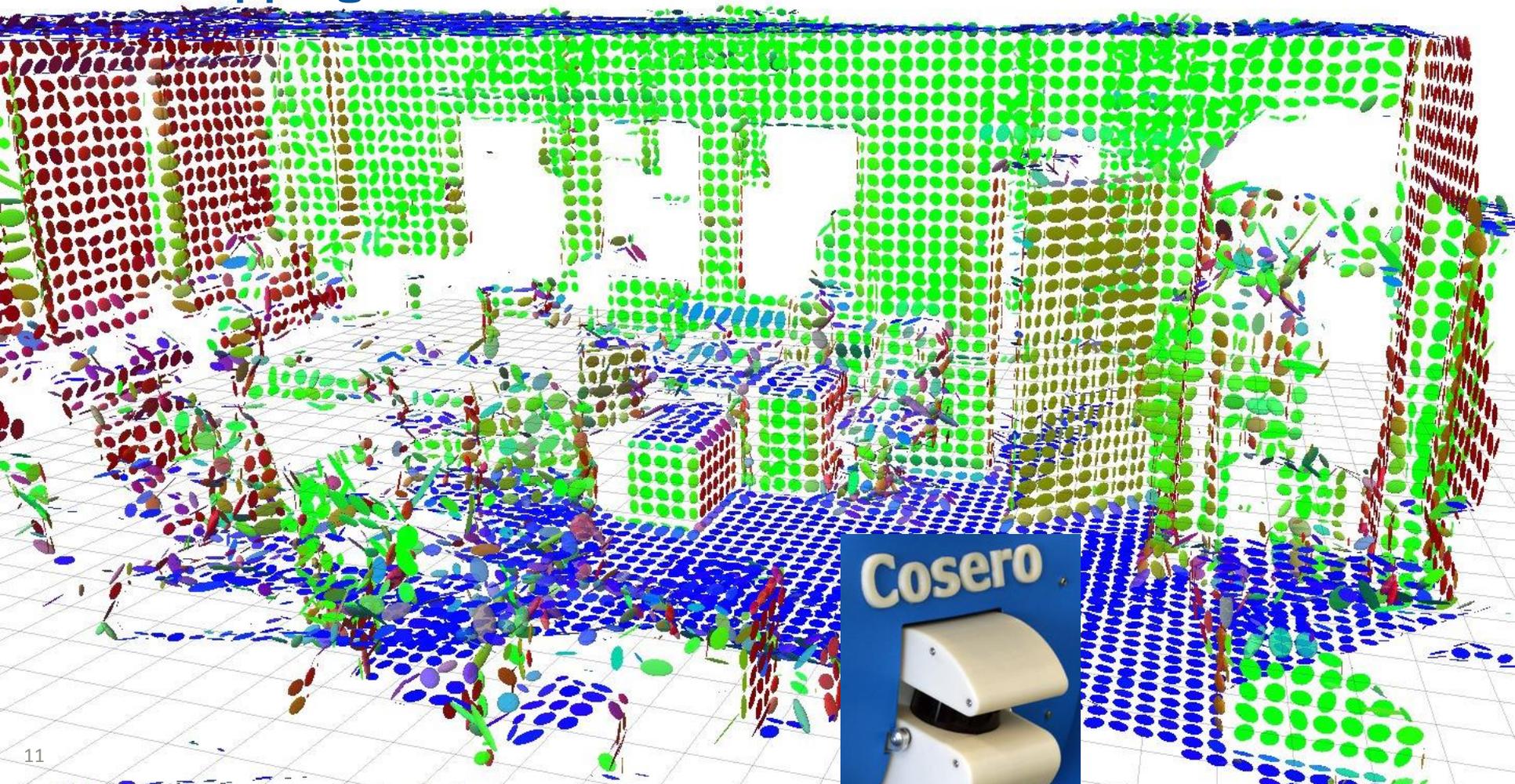


[Stückler et al, Robotics and Autonomous Systems, 2013]

# 3D-Mapping with Surfels

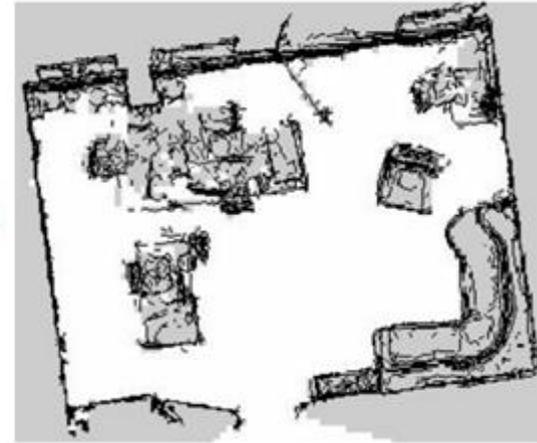
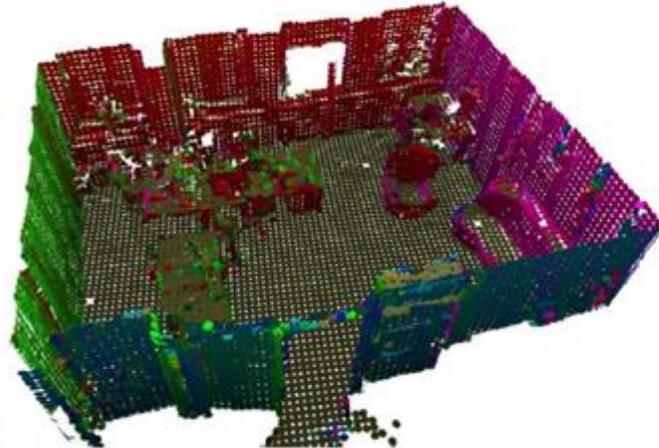


# 3D-Mapping with Surfels



# 3D-Mapping and Localization

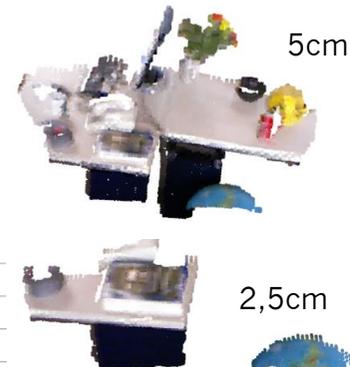
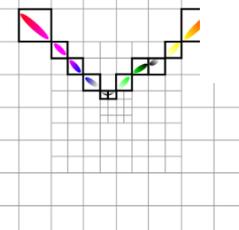
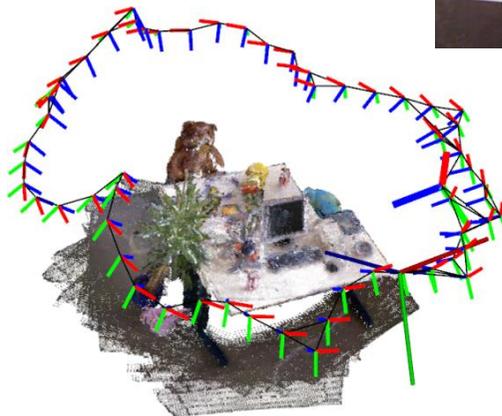
- Registration of 3D laser scans
- Representation of point distributions in voxels
- Drivability assessment through region growing
- Robust localization using 2D laser scans



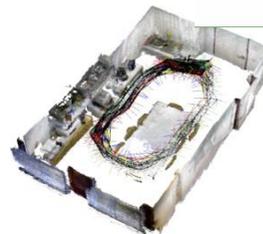
# 3D Mapping by RGB-D SLAM

[Stückler, Behnke:  
Journal of Visual Communication  
and Image Representation 2013]

- Modelling of shape and color distributions in voxels
- Local multiresolution
- Efficient registration of views on CPU
- Global optimization



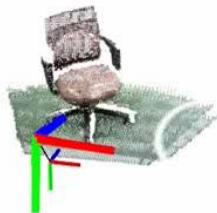
- Multi-camera SLAM



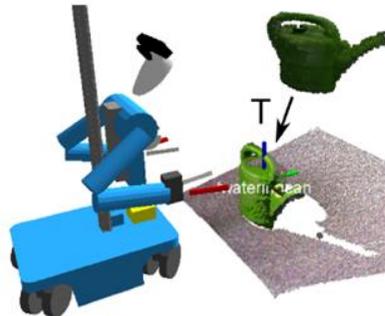
[Stoucken]

# Learning and Tracking Object Models

- Modeling of objects by RGB-D-SLAM

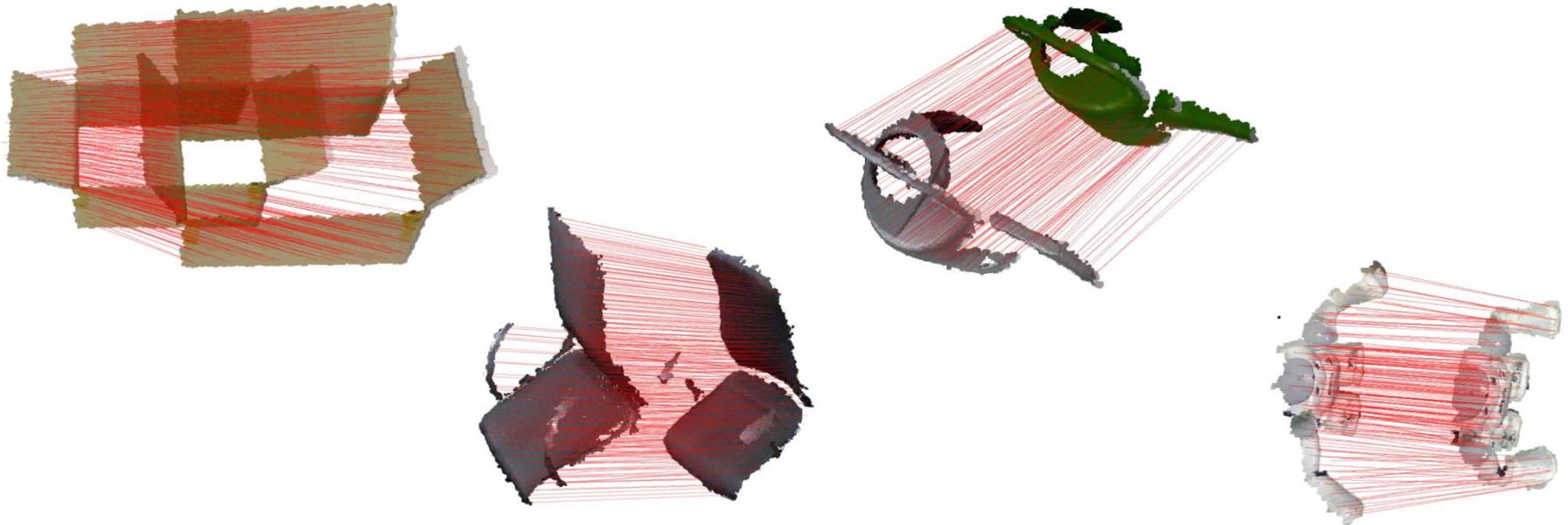


- Real-time registration with current RGB-D frame



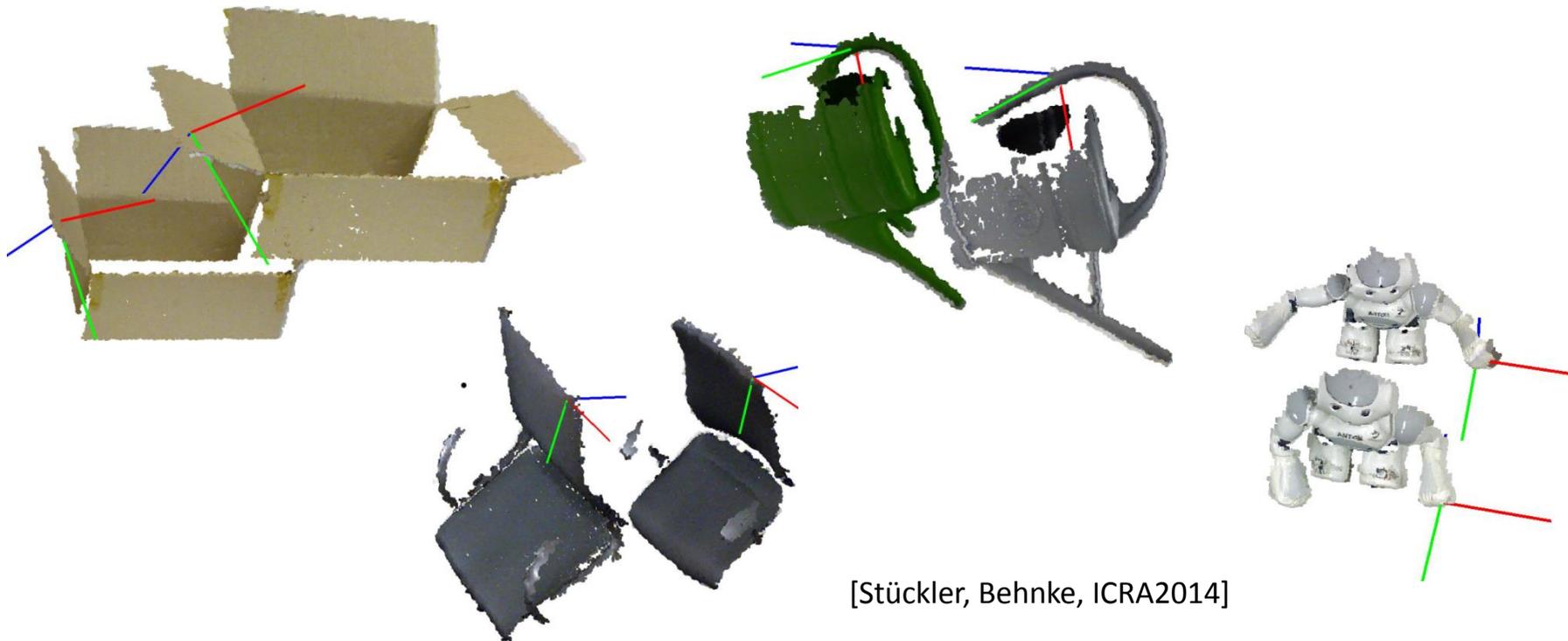
# Deformable RGB-D-Registration

- Based on Coherent Point Drift method [Myronenko & Song, PAMI 2010]
- Multiresolution Surfel Map allows real-time registration



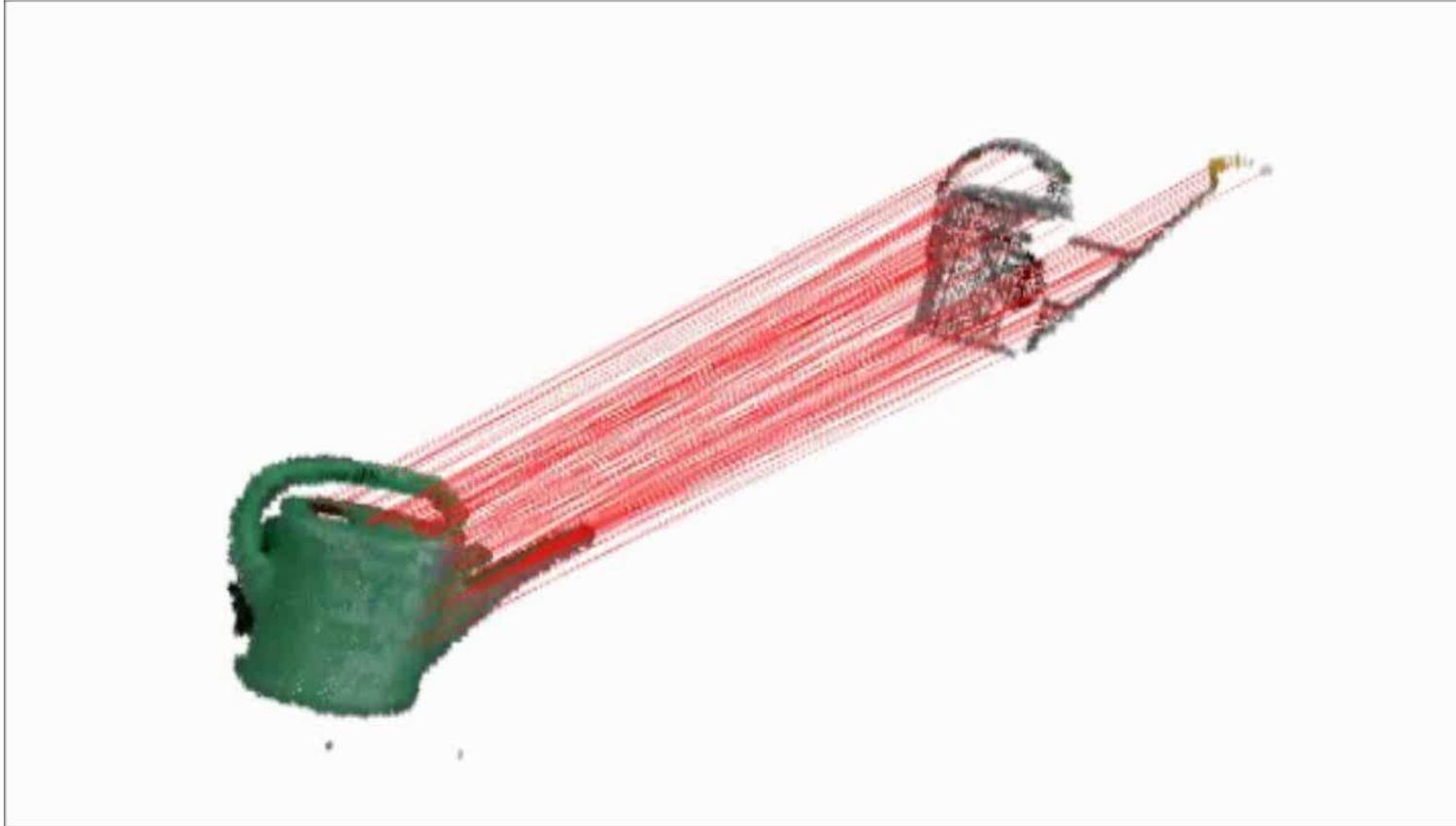
# Transformation of Poses on Object

- Derived from the deformation field



[Stückler, Behnke, ICRA2014]

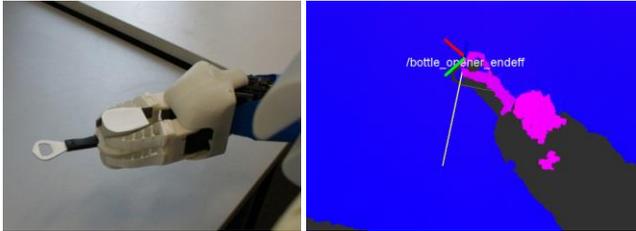
# Grasp & Motion Skill Transfer



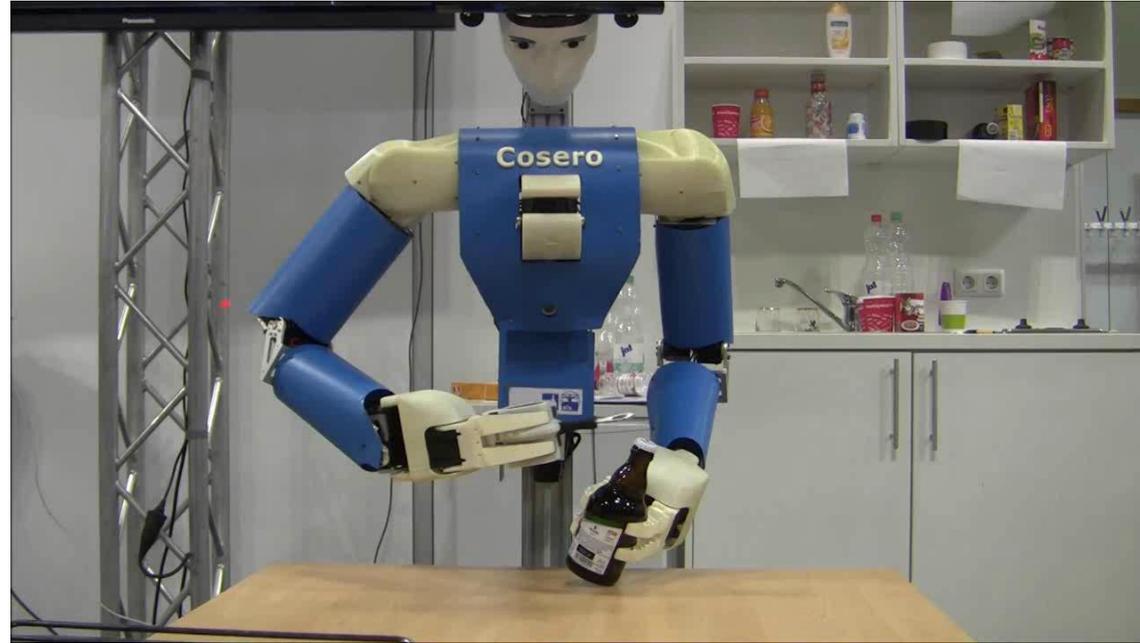
[Stückler,  
Behnke,  
ICRA2014]

# Tool use: Bottle Opener

- Tool tip perception



- Extension of arm kinematics
- Perception of crown cap
- Motion adaptation



[Stückler, Behnke, Humanoids 2014]

# Picking Sausage, Bimanual Transport

- Perception of tool tip and sausage
- Alignment with main axis of sausage



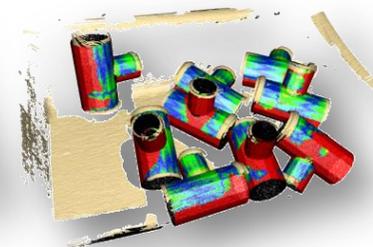
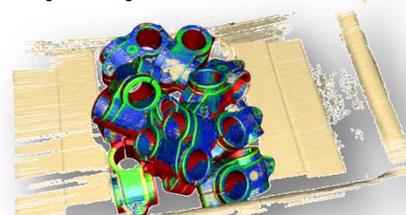
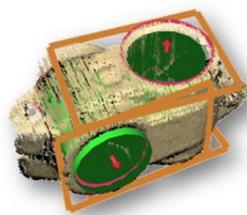
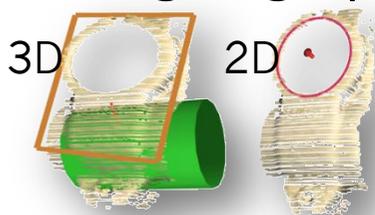
- Our team NimbRo won the RoboCup@Home League in three consecutive years

# Bin Picking

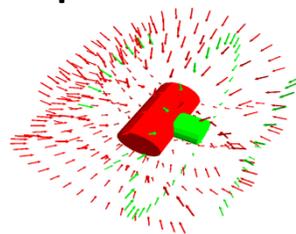
- Known objects in transport box



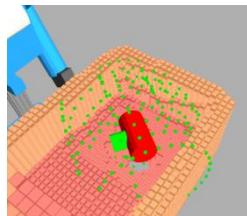
- Matching of graphs of 2D and 3D shape primitives



- Grasp and motion planning



Offline

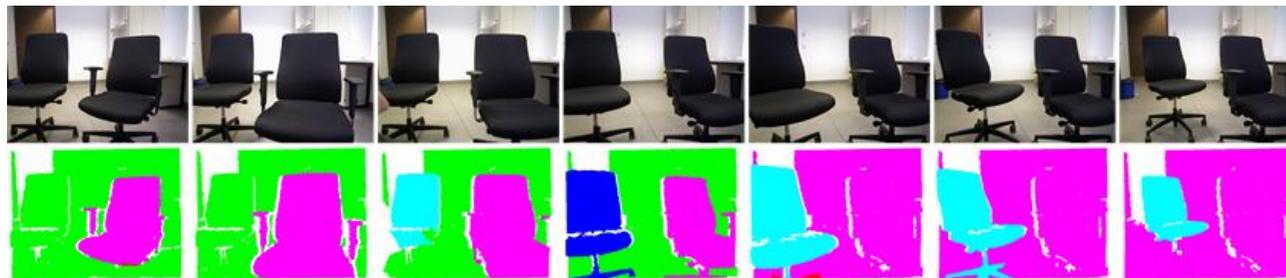


Online

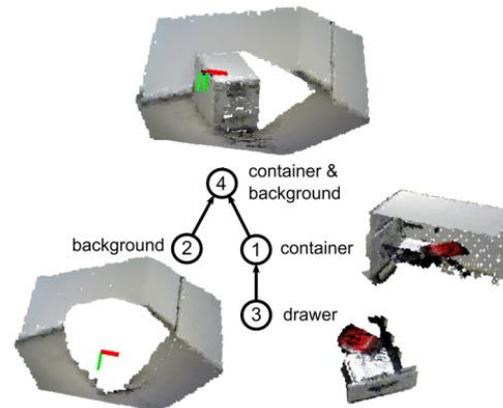
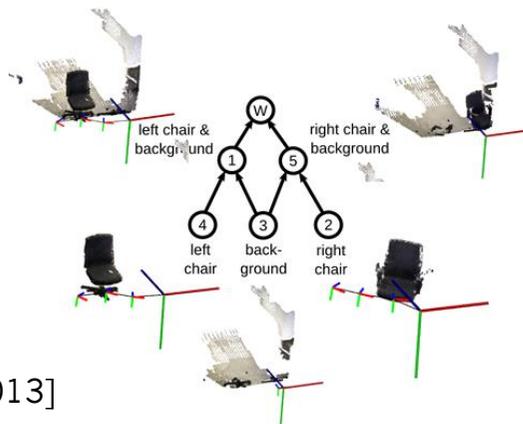


# Hierarchical Object Discovery through Motion Segmentation

- Simultaneous object modeling and motion segmentation



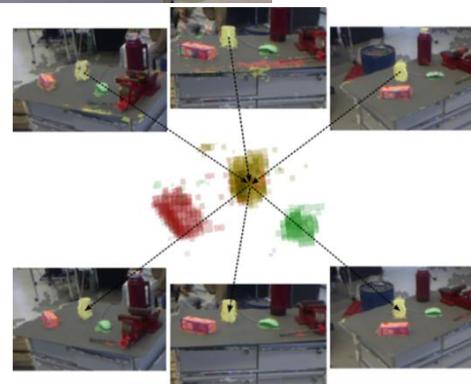
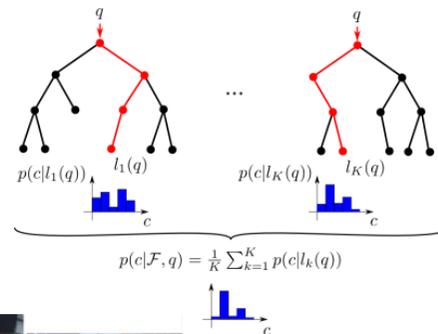
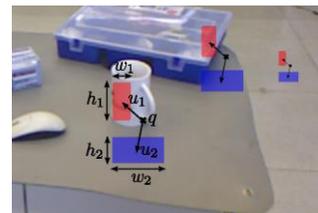
- Inference of a segment hierarchy



[Stückler, Behnke: IJCAI 2013]

# Semantic Mapping

- Pixel-wise classification of RGB-D images by random forests
- Compare color / depth of regions
- Size normalization
- 3D fusion through RGB-D SLAM
- Evaluation on NYU depth v2



[Stückler, Biresev, Behne: IROS 2012]



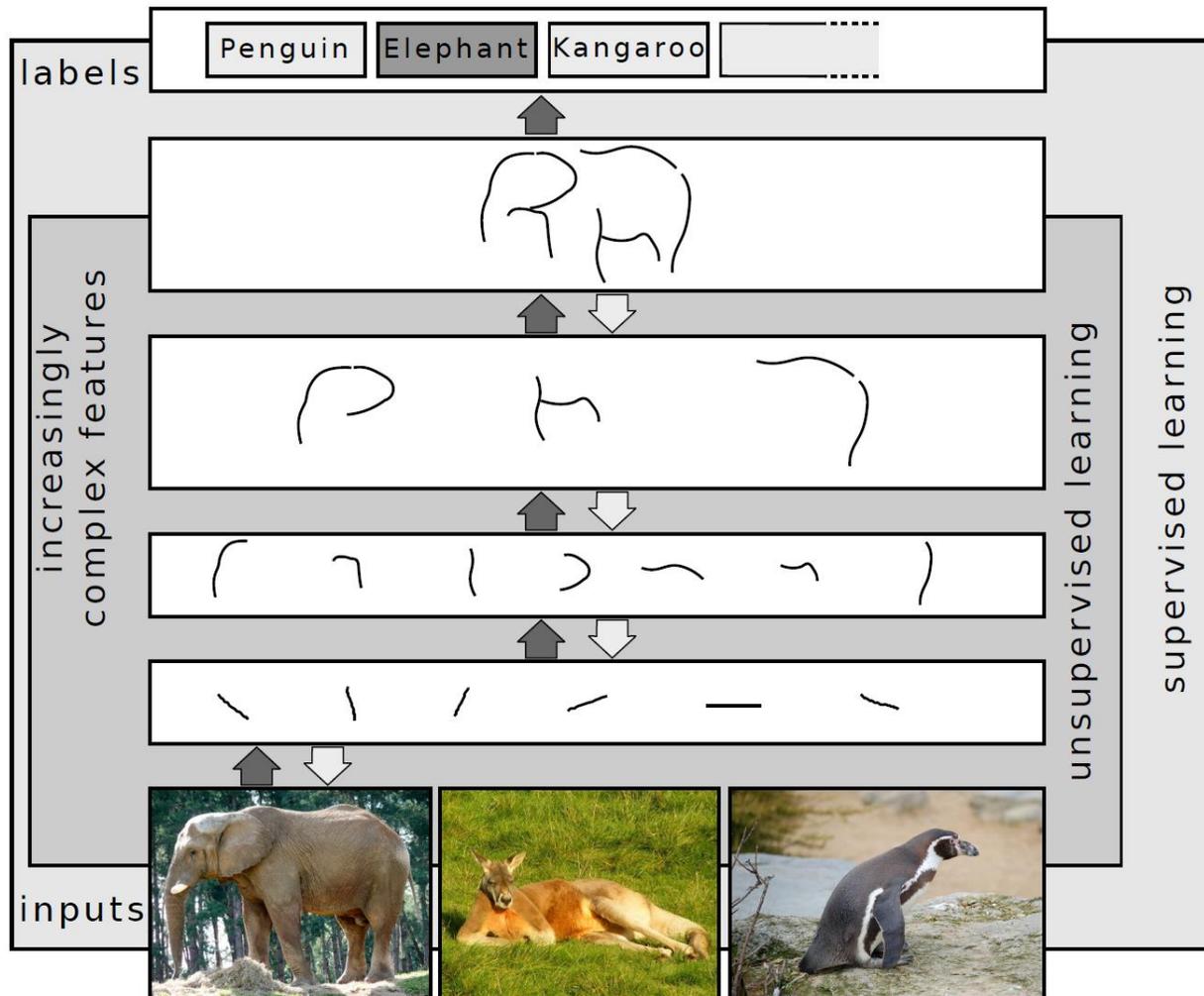
Ground truth

Segmentation

	Accuracy in %	Ø Classes	Ø Pixels
Silberman et al. 2012	59,6	59,6	58,6
Coupric et al. 2013	63,5	63,5	64,5
Random forest	65,0	65,0	68,1
3D-Fusion	<b>66,8</b>		

# Deep Learning

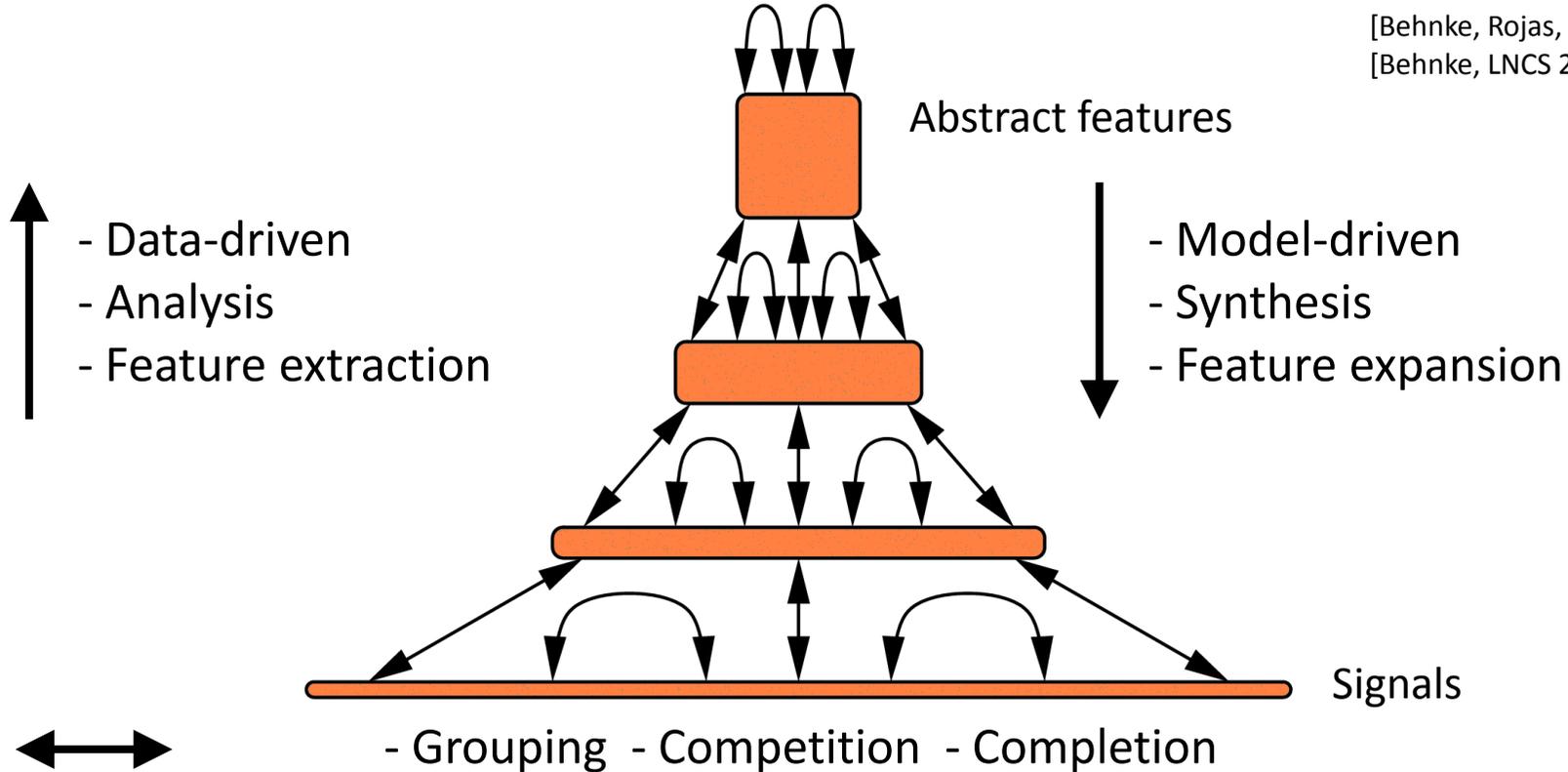
- Learning layered representations



[Schulz;  
Behnke,  
KI 2012]

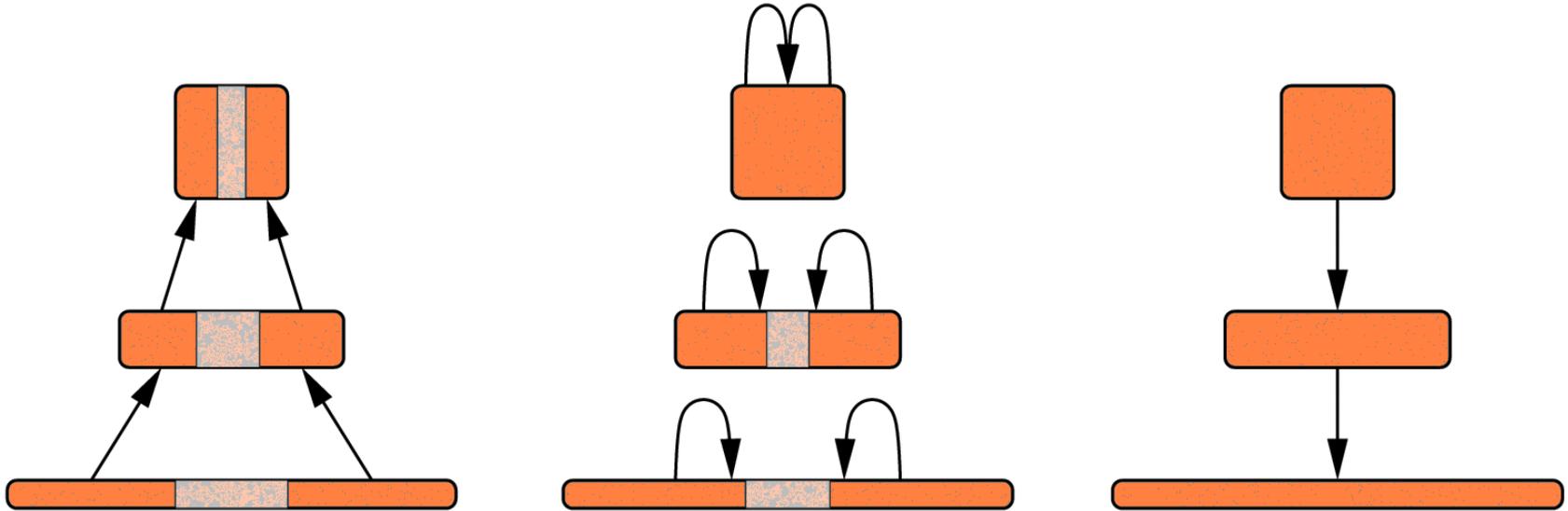
# Neural Abstraction Pyramid

[Behnke, Rojas, IJCNN 1998]  
[Behnke, LNCS 2766, 2003]



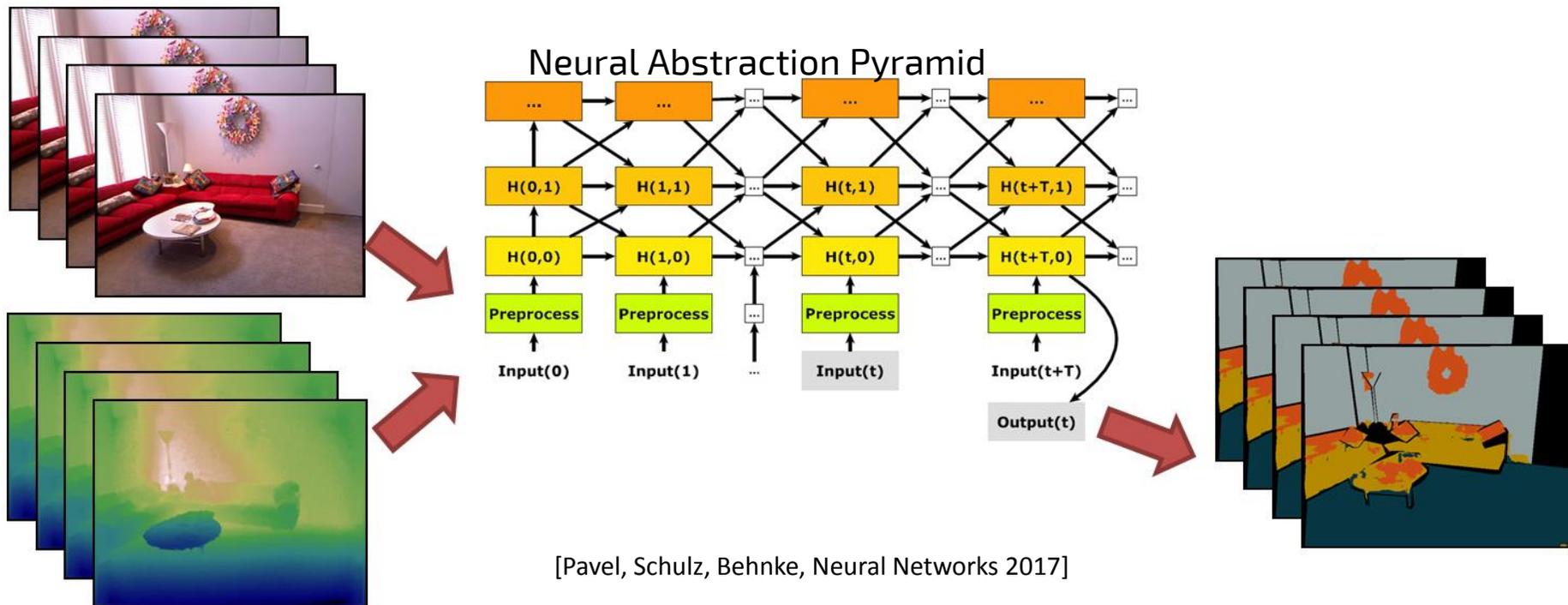
# Iterative Image Interpretation

- Interpret most obvious parts first
- Use partial interpretation as context to resolve local ambiguities



# Neural Abstraction Pyramid for RGB-D Video Object-class Segmentation

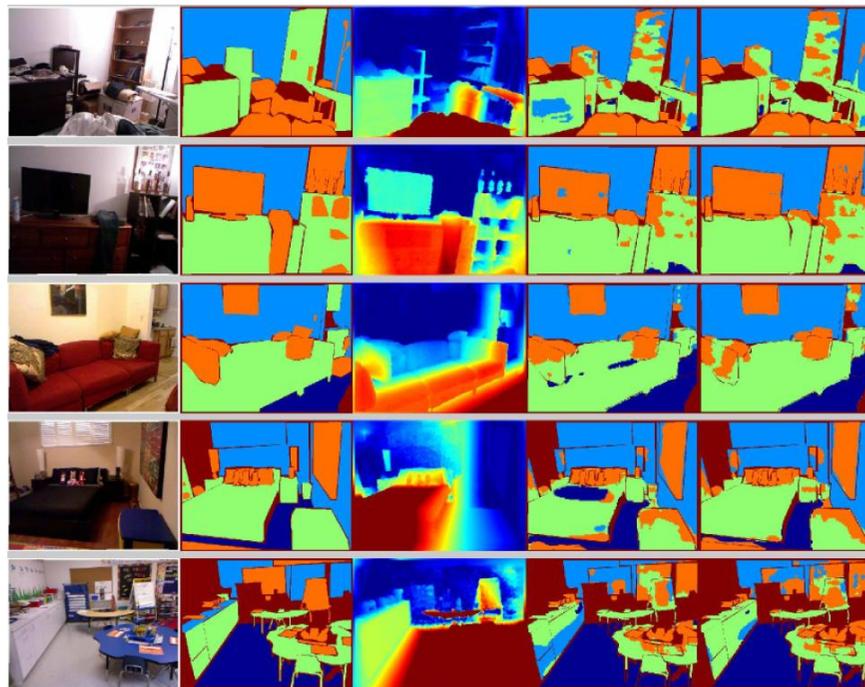
- Recursive computation is efficient for temporal integration



[Pavel, Schulz, Behnke, Neural Networks 2017]

# Geometric and Semantic Features for RGB-D Object-class Segmentation

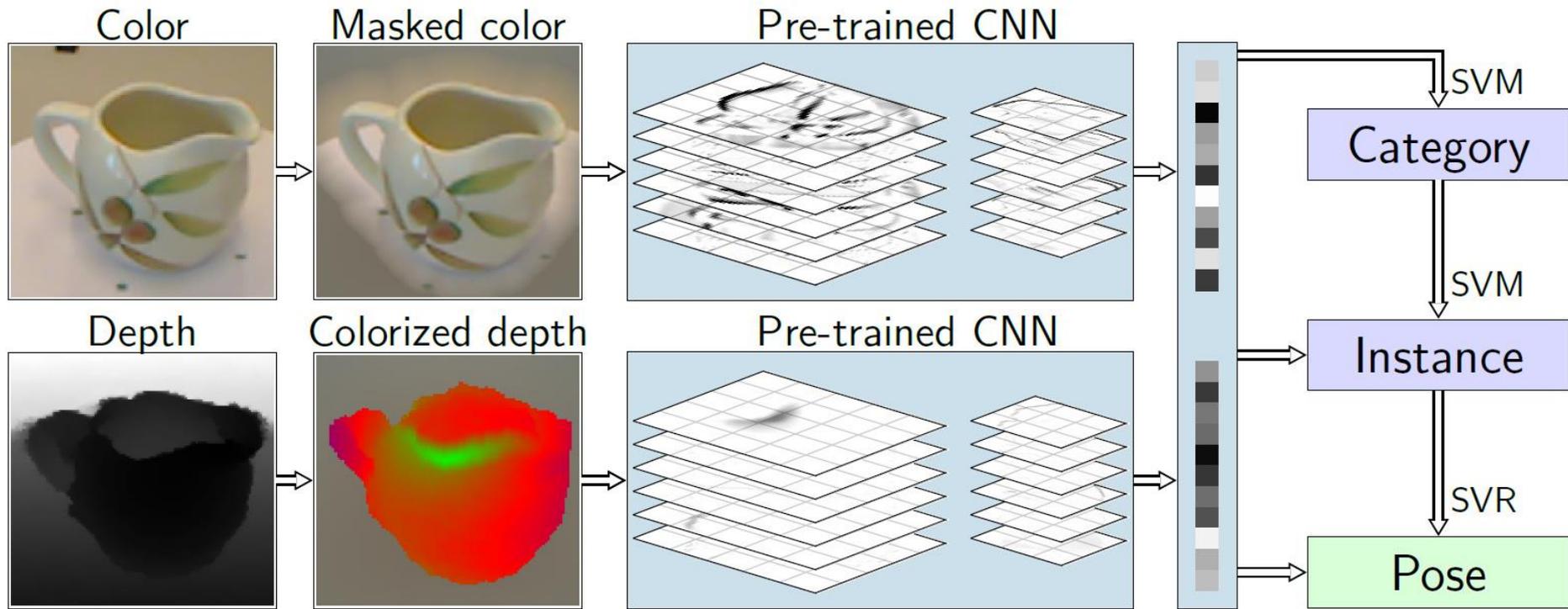
- New **geometric** feature: distance from wall
- **Semantic** features pretrained from ImageNet
- Both help significantly



RGB Truth DistWall OutWO OutWithDistWall

[Husain et al. RA-L 2017]

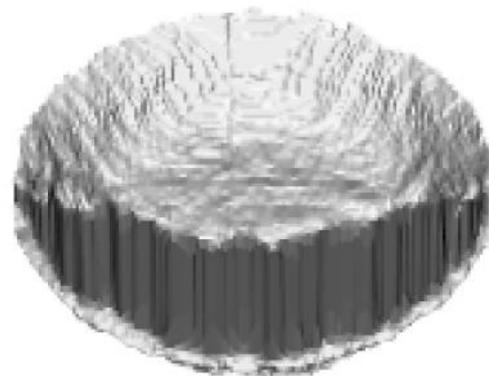
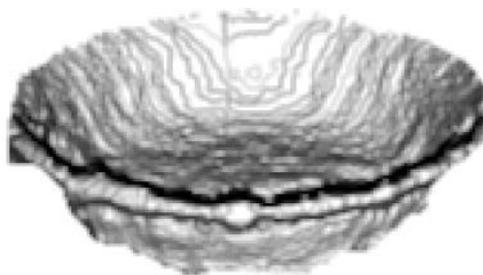
# RGB-D Object Recognition and Pose Estimation



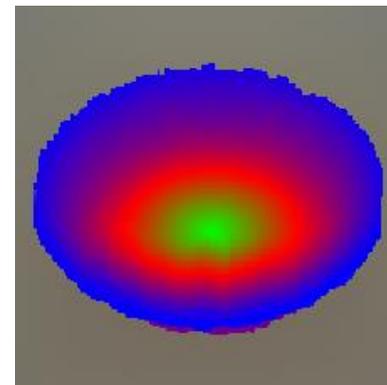
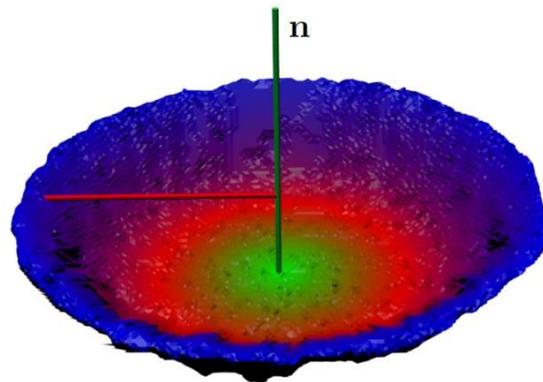
[Schwarz, Schulz, Behnke, ICRA2015]

# Canonical View, Colorization

- Objects viewed from different elevation
- Render canonical view

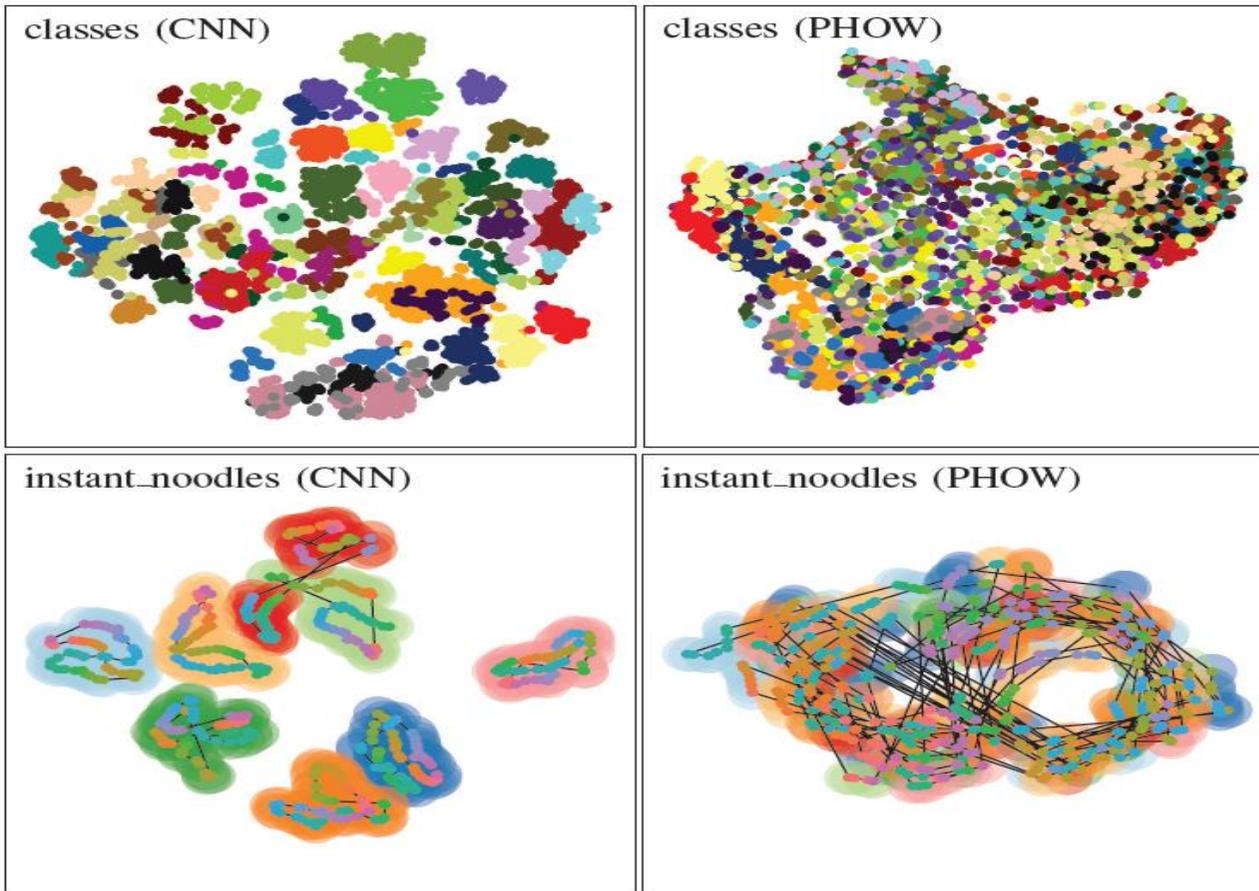


- Colorization based on distance from center vertical



# Pretrained Features Disentangle Data

- t-SNE embedding



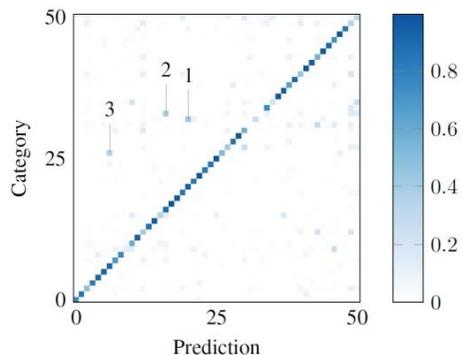
[Schwarz, Schulz,  
Behnke ICRA2015]

# Recognition Accuracy

- Improved both category and instance recognition

Method	Category Accuracy (%)		Instance Accuracy (%)	
	RGB	RGB-D	RGB	RGB-D
Lai <i>et al.</i> [1]	74.3 ± 3.3	81.9 ± 2.8	59.3	73.9
Bo <i>et al.</i> [2]	82.4 ± 3.1	87.5 ± 2.9	<b>92.1</b>	92.8
PHOW[3]	80.2 ± 1.8	—	62.8	—
<b>Ours</b>	<b>83.1 ± 2.0</b>	88.3 ± 1.5	92.0	<b>94.1</b>
<b>Ours</b>	<b>83.1 ± 2.0</b>	<b>89.4 ± 1.3</b>	92.0	<b>94.1</b>

- Confusion:



[Schwarz, Schulz,  
Behnke, ICRA2015]

1: pitcher / coffe mug

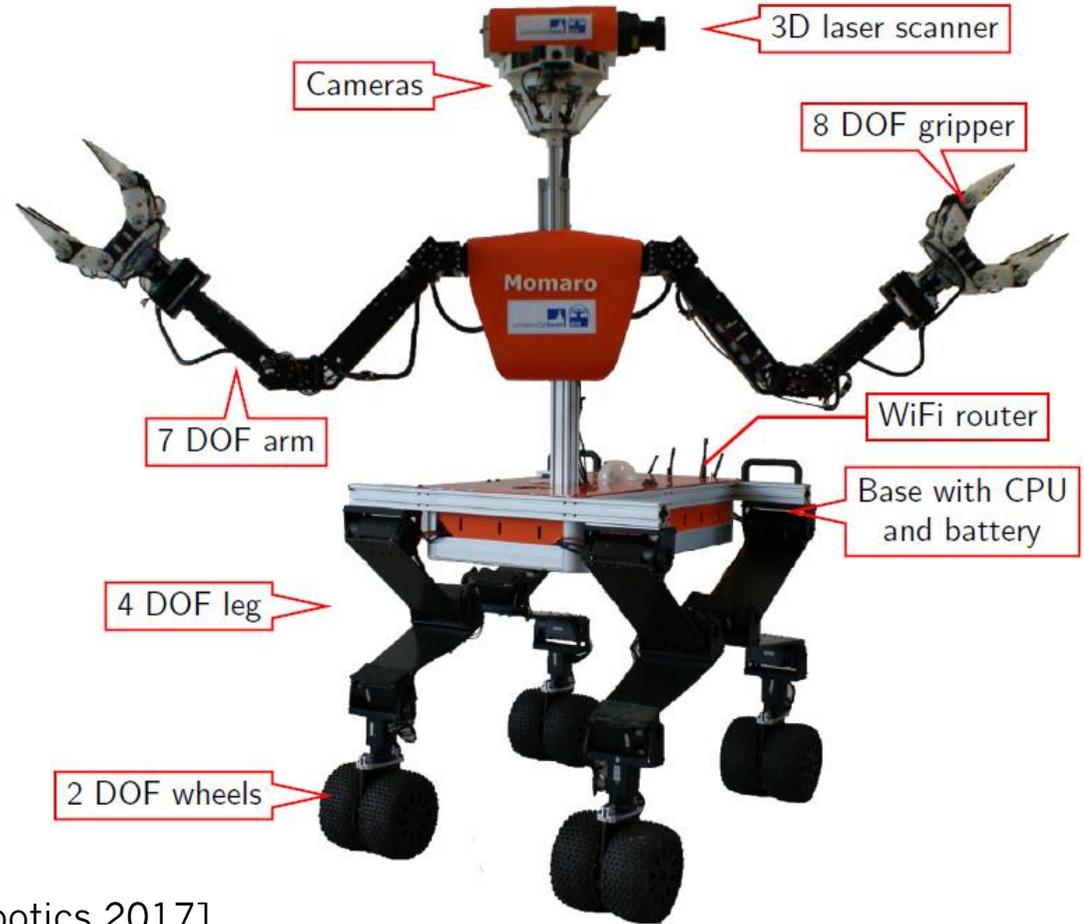


2: peach / sponge



# Mobile Manipulation Robot Momaro

- Four compliant legs ending in pairs of steerable wheels
- Anthropomorphic upper body
- Sensor head
  - 3D laser scanner
  - IMU, cameras



[Schwarz et al. Journal of Field Robotics 2017]

FAIRPLEX

FAIRPLEX

FAIRPLEX

FA



23:15:03 05/06/2015 UTC

4x

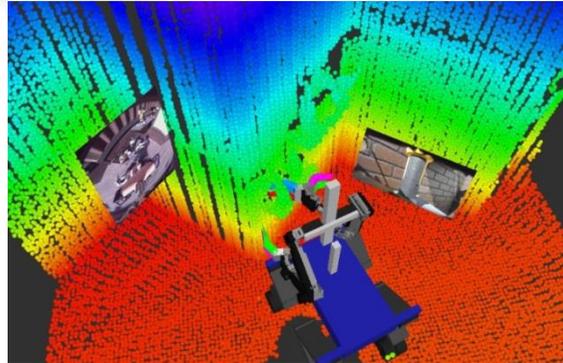


23:16:59 05/06/2015 UTC

4x

# Manipulation Operator Interface

- 3D head-mounted display
- 3D environment model + images
- 6D magnetic tracker



[Rodehutsors et al., Humanoids 2015]





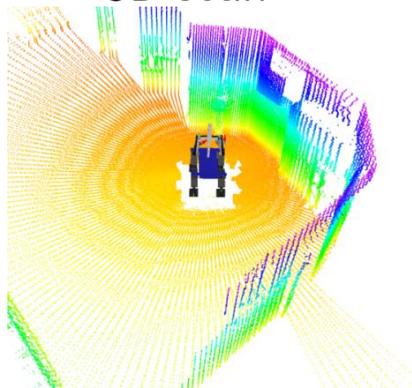
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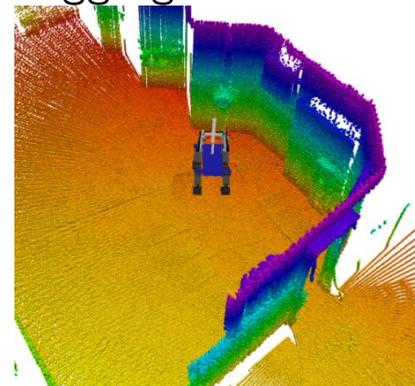
# Local Multiresolution Surfel Map

- Registration and aggregation of 3D laser scans
- Local multi-resolution grid
- Surfel in grid cells

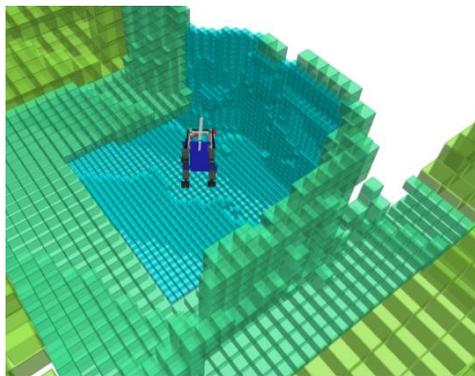
3D scan



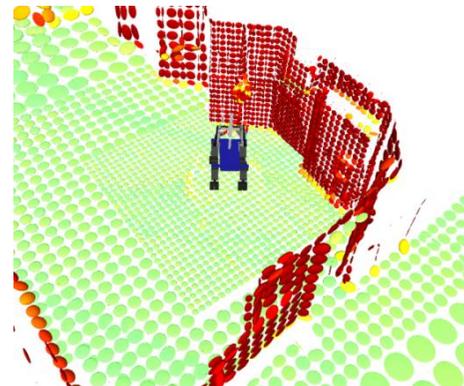
Aggregated scans



Multiresolution grid



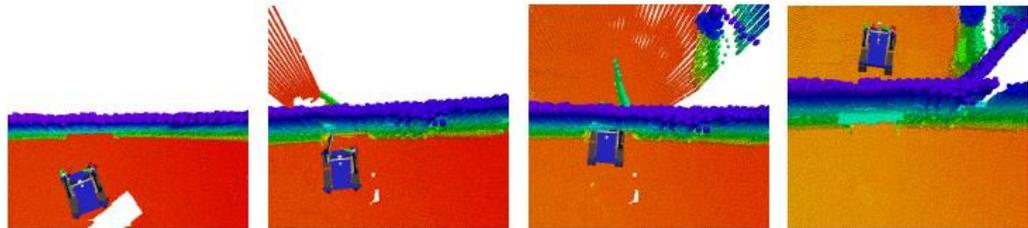
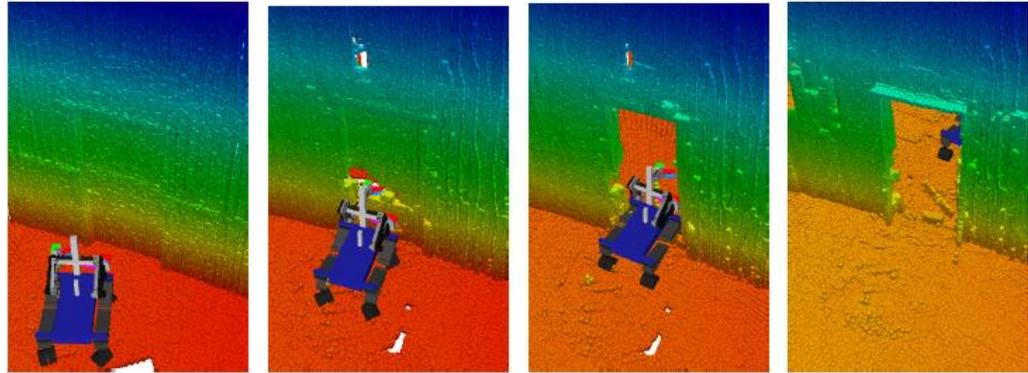
Surfels



[Droeschel et al., Robotics and Autonomous Systems 2017]

# Filtering Dynamic Objects

- Maintain occupancy in each cell
- Remove measurements of empty cells



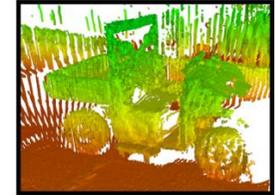
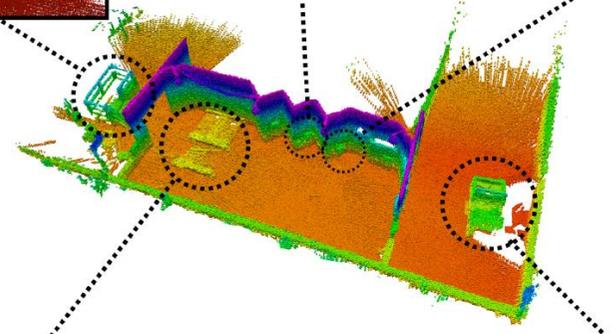
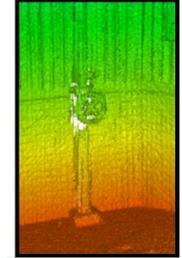
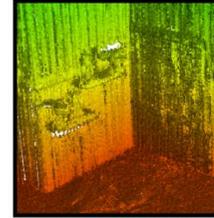
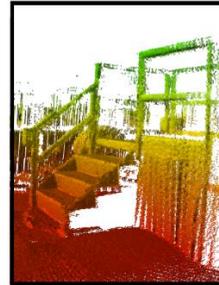
1 scan (5 s)

2 scans (10 s)

5 scans (25 s)

# Allocentric 3D Mapping

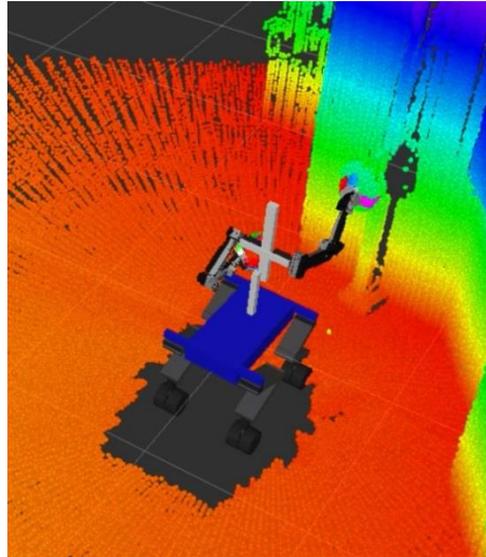
- Registration of egocentric maps by graph optimization



[Droeschel et al., Robotics and Autonomous Systems 2017]

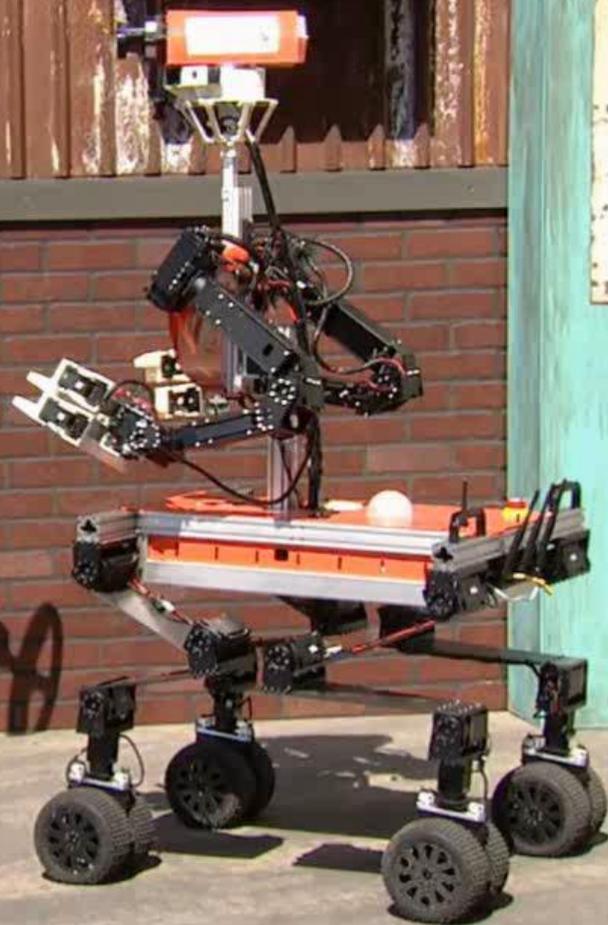
# Valve Turning Interface

- Align wheel model with 3D points using interactive marker



[Schwarz et al. Journal of Field Robotics 2017]

23:25:56 05/06/2015 UTC

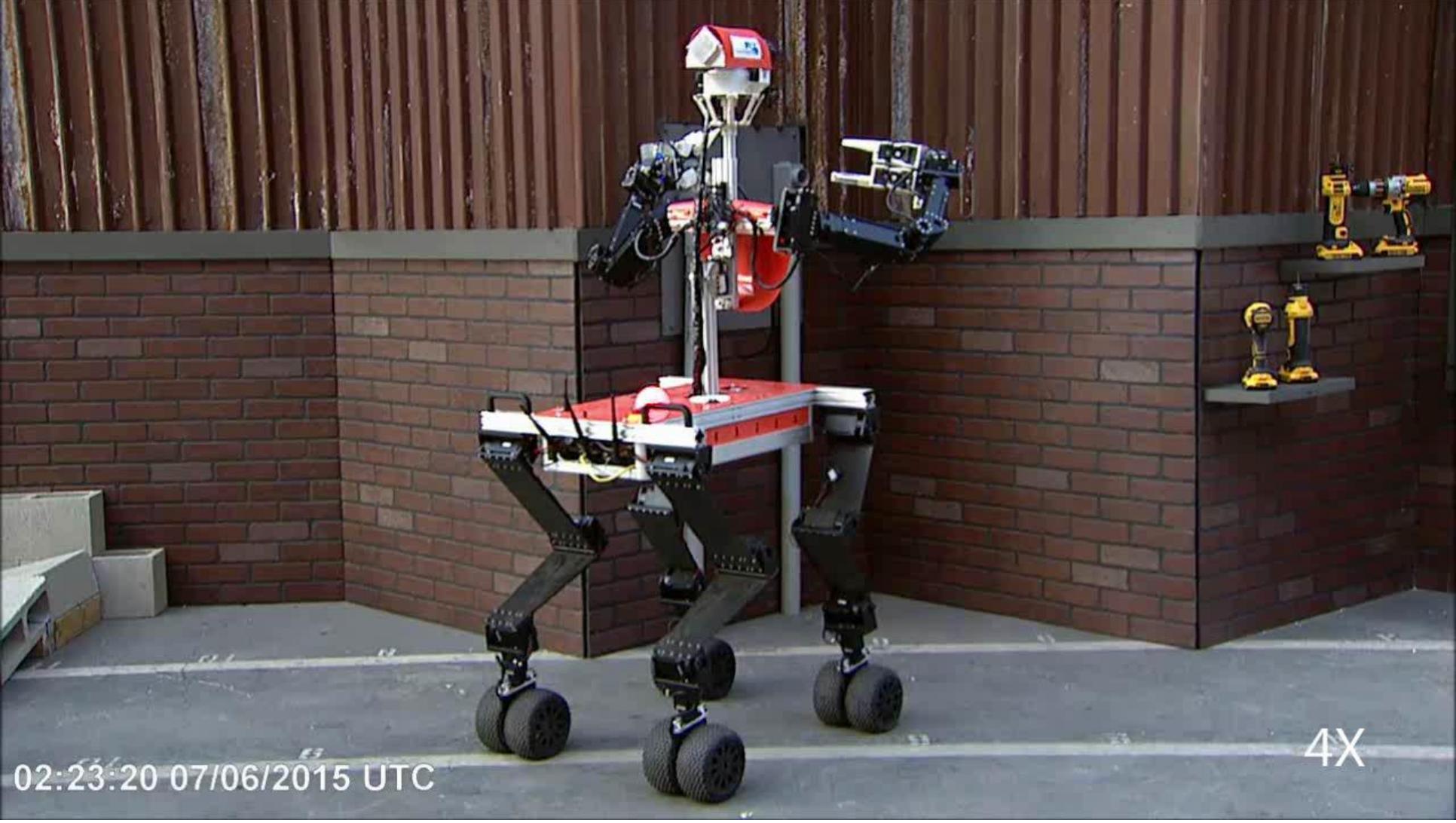


4x



23:28:21 05/06/2015 UTC

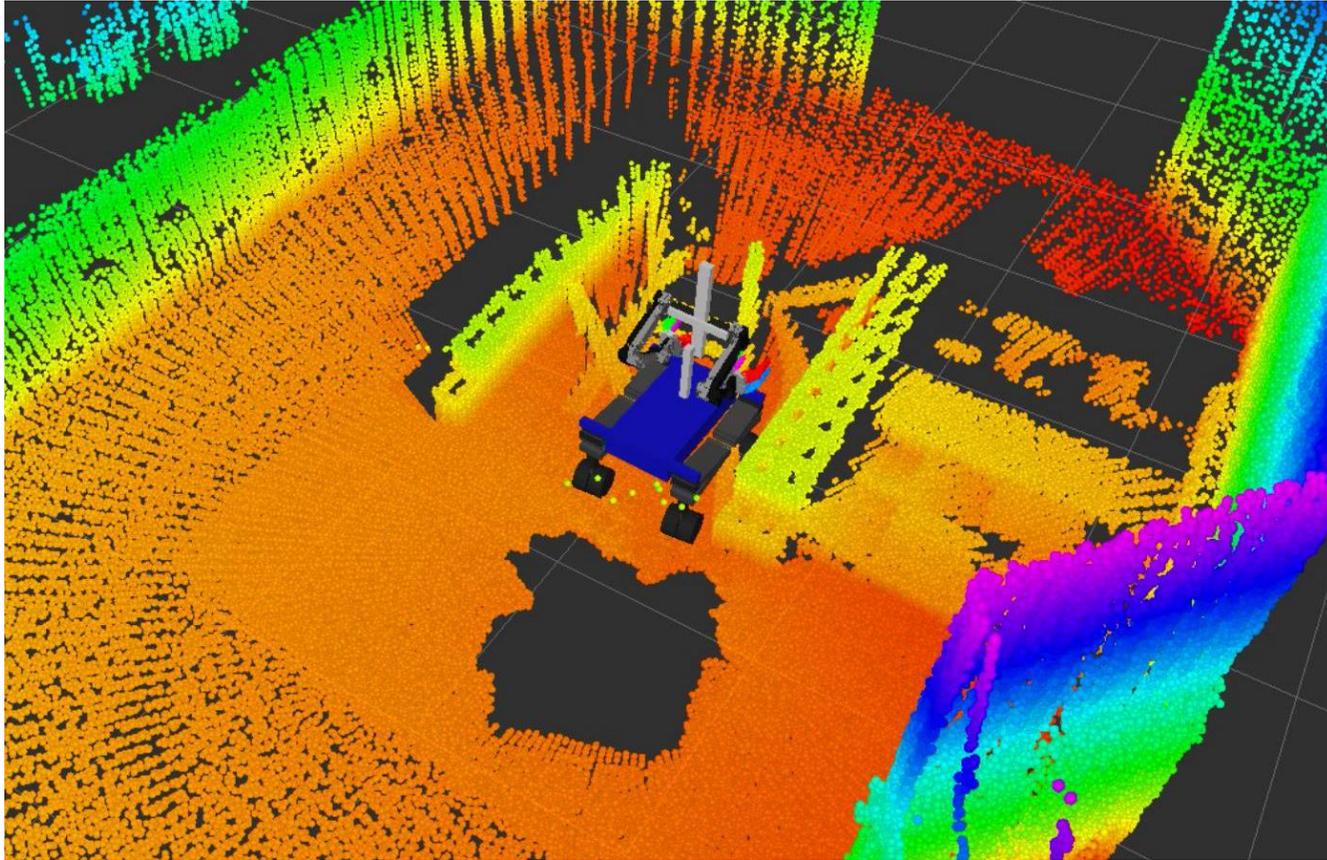
4x

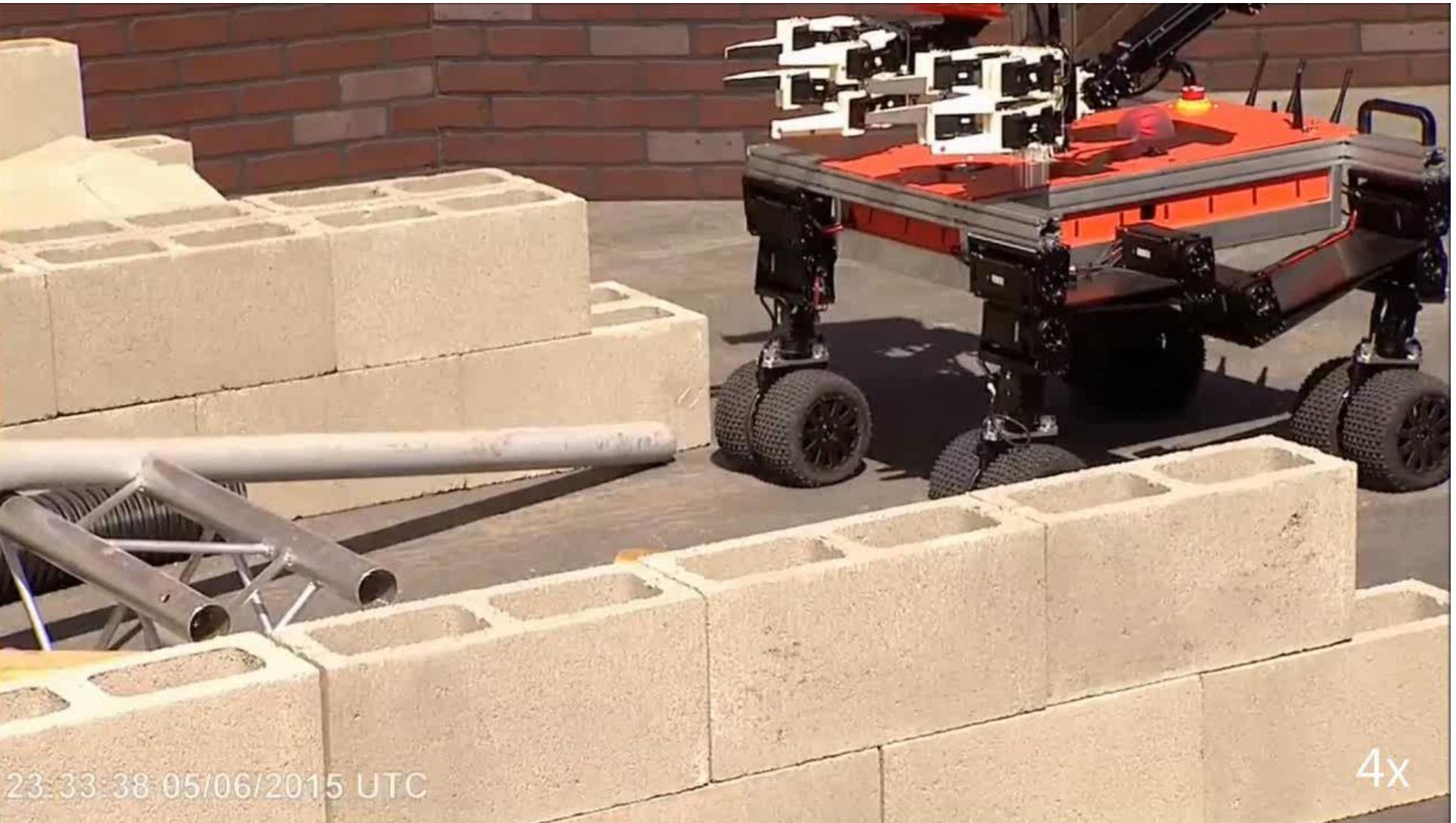


02:23:20 07/06/2015 UTC

4X

# Debris Tasks





23:33:38 05/06/2015 UTC

4x

23:36:46 05/06/2015 UTC



CHALLENGE  
2015

DARPA

4x

# Team NimbRo Rescue

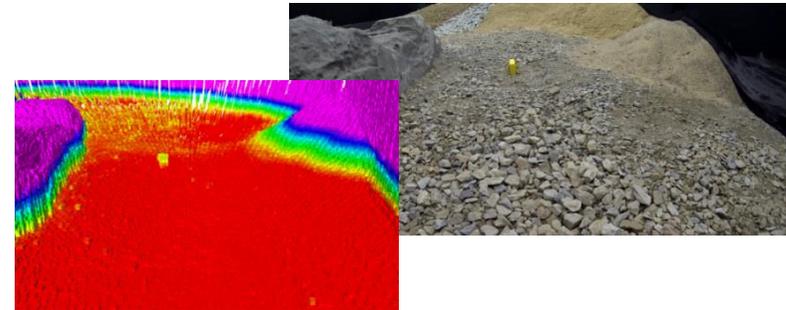
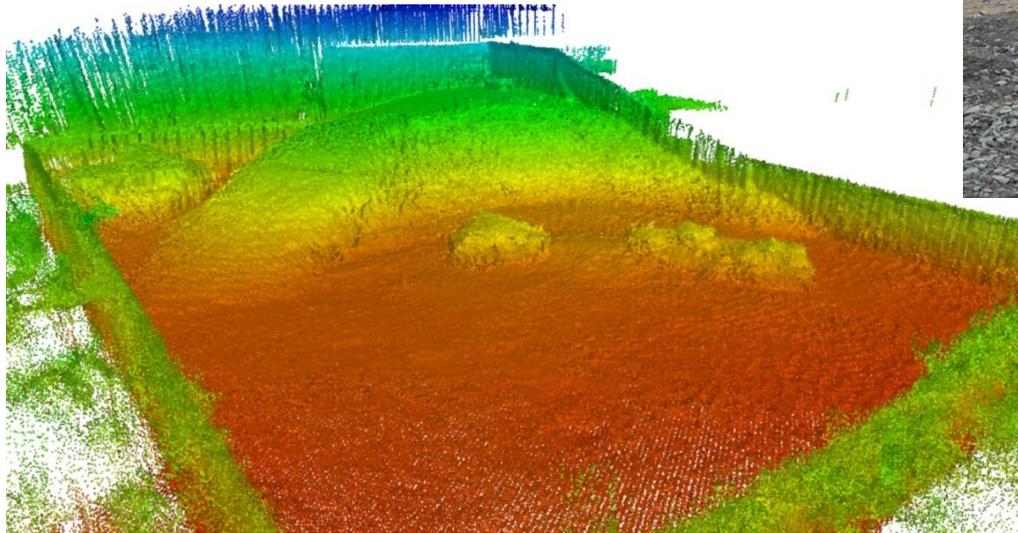


**Best European Team (4<sup>th</sup> place overall),  
solved seven of eight tasks in 34 minutes**

# DLR SpaceBot Cup 2015

- Mobile manipulation in rough terrain

[Schwarz et al., Frontiers on Robotics and AI 2016]

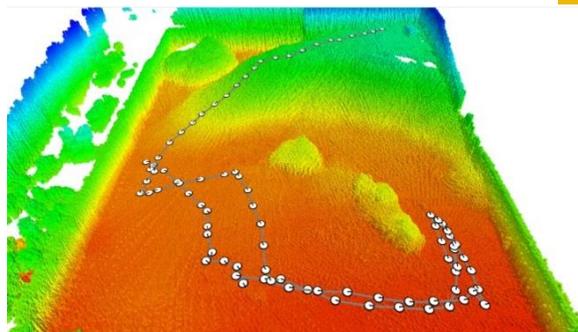




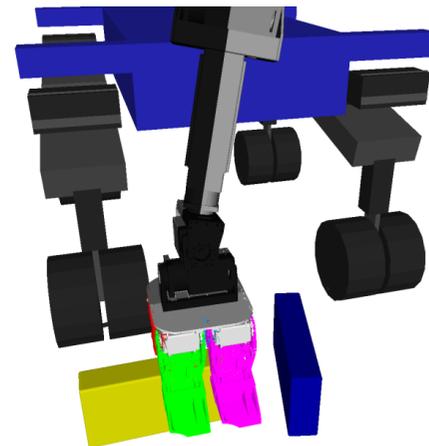
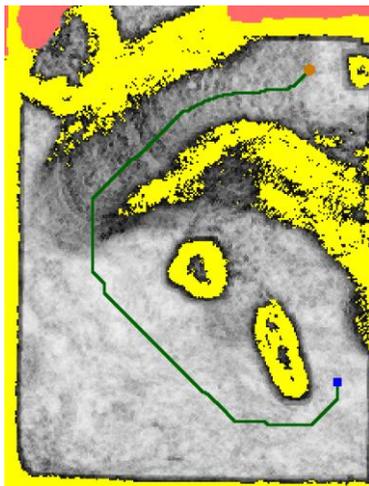
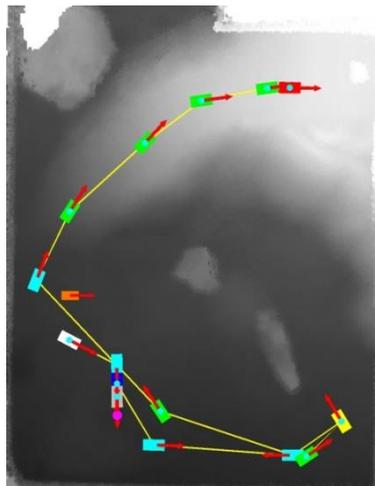
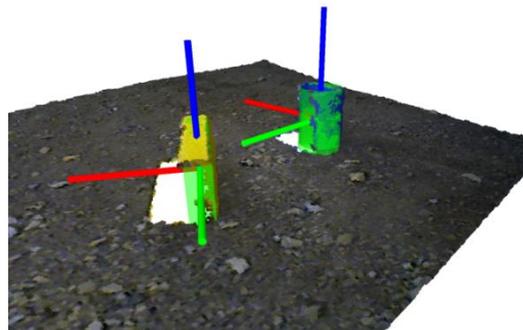
8X

# Autonomous Mission Execution

- 3D mapping, localization, mission and navigation planning



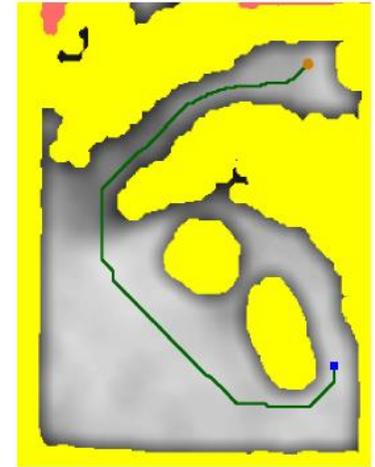
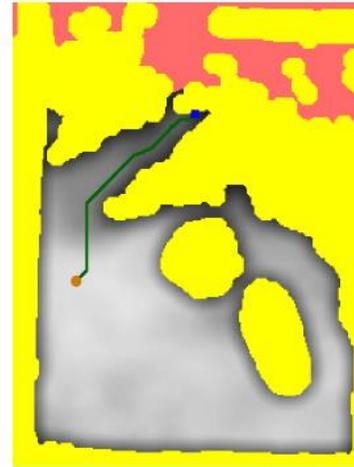
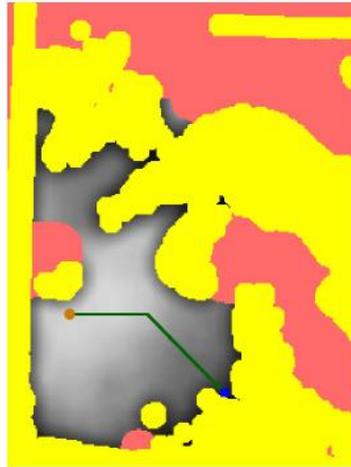
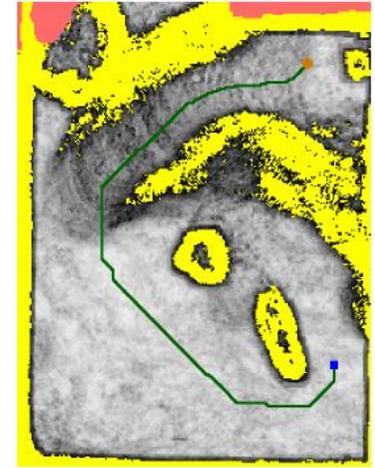
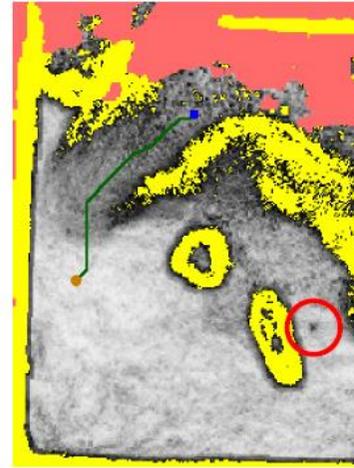
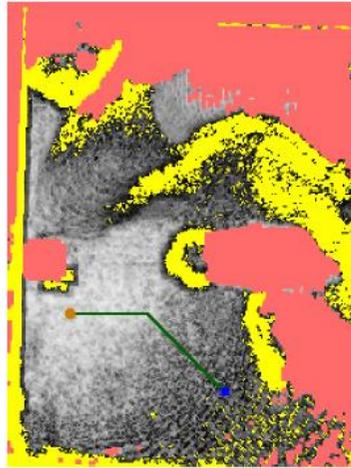
- 3D object perception and grasping



[Schwarz et al. Frontiers 2016]

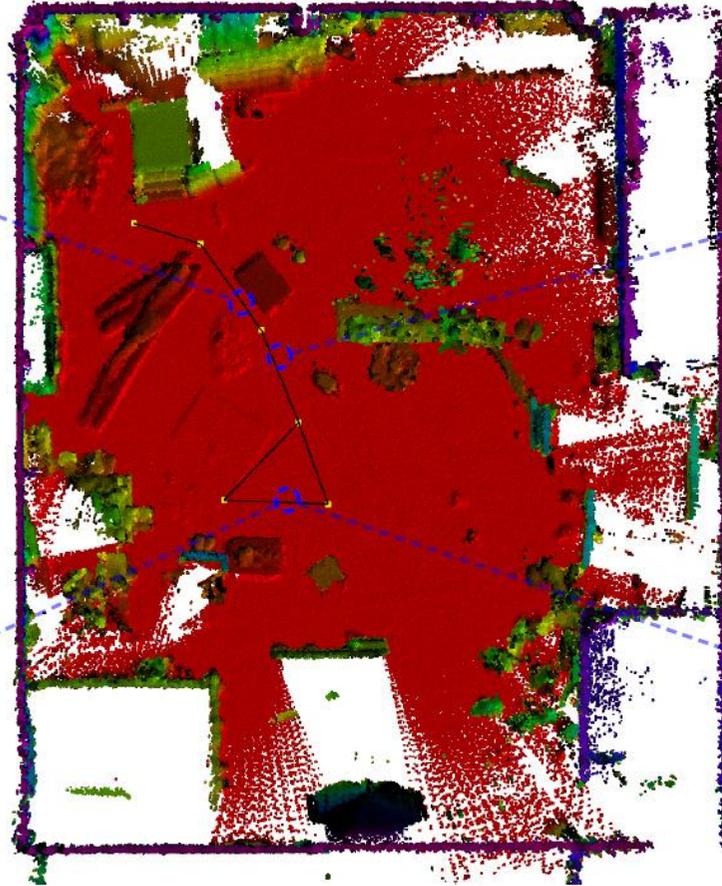
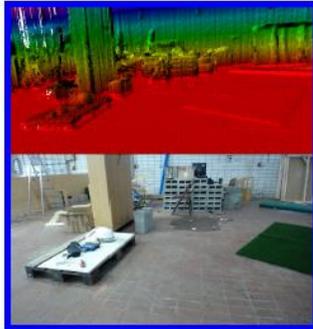
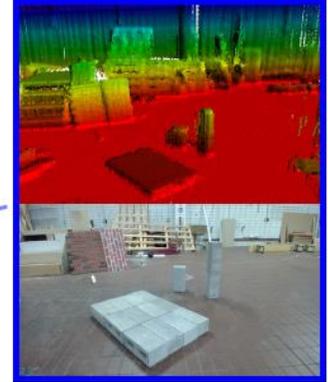
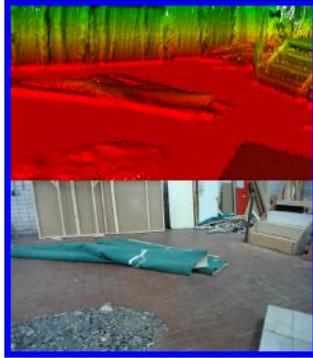
# Navigation Planning

- Costs from local height differences
- A\* path planning



[Schwarz et al., Frontiers  
in Robotics and AI 2016]

# 3D Map

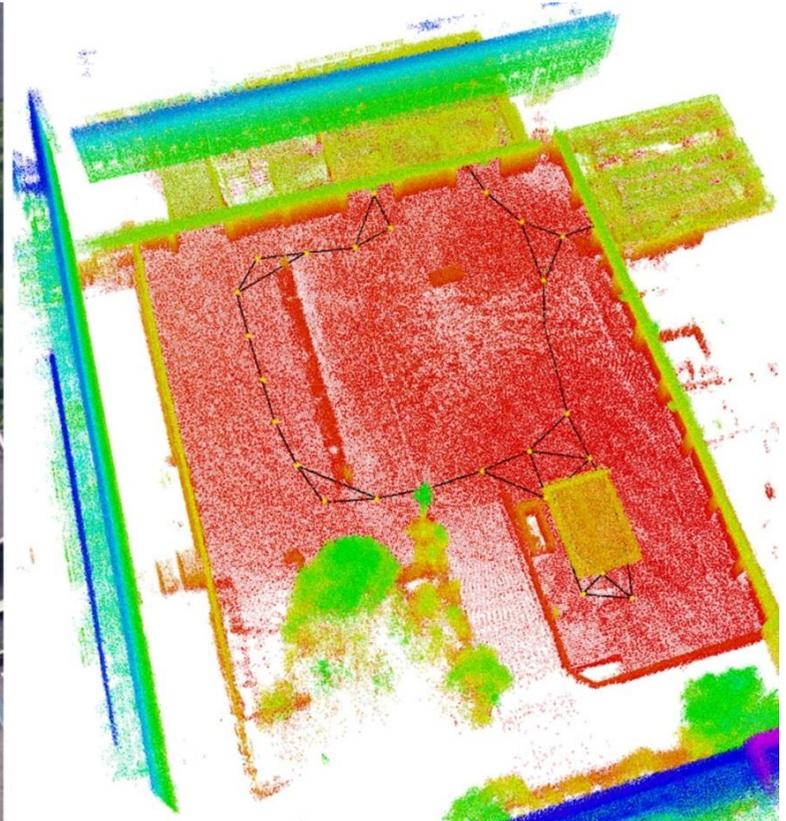


# Improved Sensor Head

- Continuously rotating Velodyne Puck VLP-16
  - 300,000 3D points/s
  - 100 m range
  - Spherical field of view
- Three wide-angle color cameras (total FoV 210×103°)
- Kinect V2 RGB-D camera on pan-tilt unit



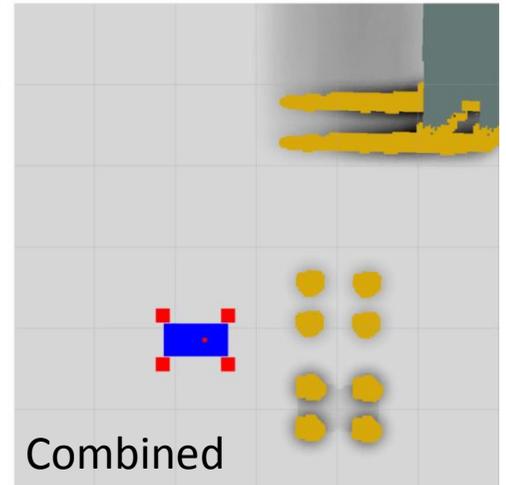
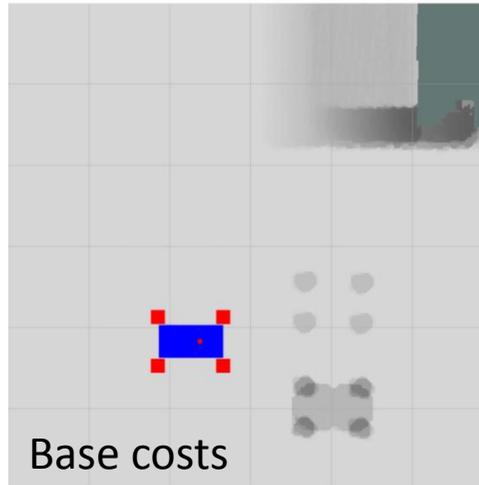
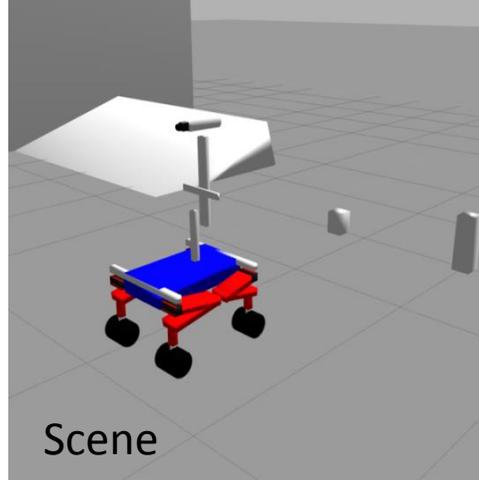
# 3D Map of Indoor+Outdoor Scene



[Droeschel et al., Robotics and Autonomous Systems 2017]

# Considering Robot Footprint

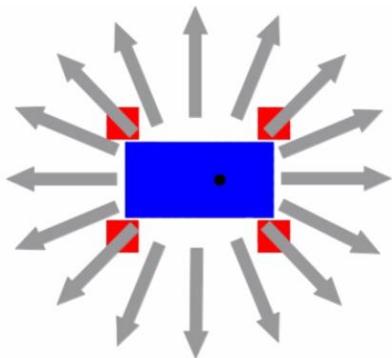
- Costs for individual wheel pairs from height differences
- Base costs
- Non-linear combination yields 3D  $(x, y, \theta)$  cost map



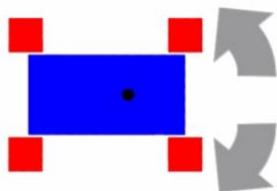
[Klamt and Behnke, IROS 2017]

# 3D Driving Planning ( $x, y, \theta$ ): A\*

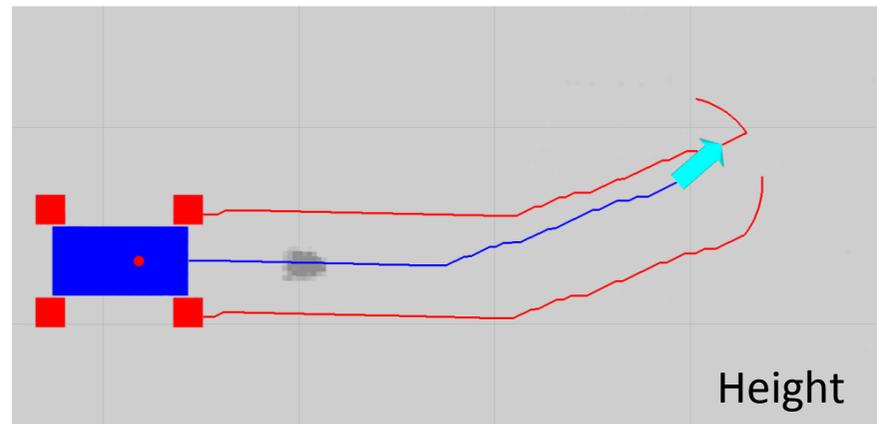
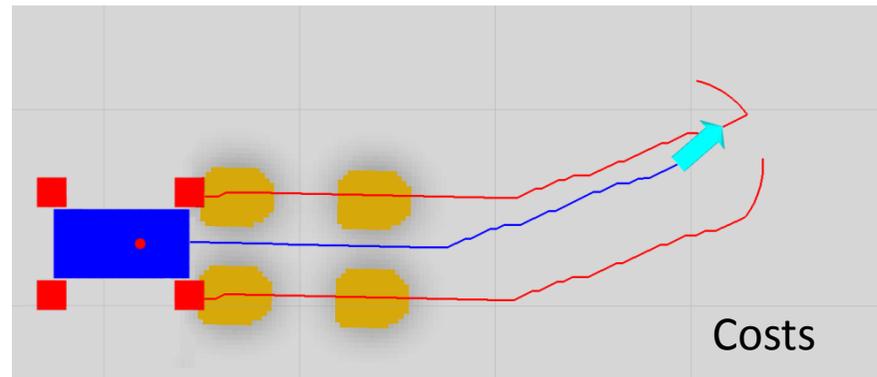
- 16 driving directions



- Orientation changes



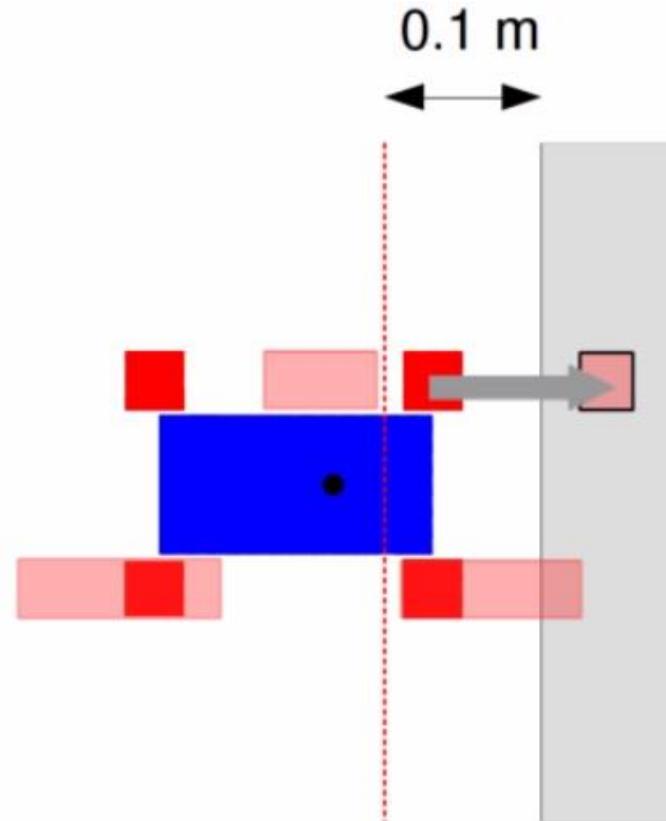
**=> Obstacle between wheels**



[Klamt and Behnke, IROS 2017]

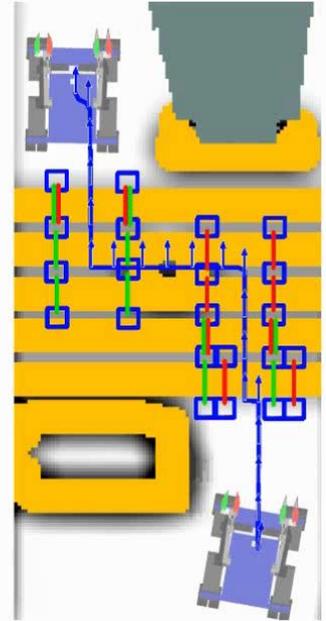
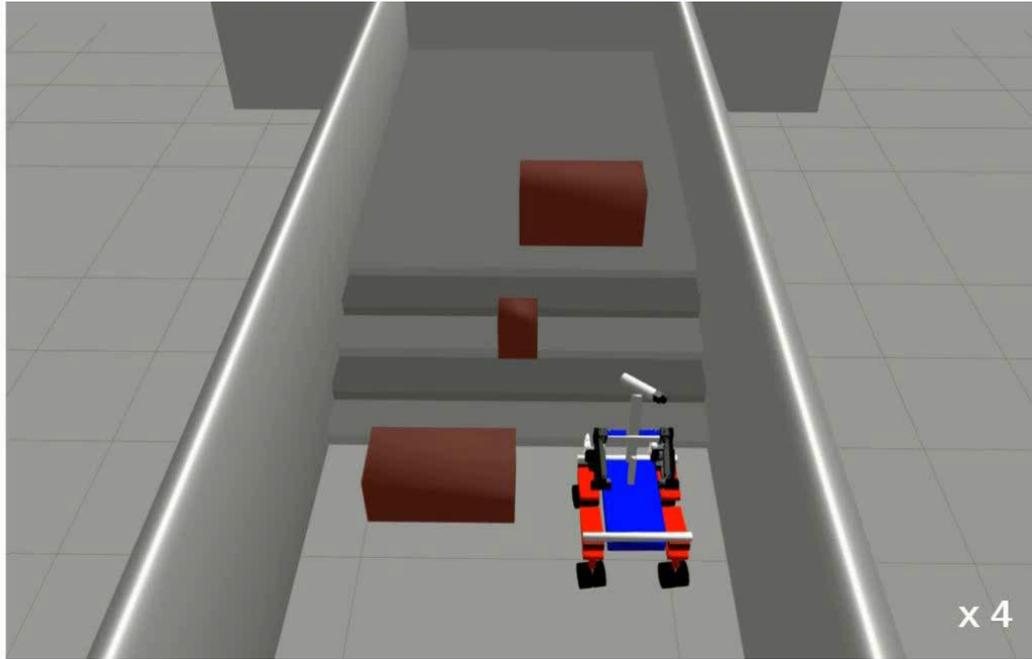
# Making Steps

- If not drivable obstacle in front of a wheel
- Step landing must be drivable
- Support leg positions must be drivable

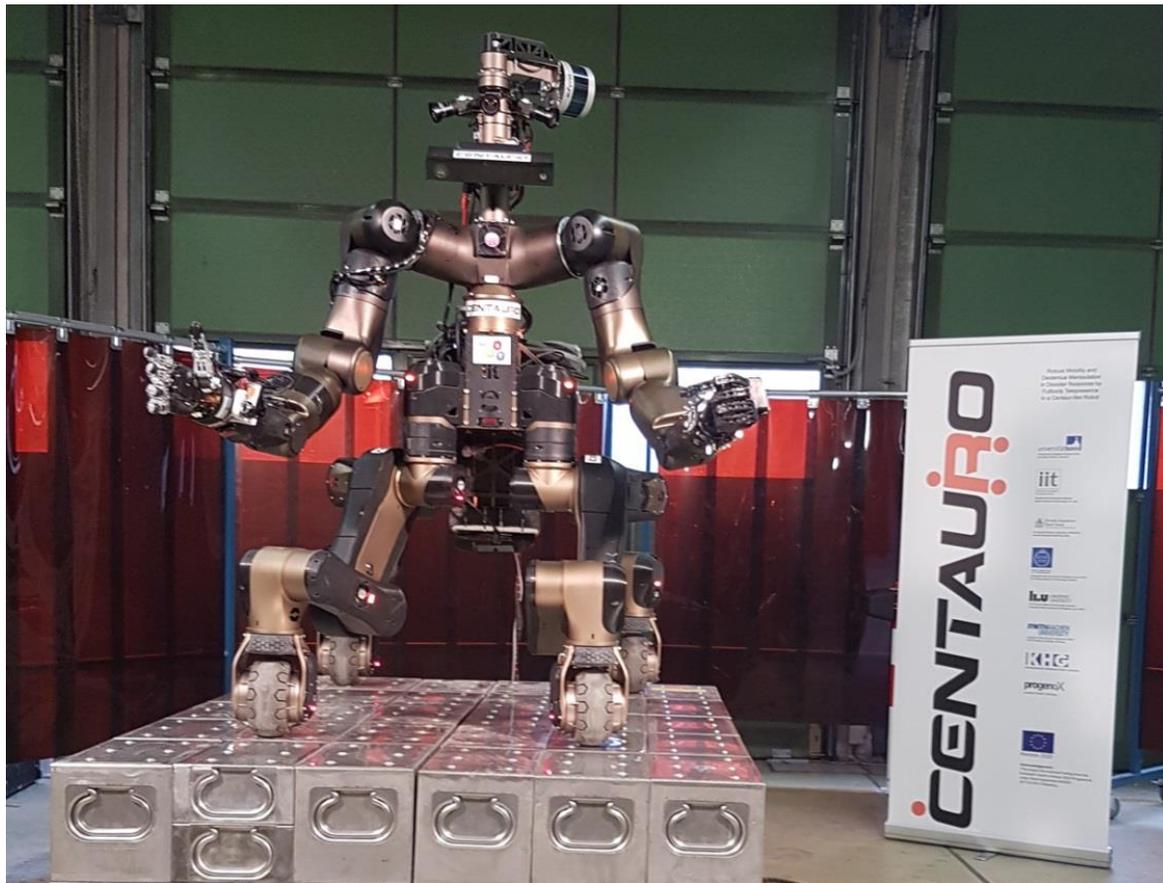


[Klamt and Behnke: IROS 2017]

# Planning for Challenging Scenarios



# Centauro Robot



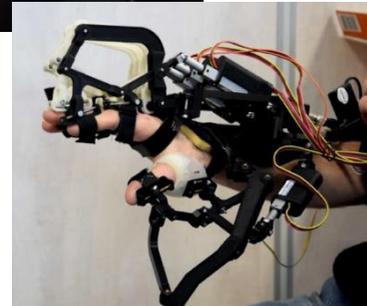
# CENTAURO

- Serial elastic actuators
- 42 main DoFs
- Schunk hand
- 3D laser
- RGB-D camera
- Color cameras
- Two GPU PCs

[Tsagarakis et al., IIT 2017]

# Main Operator Telepresence Interface

- Tendon-driven dual-arm exoskeleton
- Active wrist with differential tendon transmission
- Underactuated hand exoskeleton
- Head-mounted display
- Foot pedals



# Main Operator Control



## Manipulation Tasks

- Surface
- Valve (lever)
- **Valve (gate)**
- Snap hook
- Fire hose
- 230V connector
- Cutting tool
- Driller
- Screw driver
- Grasping

## Used control interfaces



Joystick



Exus



6D



Keyframes



Stepping

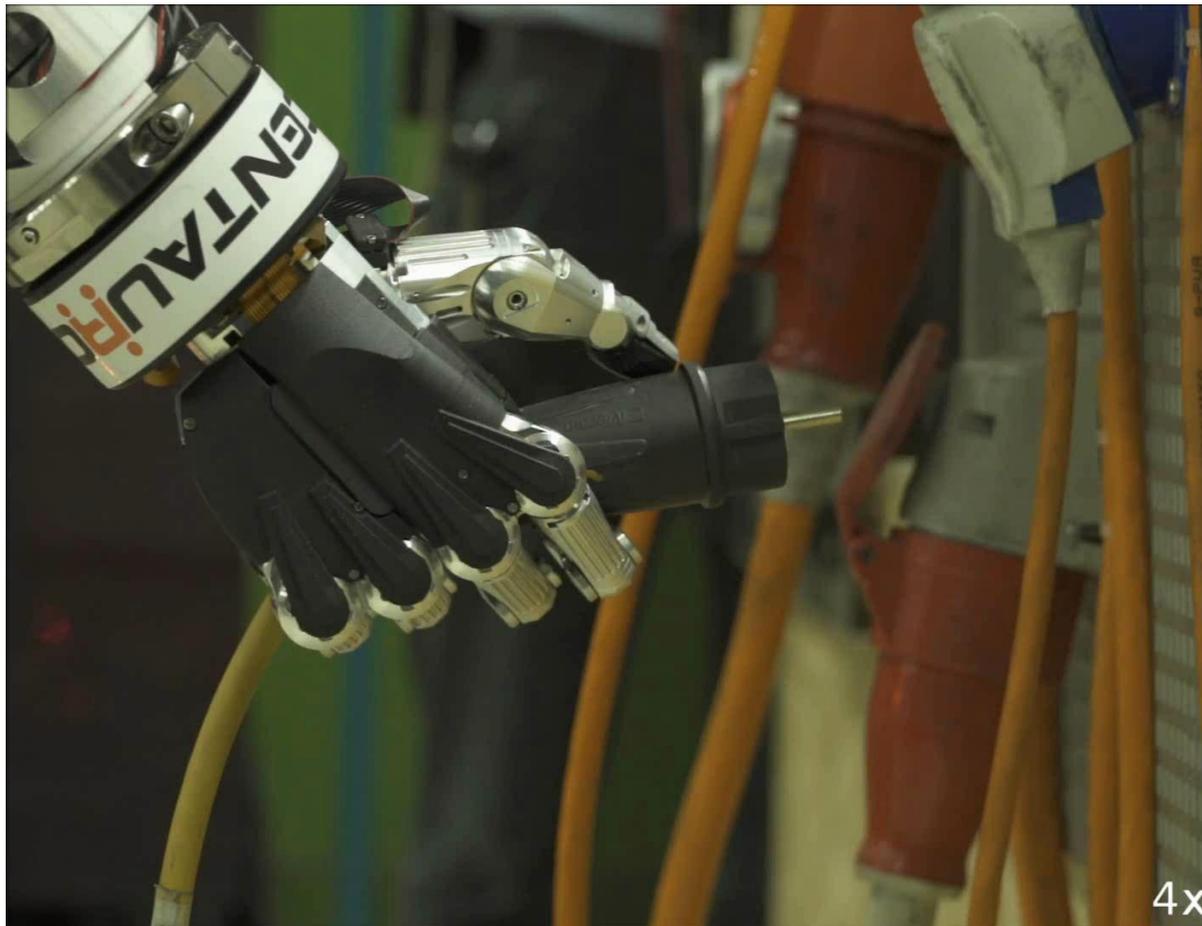


Autonomous

# Turning a Valve



# Connecting a Plug



## Manipulation Tasks

- Surface
- Valve (lever)
- Valve (gate)
- Snap hook
- Fire hose
- 230V connector
- Cutting tool
- Driller
- Screw driver
- Grasping

## Used control interfaces



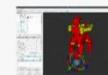
Joystick



Exus



6D



Keyframes

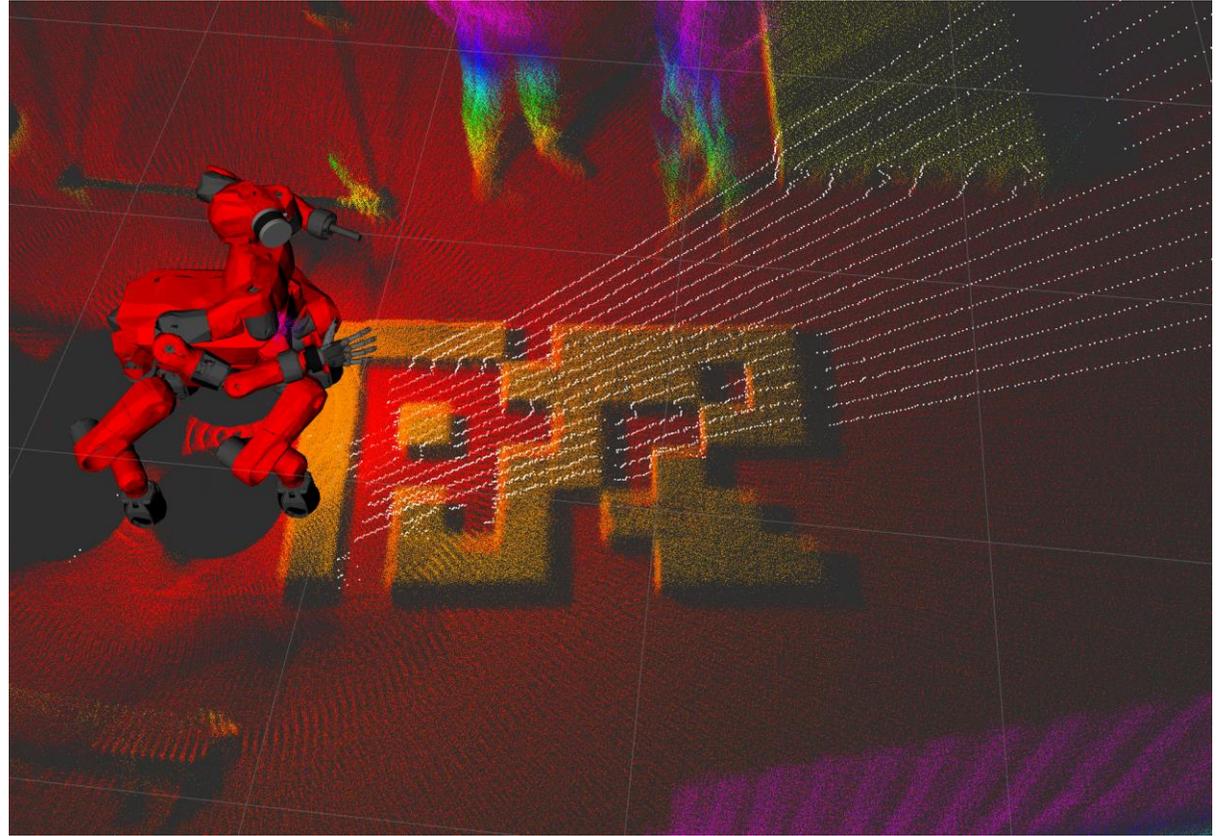


Stepping



Autonomous

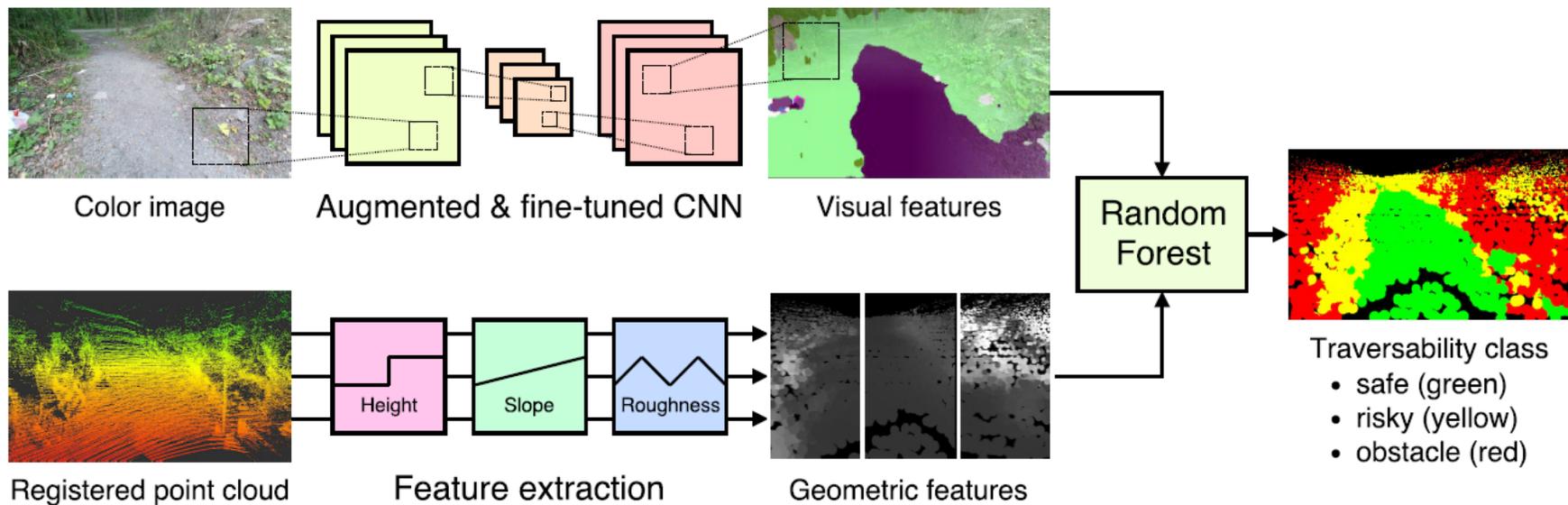
# 3D Mapping and Localization



# Walking over a Step Field

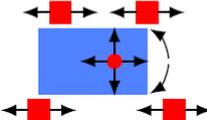
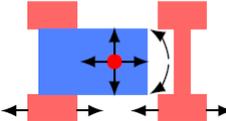
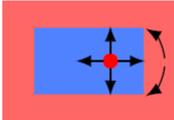


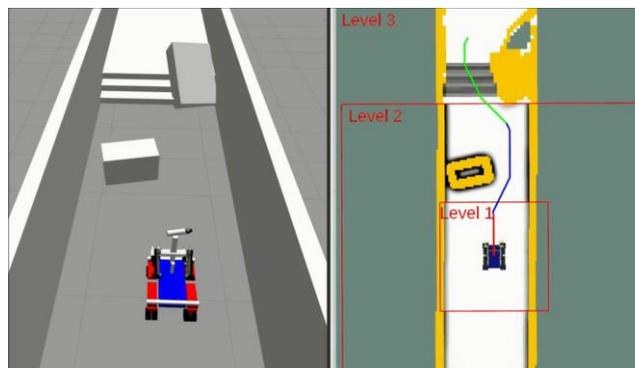
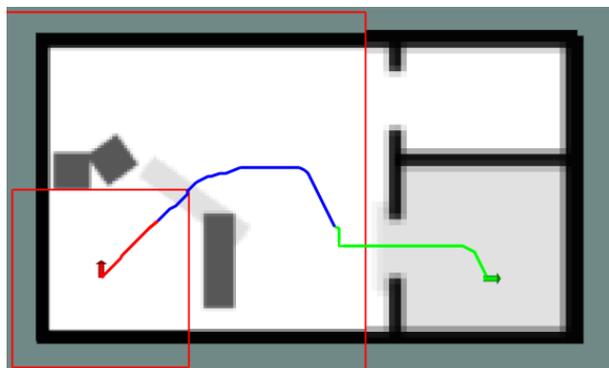
# Terrain Classification



[Schilling et al., IROS 2017]

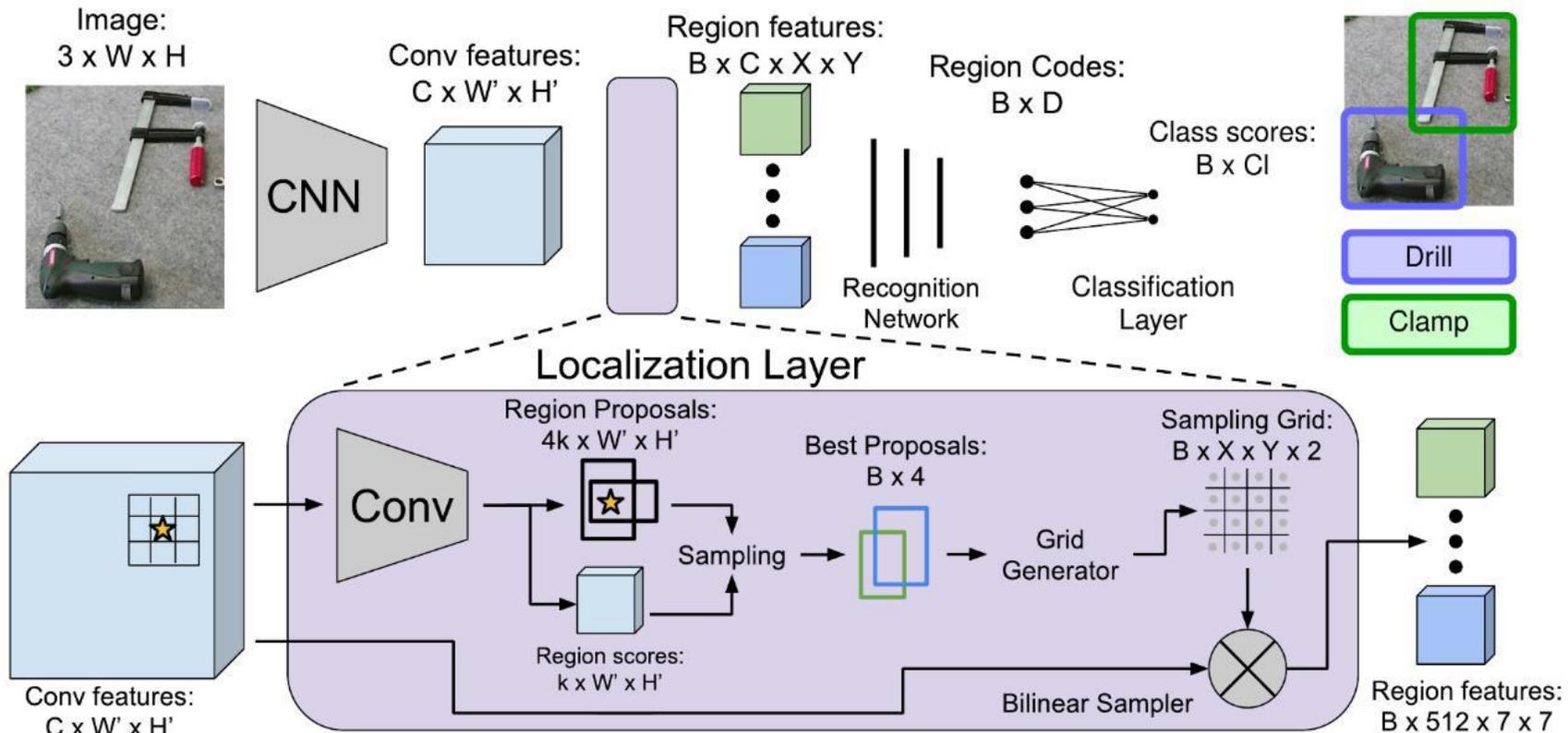
# Hybrid Driving-Stepping Locomotion Planning: Abstraction

Level	Map Resolution	Map Features	Robot Representation	Action Semantics
1	<ul style="list-style-type: none"> <li>• 2.5 cm</li> <li>• 64 orient.</li> </ul>	<ul style="list-style-type: none"> <li>• Height</li> </ul>		<ul style="list-style-type: none"> <li>• Individual Foot Actions</li> </ul>
2	<ul style="list-style-type: none"> <li>• 5.0 cm</li> <li>• 32 orient.</li> </ul>	<ul style="list-style-type: none"> <li>• Height</li> <li>• Height Difference</li> </ul>		<ul style="list-style-type: none"> <li>• Foot Pair Actions</li> </ul>
3	<ul style="list-style-type: none"> <li>• 10 cm</li> <li>• 16 orient.</li> </ul>	<ul style="list-style-type: none"> <li>• Height</li> <li>• Height Difference</li> <li>• Terrain Class</li> </ul>		<ul style="list-style-type: none"> <li>• Whole Robot Actions</li> </ul>



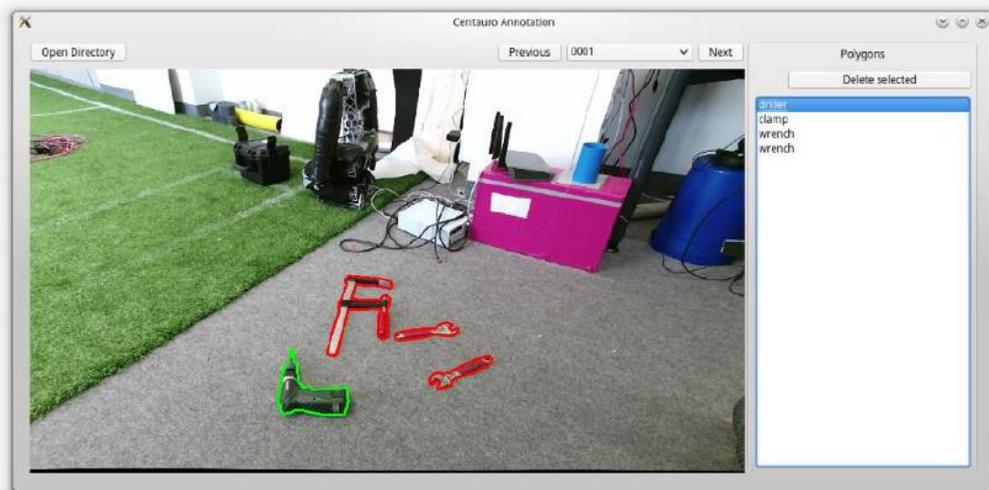
[Klamt and Behnke,  
IROS 2017, ICRA 2018]

# Deep Learning Object Detection

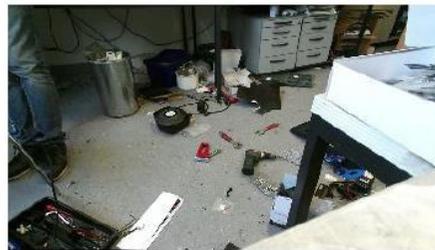


[Johnson et al. 2015]

# CENTAURO Workspace Perception Data Set



129 frames, 6 object classes



[https://www.centauro-project.eu/data\\_multimedia/tools\\_data](https://www.centauro-project.eu/data_multimedia/tools_data)

# Tool Detection Results

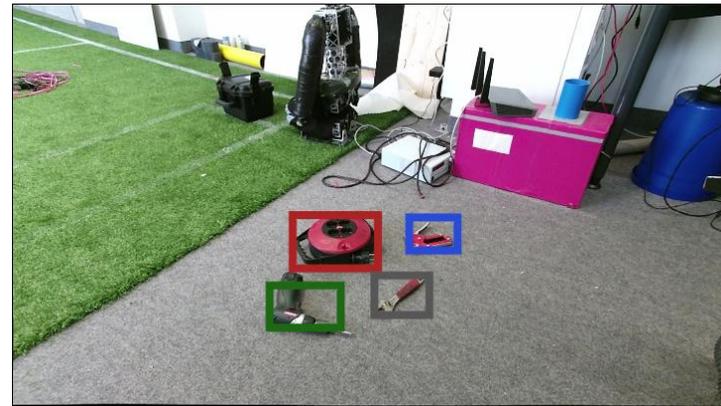
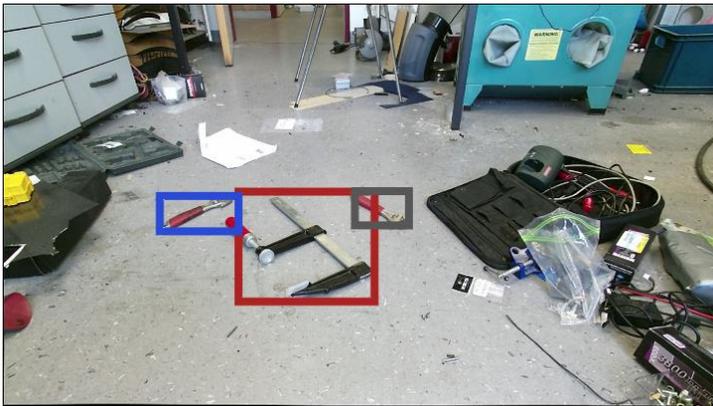


[Schwarz et al. IJRR 2017]

extension\_box stapler driller clamp [background]

Resolution	Clamp	Door handle	Driller	Extension	Stapler	Wrench	Mean
	AP / F1						
720×507	0.881/0.783	0.522/0.554	0.986/0.875	1.000/0.938	0.960/0.814	0.656/0.661	0.834/0.771
1080×760	0.926/0.829	0.867/0.632	0.972/0.893	1.000/0.950	0.992/0.892	0.927/0.848	0.947/0.841
1470×1035	0.913/0.814	0.974/0.745	1.000/0.915	1.000/0.952	0.999/0.909	0.949/0.860	0.973/0.866

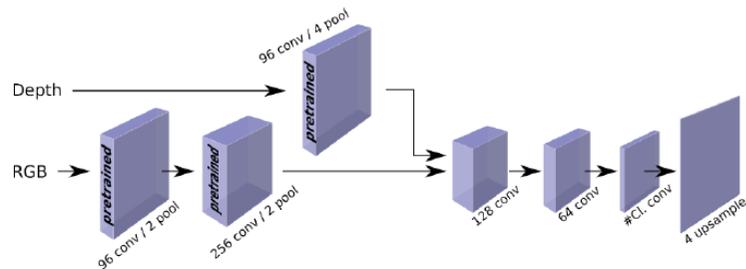
# Tools Detection Examples



[Schwarz et al. IJRR 2017]

# Semantic Segmentation

## ■ Deep CNN



[Husain et al. RA-L 2016]

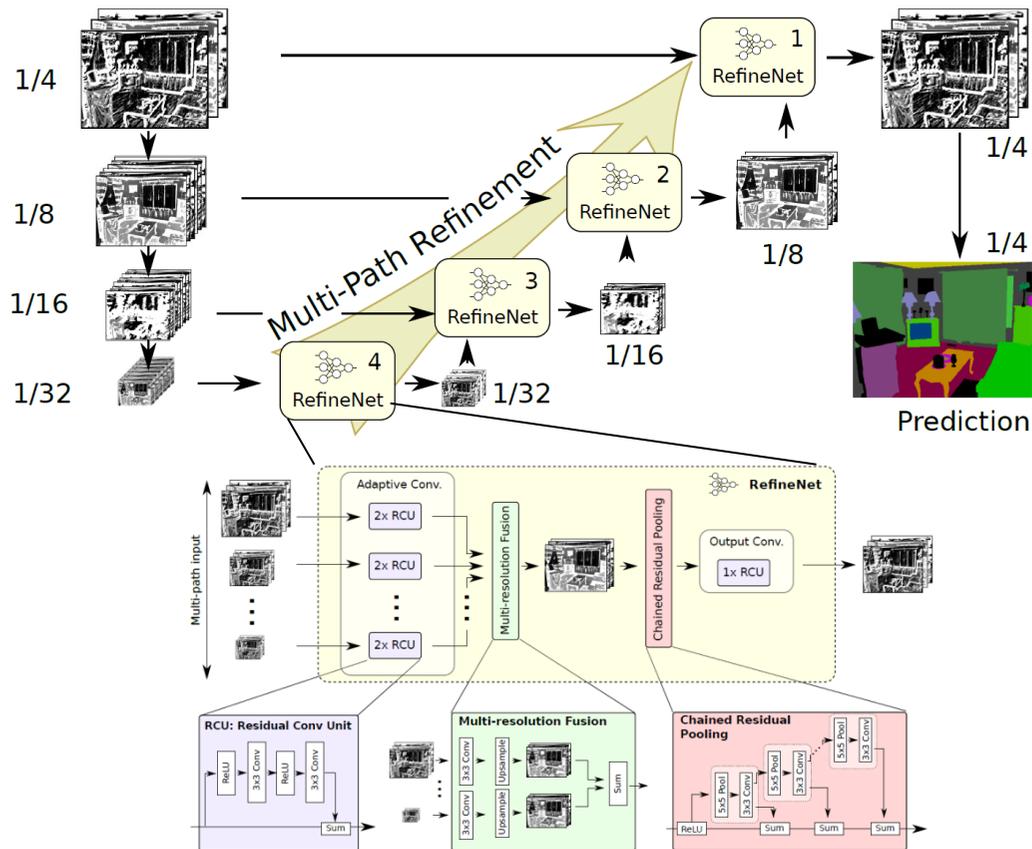


Pixel-wise accuracy:

Clamp	Door handle	Driller	Extension	Stapler	Wrench	Background	Mean
0.727	0.751	0.769	0.889	0.775	0.734	0.992	0.805

# RefineNet for Semantic Segmentation

- Scene represented as feature hierarchy
- Coarse-to-fine semantic segmentation
- Combine higher-level features with missing details



[Lin et al. CVPR 2017]

# The Data Problem

- Deep Learning in robotics (still) suffers from shortage of available examples
- We address this problem in two ways:

## 1. Generating data:

Automatic data capture,  
online mesh databases,  
scene synthesis

## 2. Improving generalization:

Object-centered models,  
deformable registration,  
transfer learning,  
semi-supervised learning



# Object Capture and Scene Rendering

## ■ Turntable + DLSR camera



## ■ Rendered scenes



[Schwarz et al. ICRA 2018]

# Semantic Segmentation Example



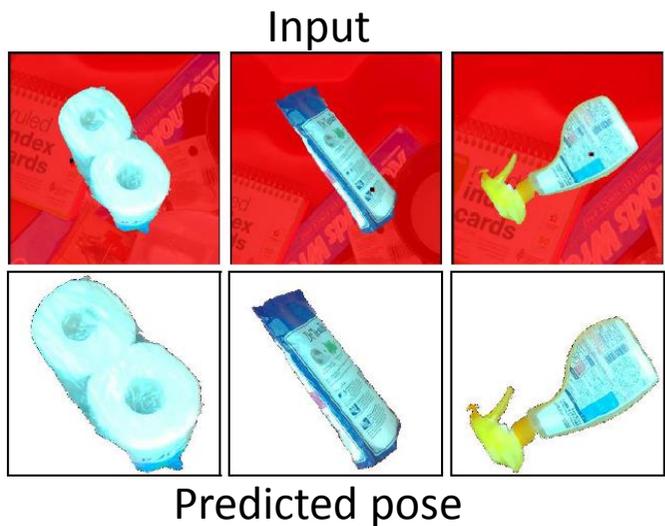
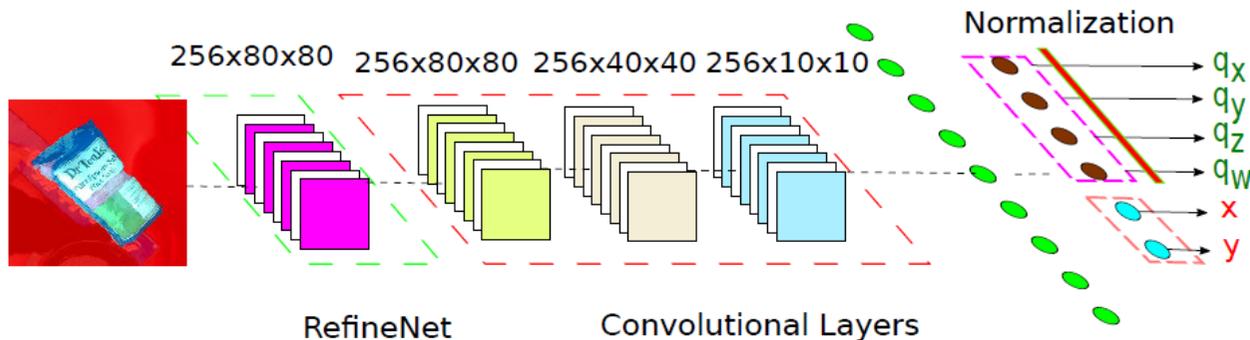
- bronze\_wire\_cup  
conf: 0.749401
- irish\_spring\_soap  
conf: 0.811500
- playing\_cards  
conf: 0.813761
- w\_aquarium\_gravel  
conf: 0.891001
- crayons  
conf: 0.422604
- reynolds\_wrap  
conf: 0.836467
- paper\_towels  
conf: 0.903645
- white\_facecloth  
conf: 0.895212
- hand\_weight  
conf: 0.928119
- robots\_everywhere  
conf: 0.930464



- mouse\_traps  
conf: 0.921731
- windex  
conf: 0.861246
- q-tips\_500  
conf: 0.475015
- fiskars\_scissors  
conf: 0.831069
- ice\_cube\_tray  
conf: 0.976856

# Object Pose Estimation

- Cut out individual segments
- Use upper layer of RefineNet as input
- Predict pose coordinates



# From Turntable Captures to Textured Meshes



Fused & textured result



# Transfer of Manipulation Skills

- Objects belonging to the same **category** can be handled in a very similar manner.



# Transfer of Manipulation Skills

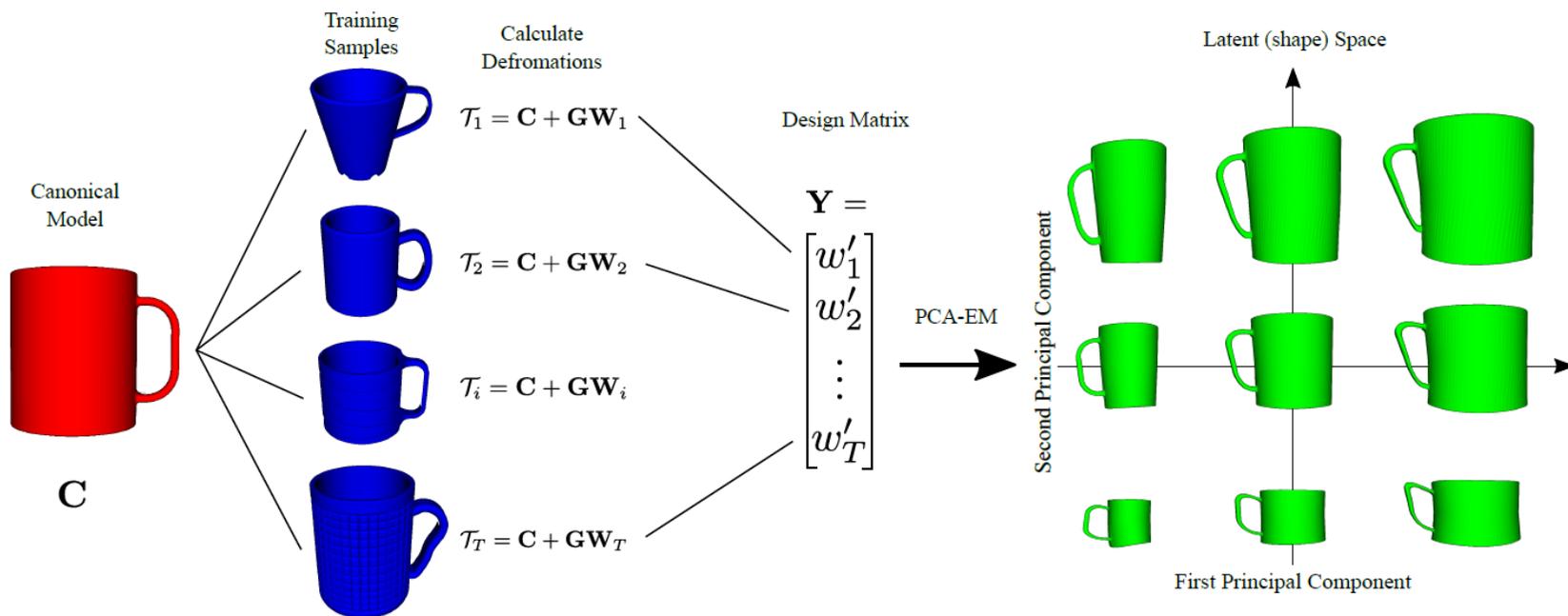


Knowledge  
Transfer

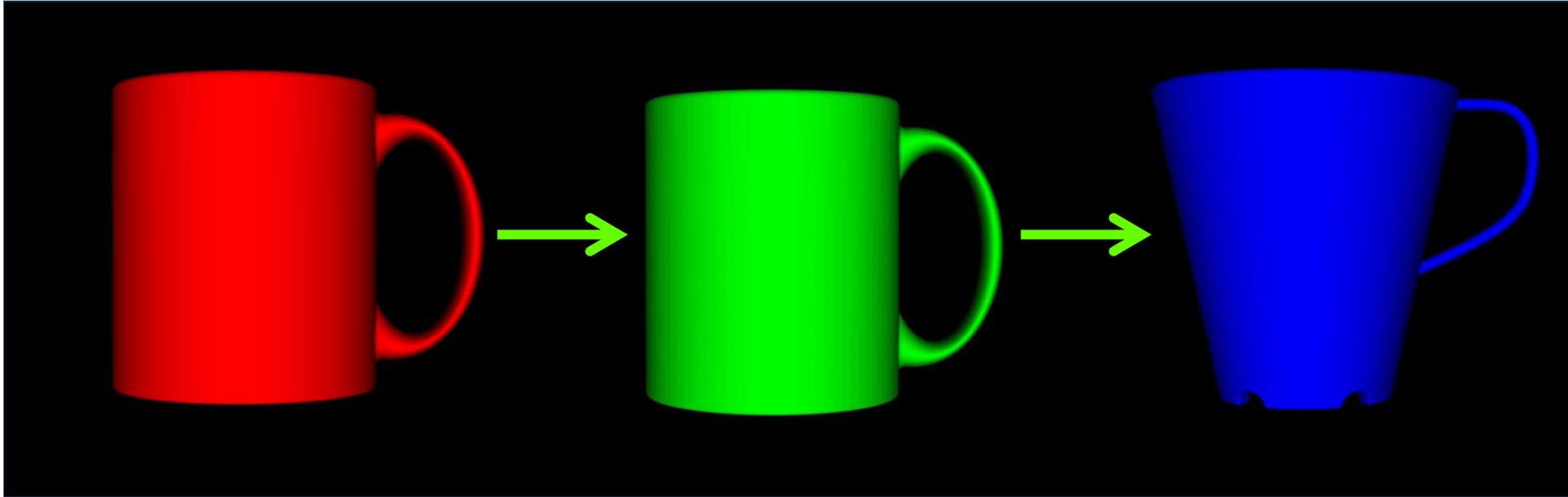


# Learning a Latent Shape Space

- Non-rigid registration of instances and canonical model
- Principal component analysis of deformations

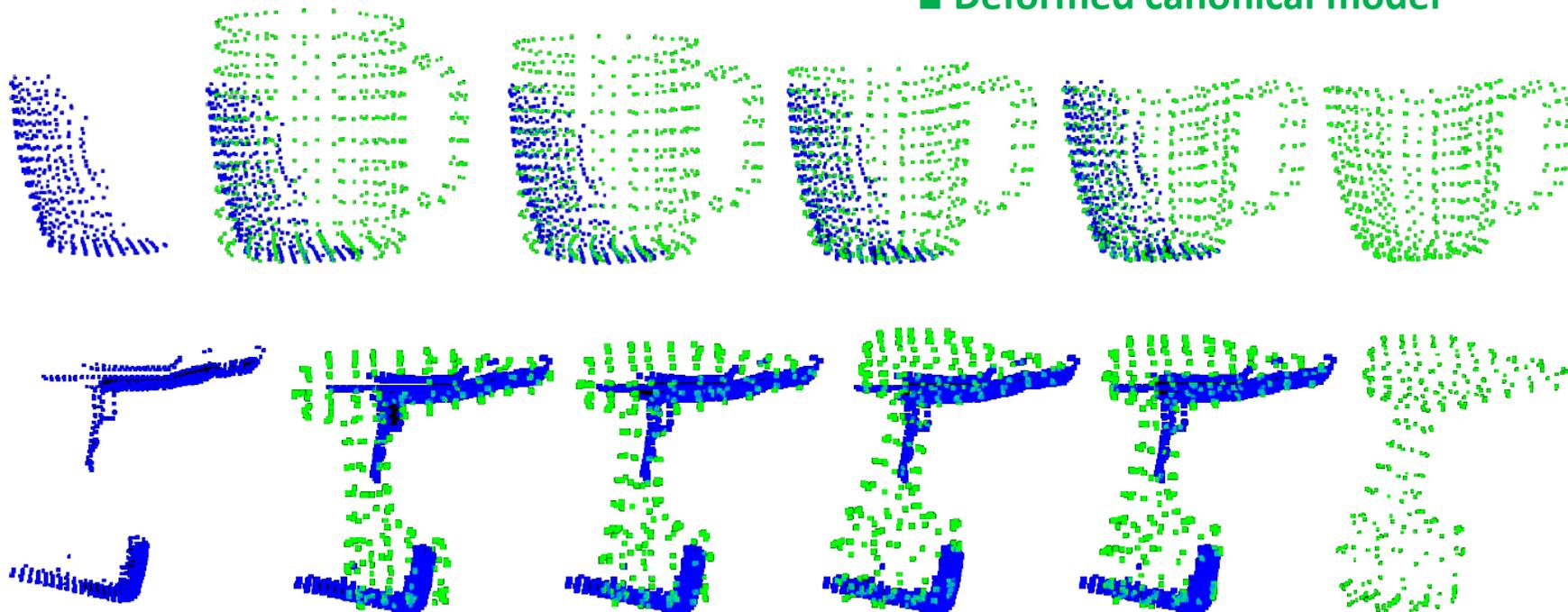


# Interpolation in Shape Space



# Shape-aware Non-rigid Registration

- Partial view of novel instance
- Deformed canonical model

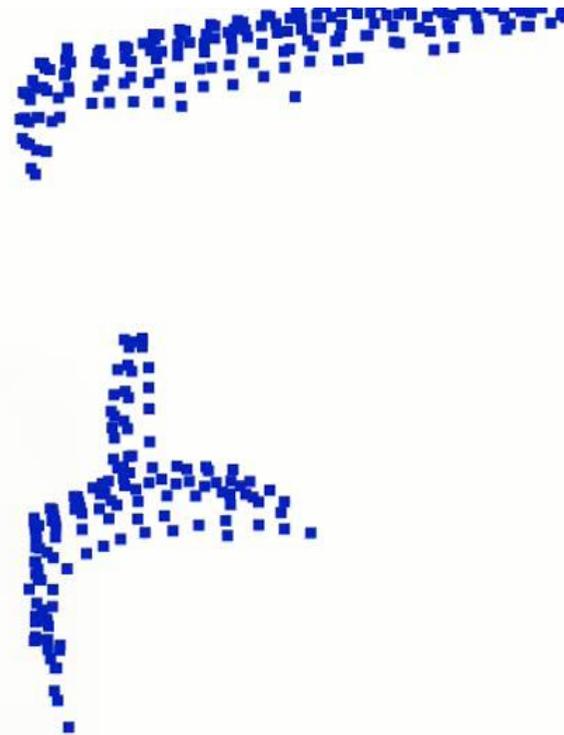


# Shape-aware Registration for Grasp Transfer

■ Full point cloud



■ Partial view



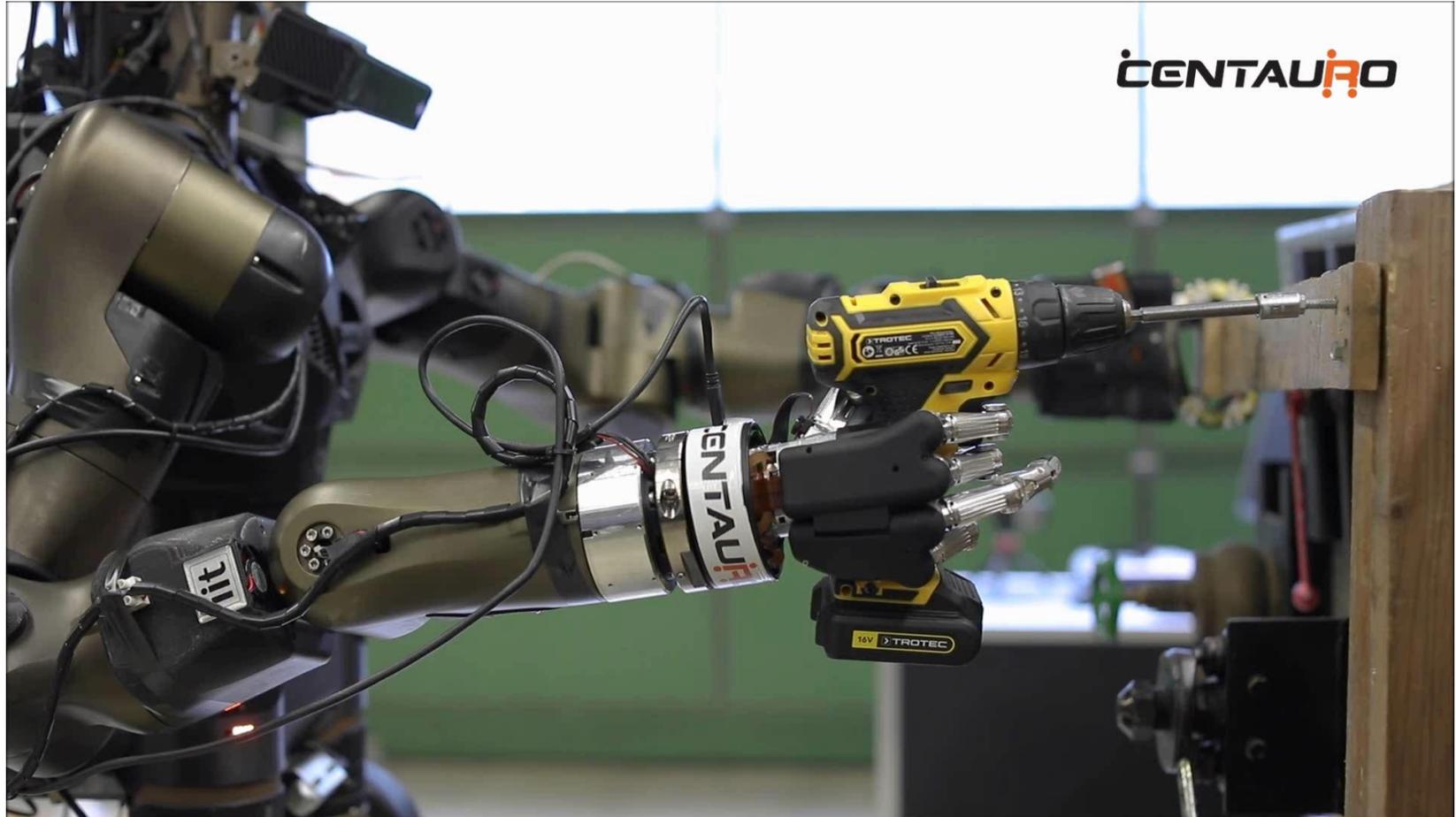
# Grasping an Unknown Power Drill



# Fastening a Screw



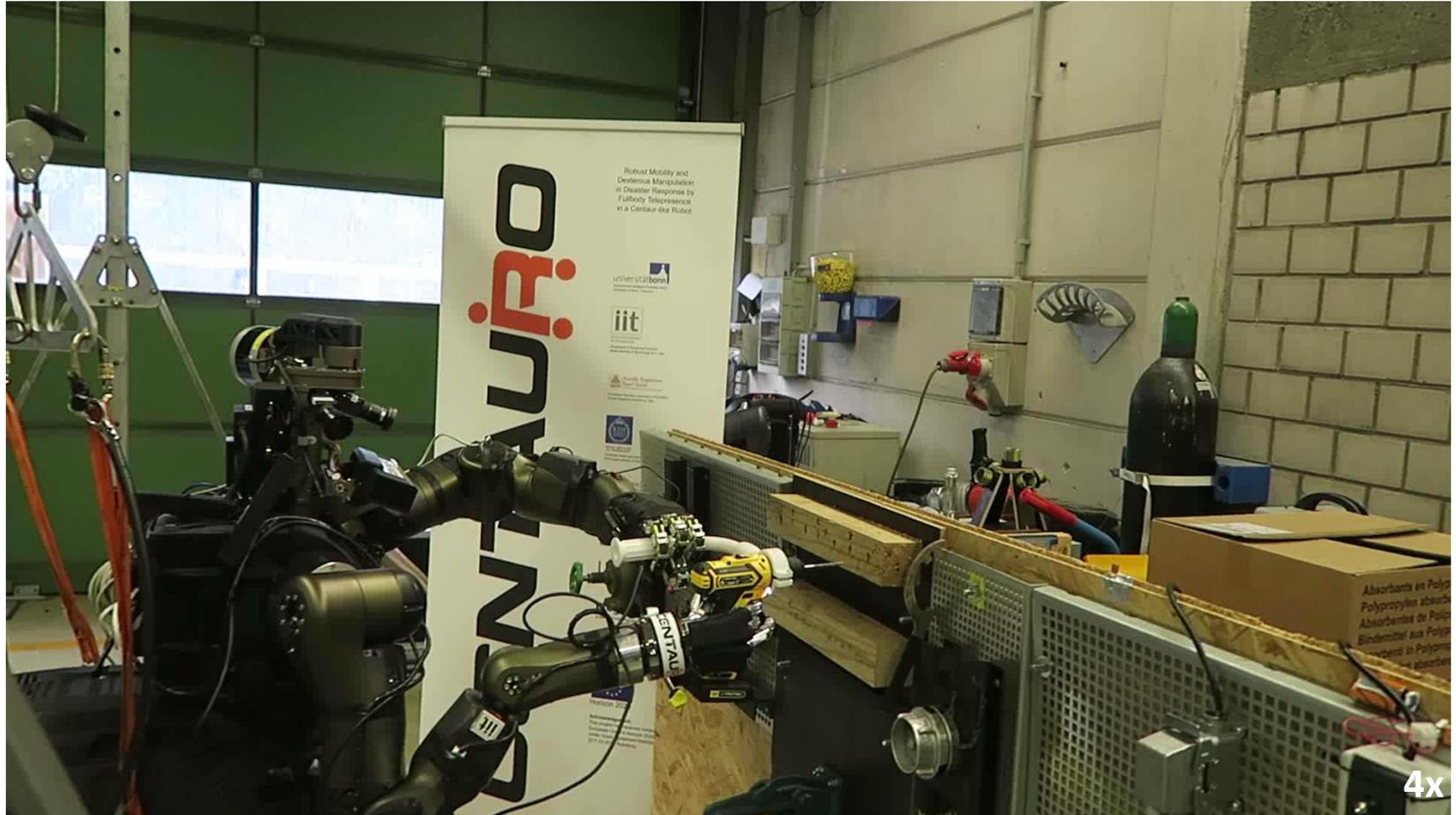
# Bimanual Fastening Task



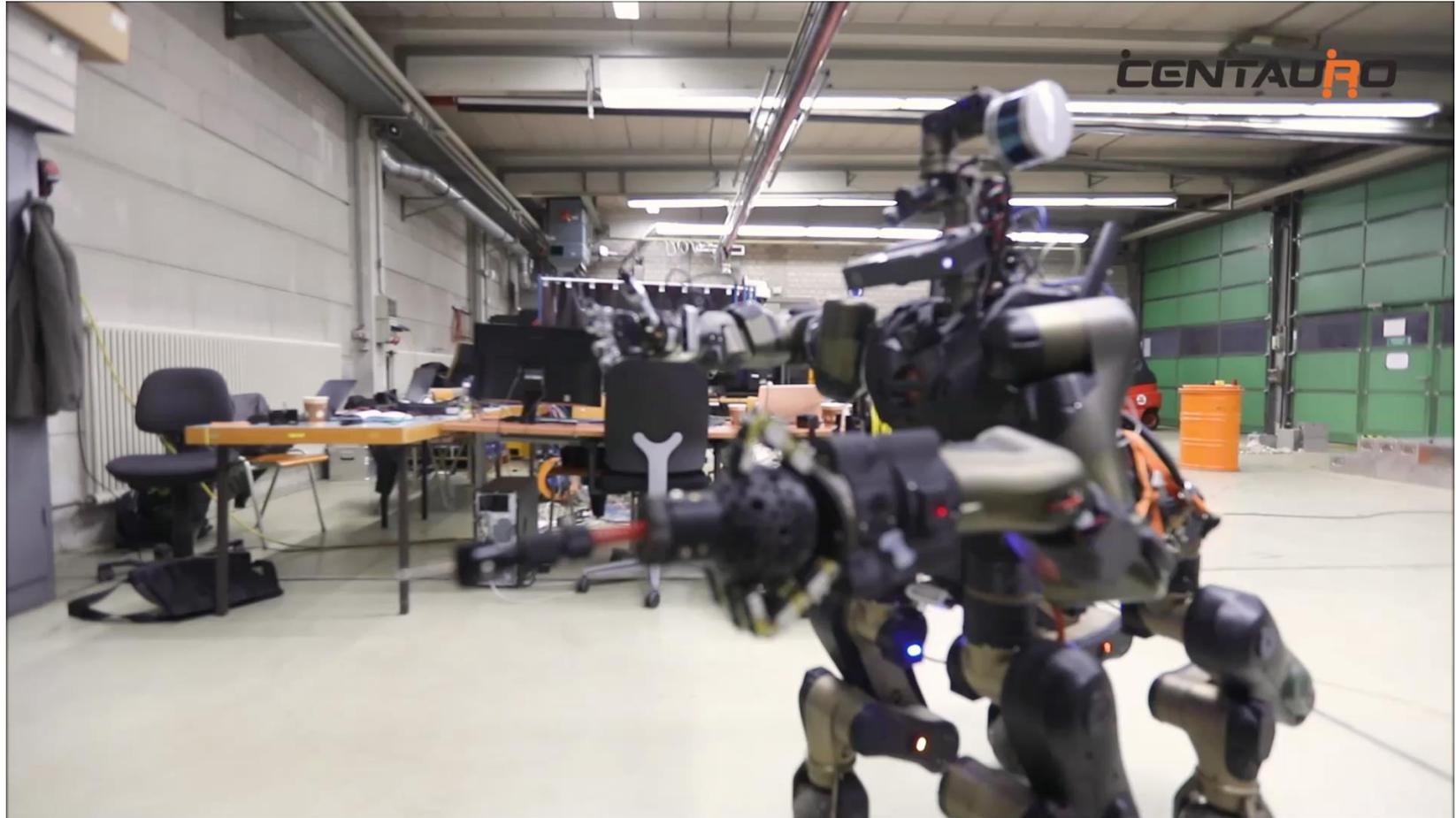
# Bimanual Grasping



# Bimanual Drilling



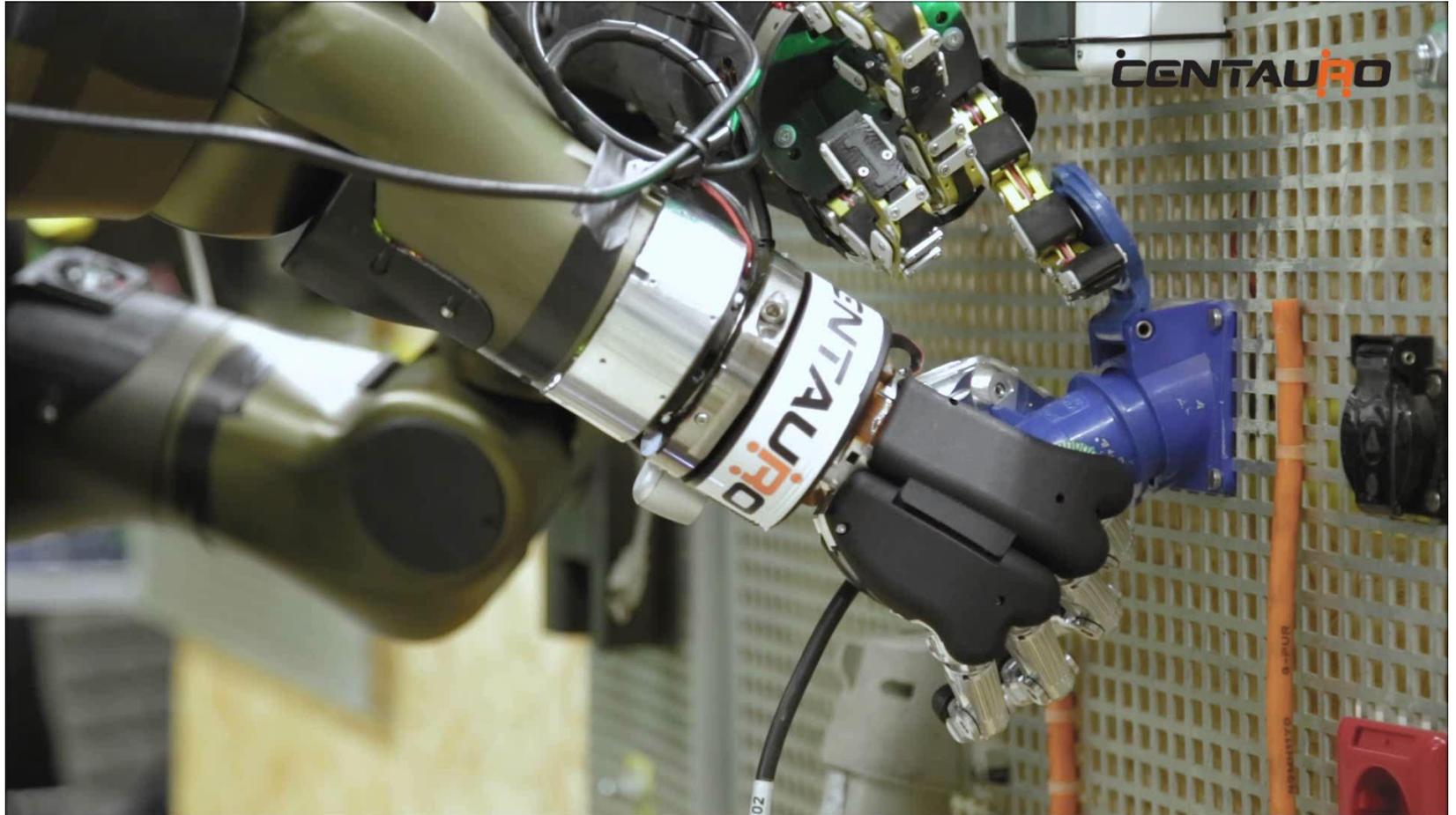
# Opening a Door with a Key



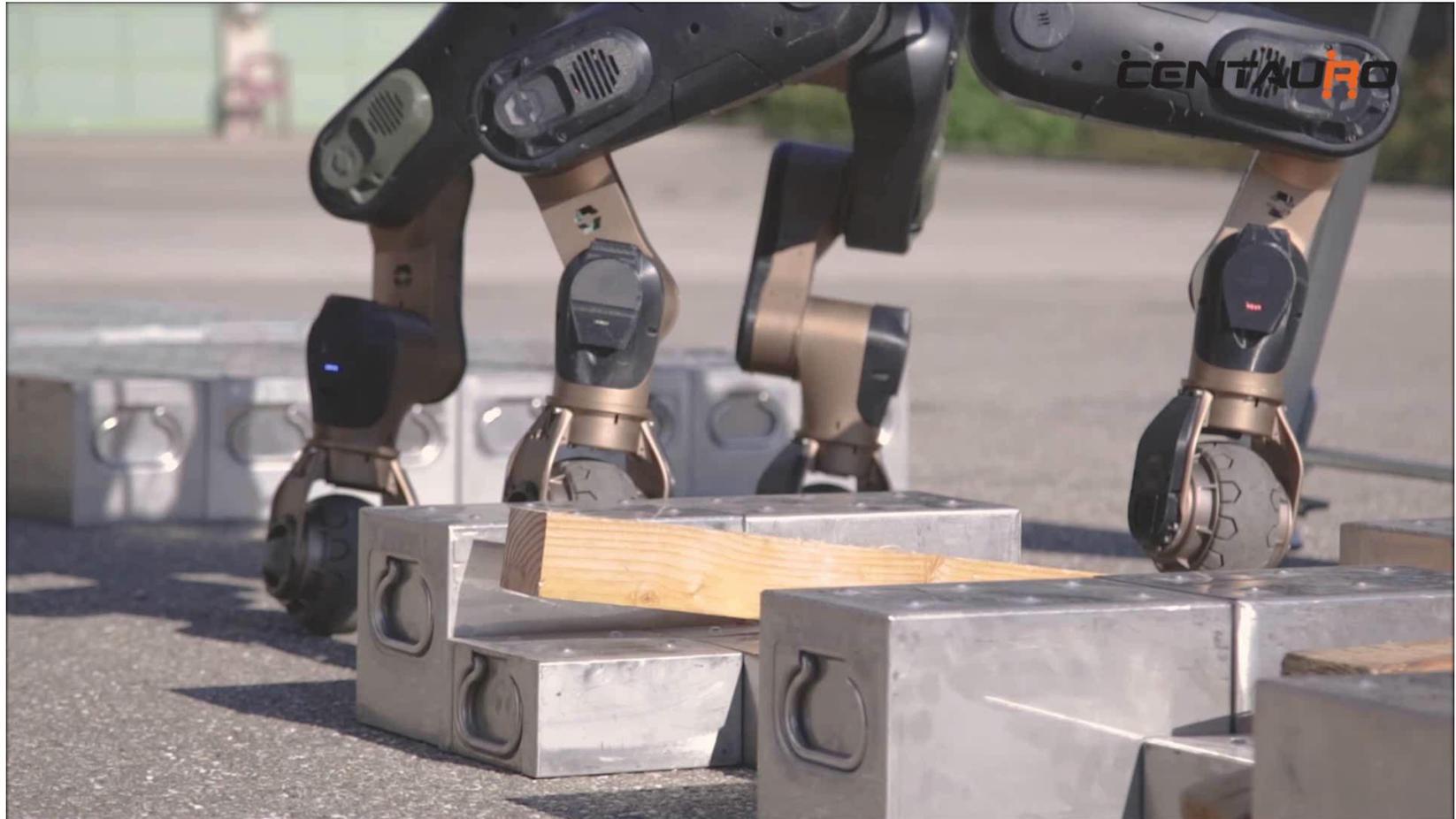
# Closing a Shackle



# Bimanual Plug Tasks



# Step Field with Debris



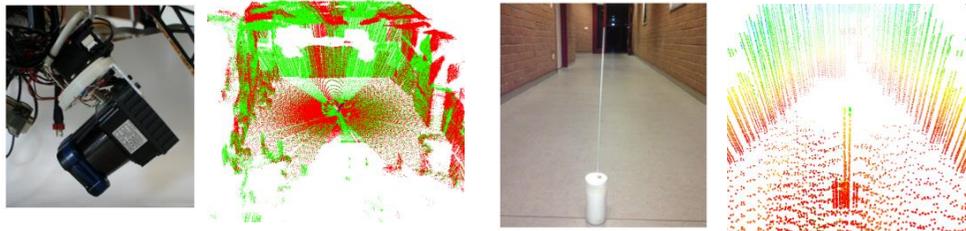
# Autonomous Navigation



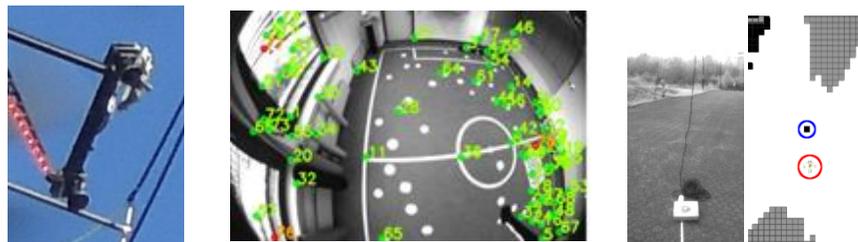
# Autonomous Flight Near Obstacles

## Multimodal obstacle detection

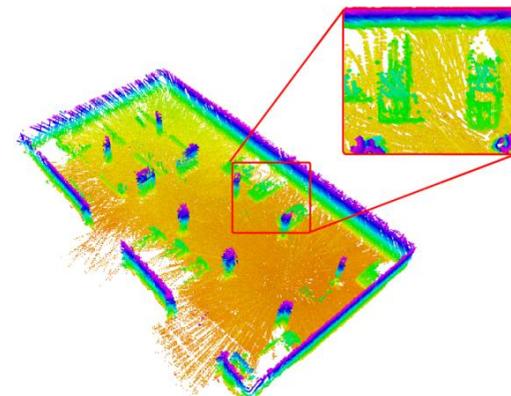
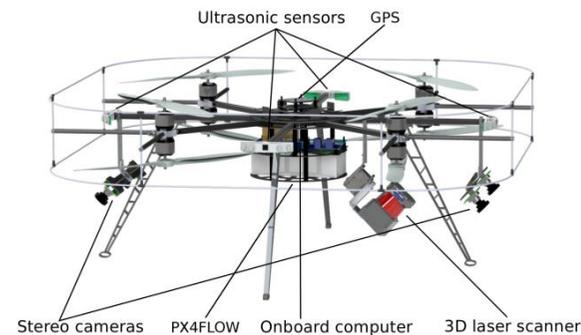
### ■ 3D laser scanner



### ■ Stereo cameras



### ■ Ultrasound

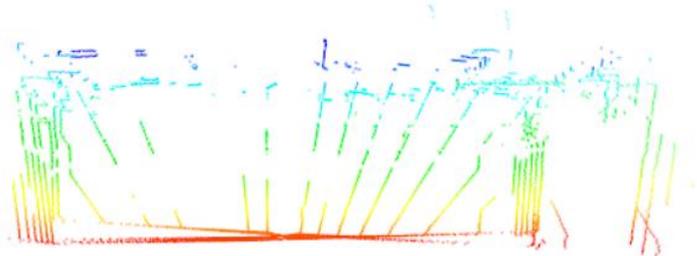


[Droeschel et al.: Journal of Field Robotics, 2015]

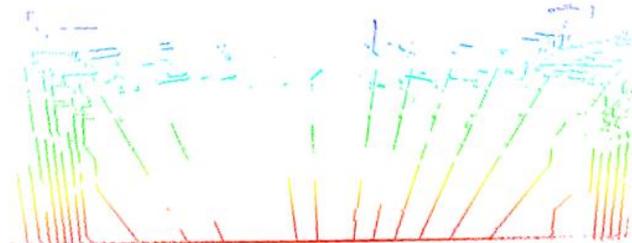
# Egocentric Laser-based 3D Mapping

## ■ Motion compensation

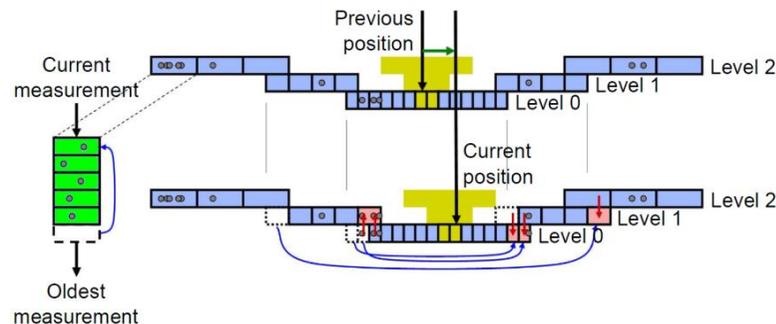
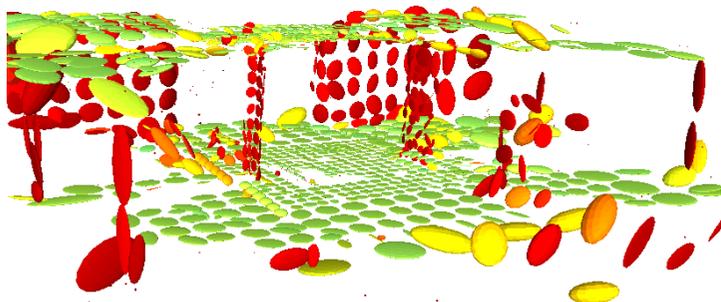
Distorted



Undistorted

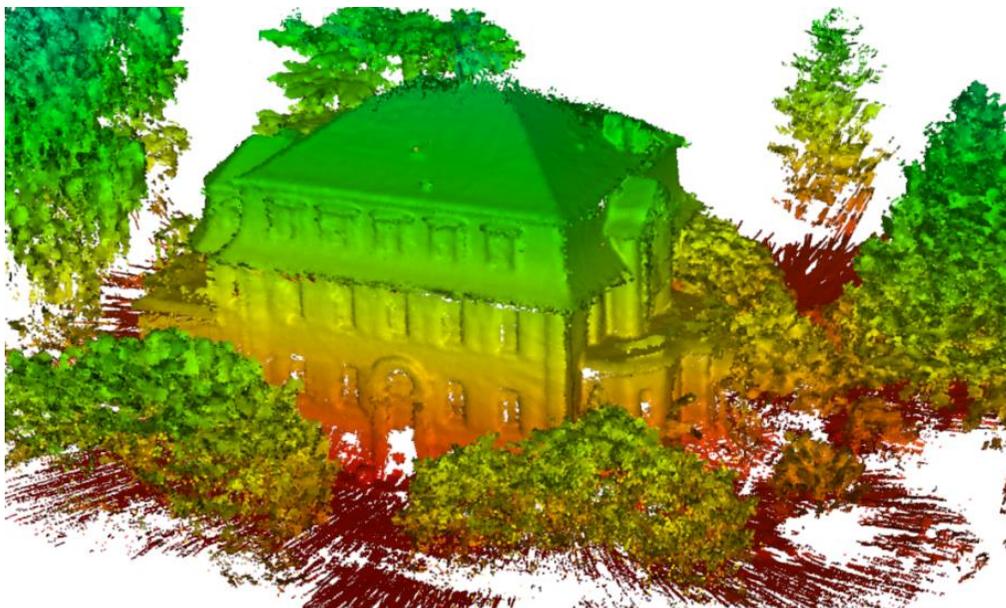


## ■ Local multiresolution surfel maps



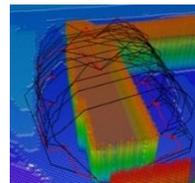
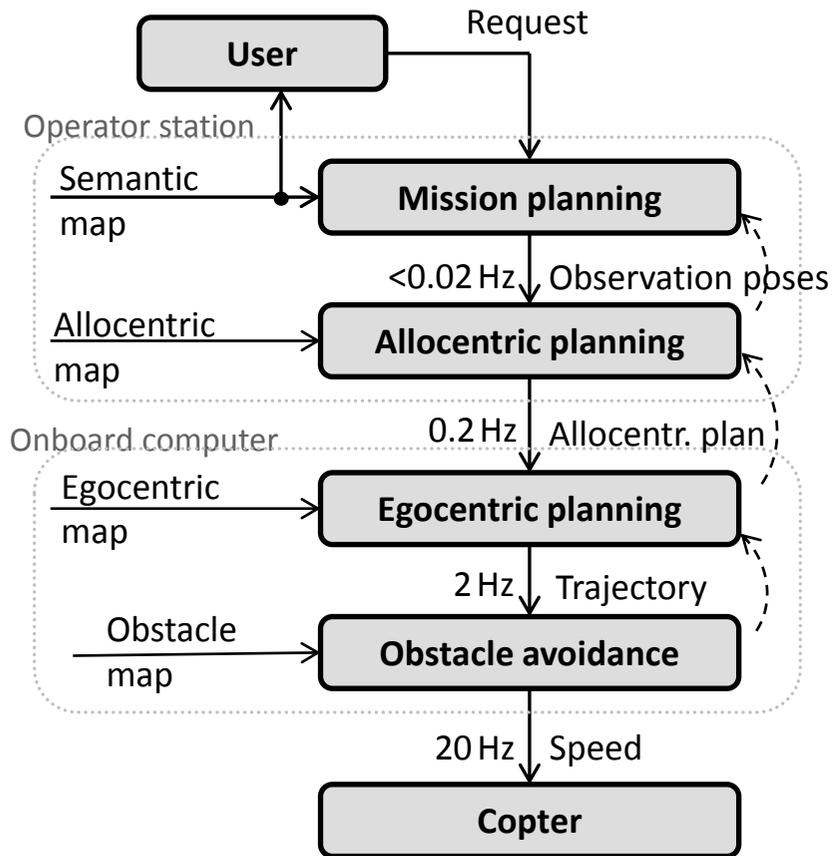
# Allocentric 3D Map

- Registration of egocentric maps
- Global optimization of registration error by GraphSLAM

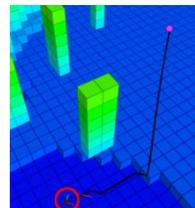


[Droeschel et al. JFR 2016]

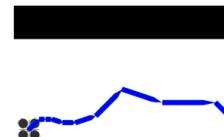
# Hierarchical Navigation



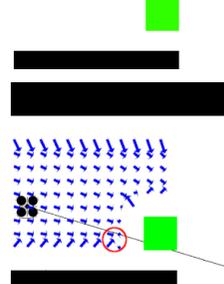
Mission plan



Allocentric planning



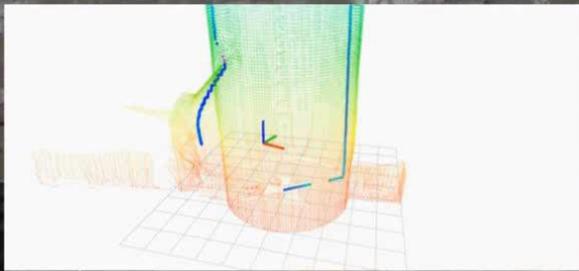
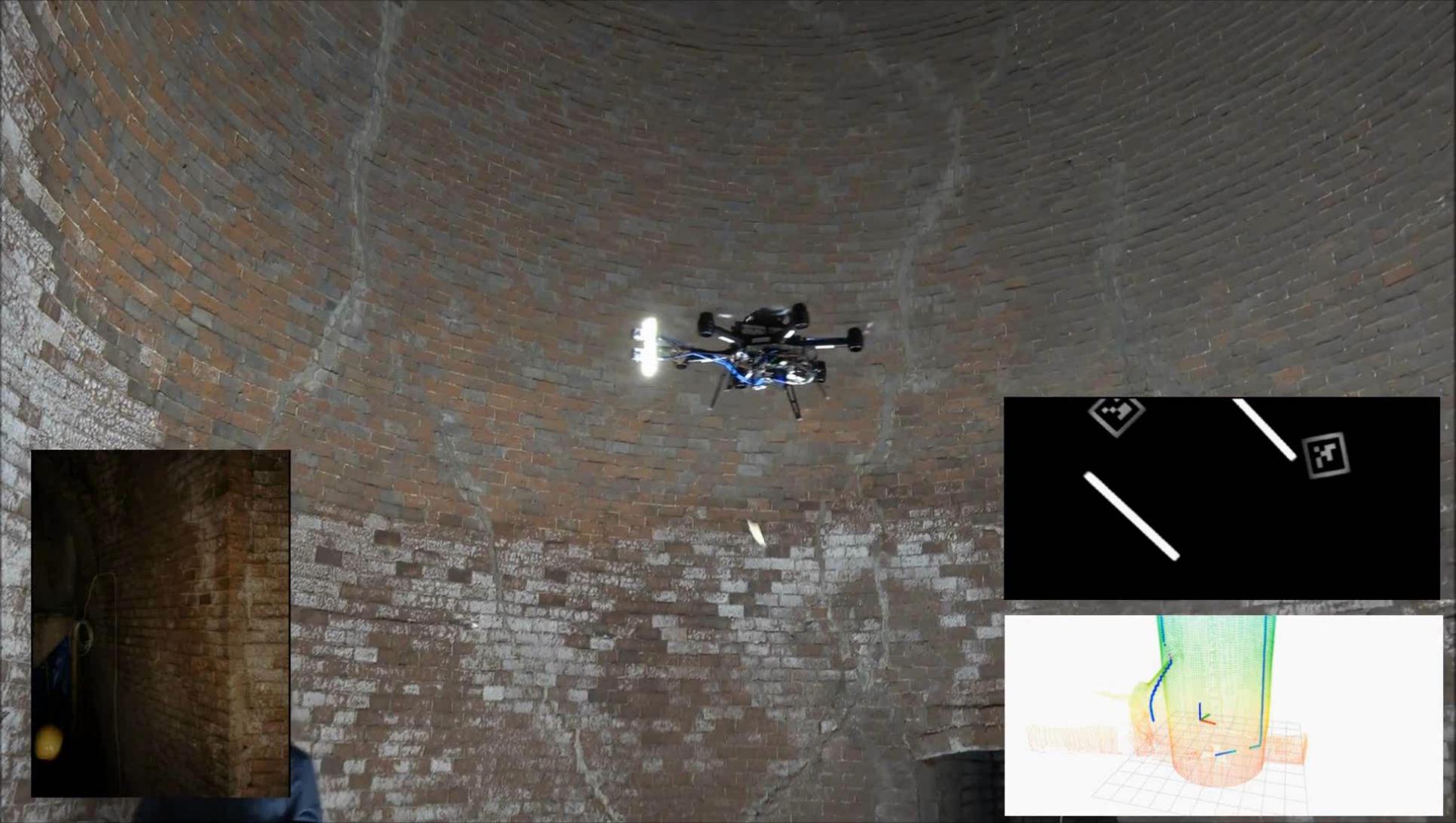
Egocentric planning



Obstacle avoidance

# Mapping on Demand

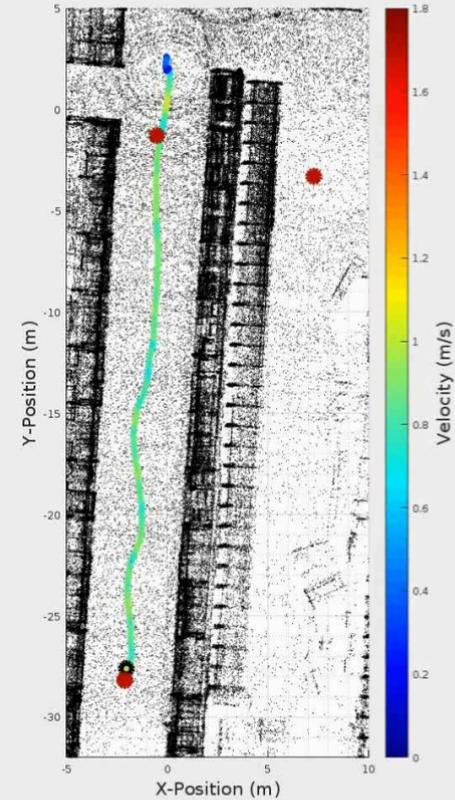
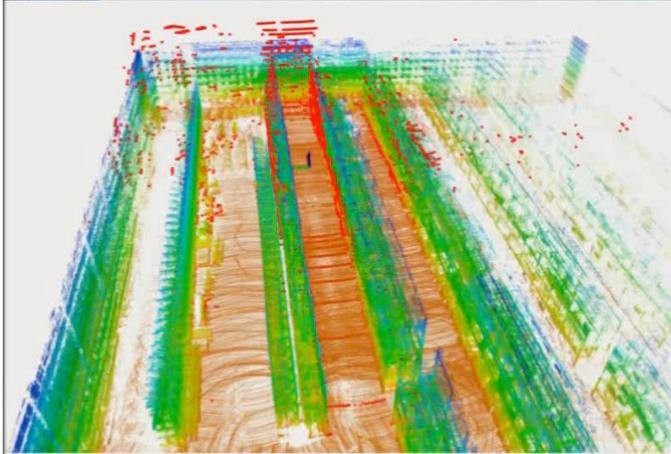
Autonomous Flight to Planned View Poses



# DJI Matrice 600 with Velodyne Puck & Cameras



# InventAIRy: Autonomous Navigation in a Warehouse

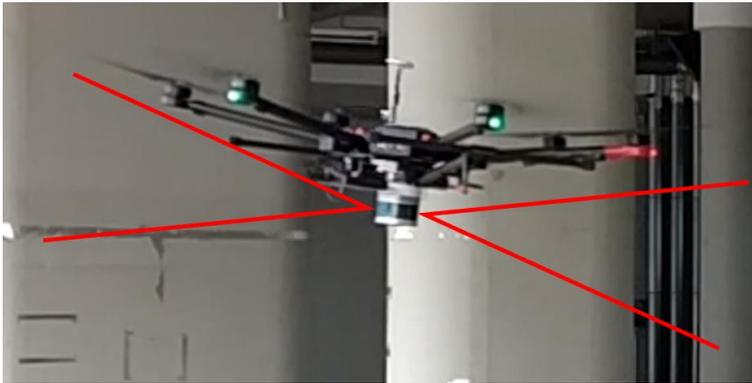


# InventAIRy: Detected Tags in Shelf

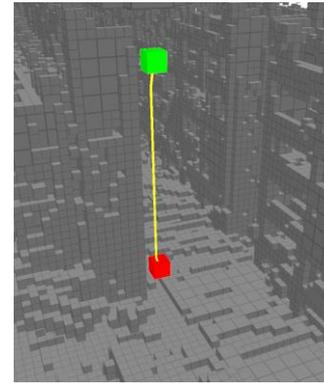


# Navigation Planning with Visibility Constraints

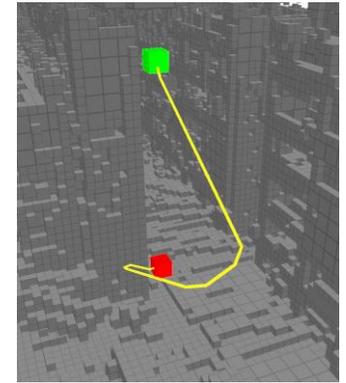
- Velodyne Puck has limited vertical field-of-view ( $30^\circ$ )
- Must be considered in navigation planning
- Only fly in directions that can be measured



Lidar field-of-view

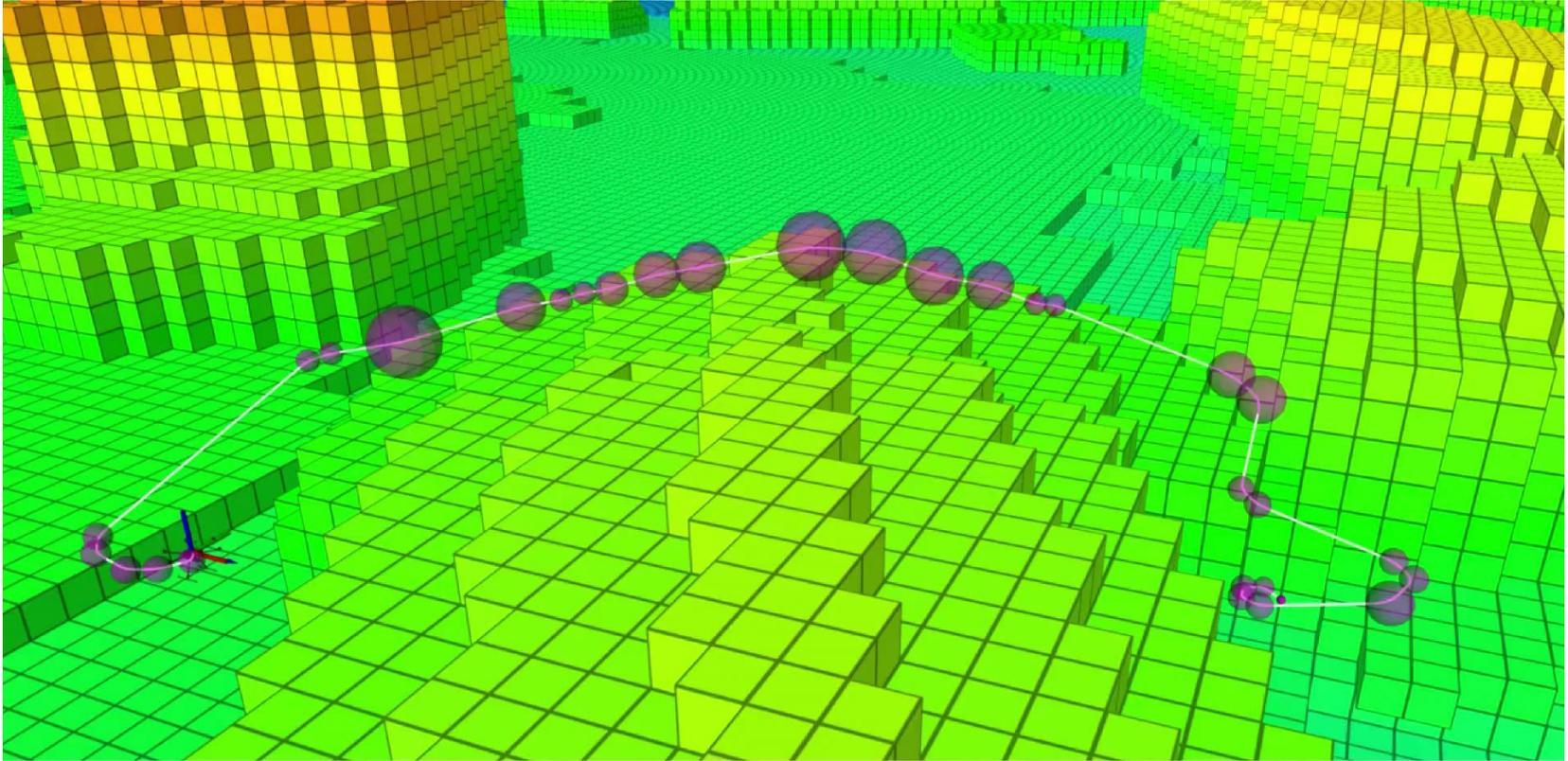


Fastest path



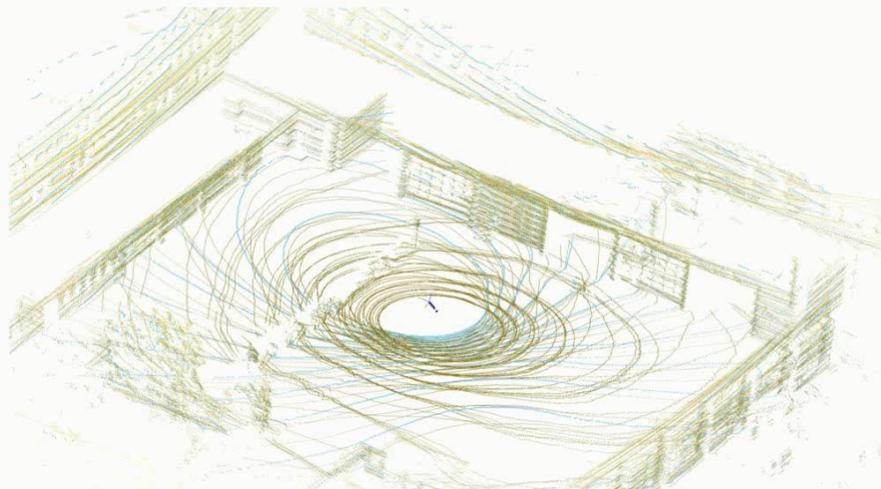
Safe path

# Navigation Planning with Visibility Constraints



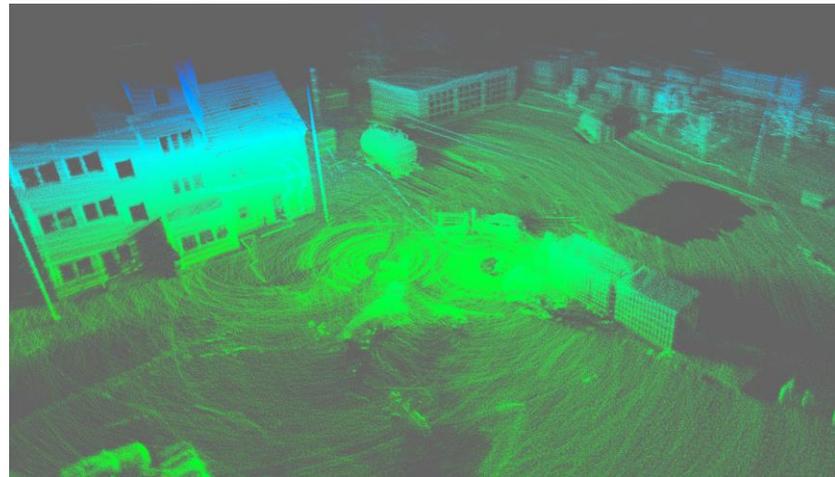
**Planned path with visibility constraints**

# Lidar-based SLAM from MAV



# Supporting Fire Fighters (A-DRZ)

- Added thermal camera
- Flight at Brandhaus Dortmund



# Mesh-based 3D Modeling + Textures

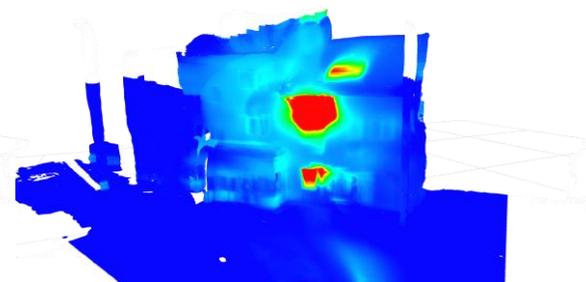
- Model 3D geometry with mesh
- Appearance and temperature as high-resolution texture



Mesh geometry

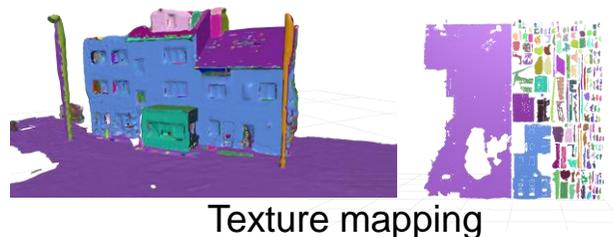


RGB texture



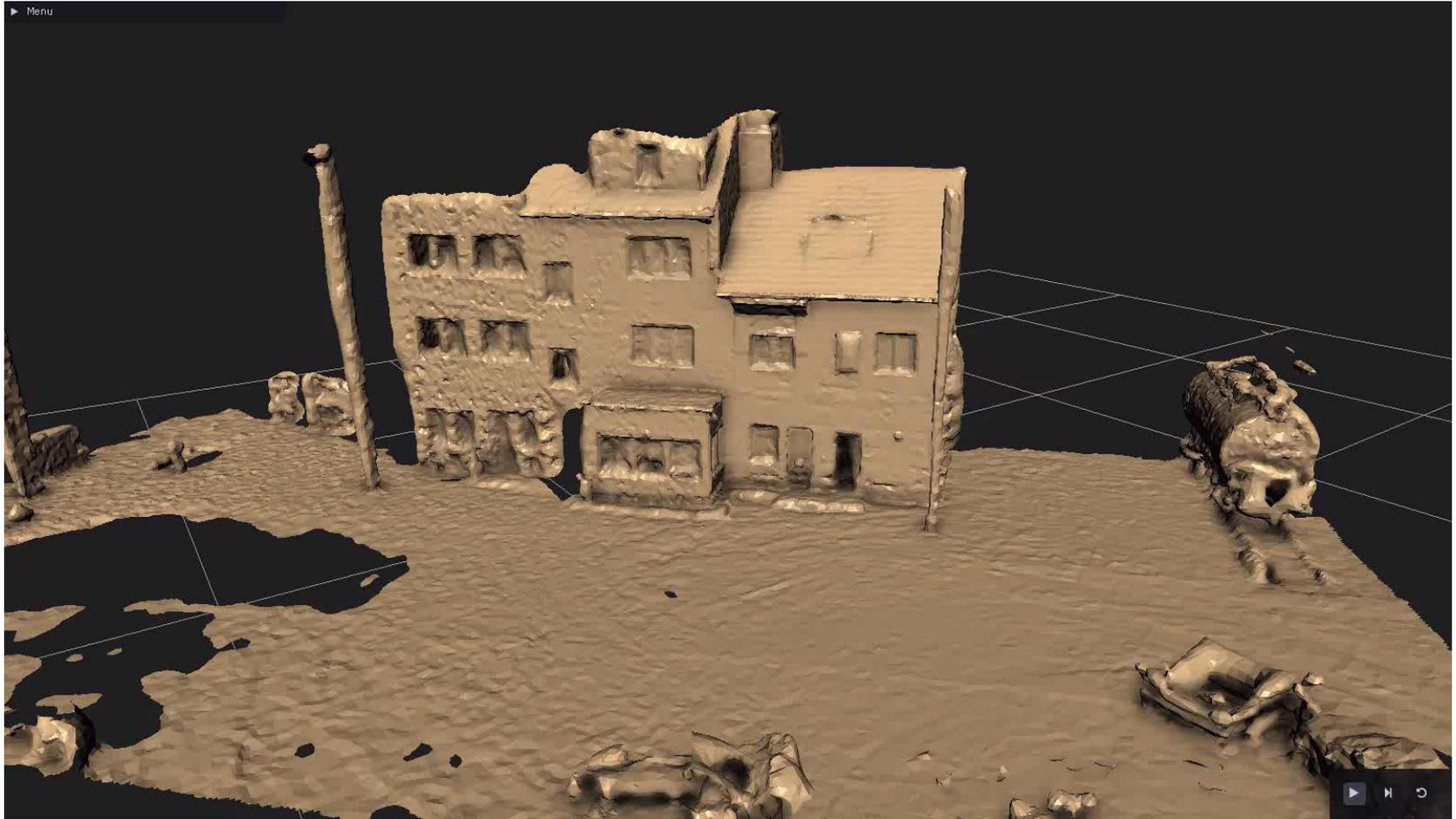
Thermal texture

- Mapping from 3D mesh to 2D texture



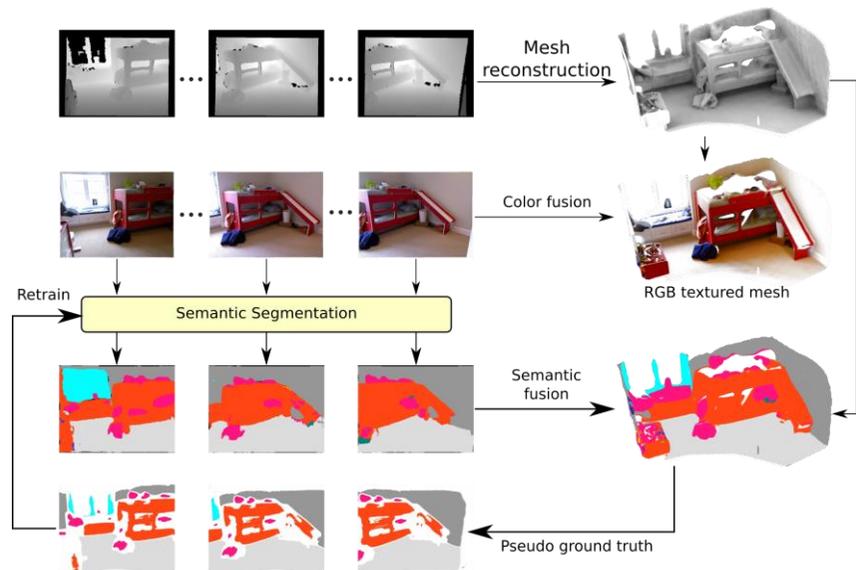
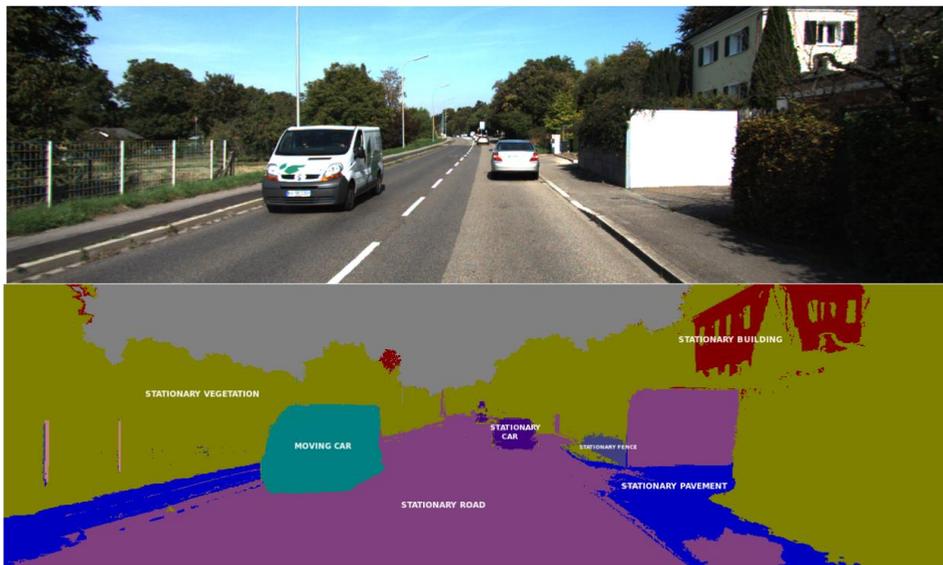
Texture mapping

# Modeling the Brandhaus Dortmund

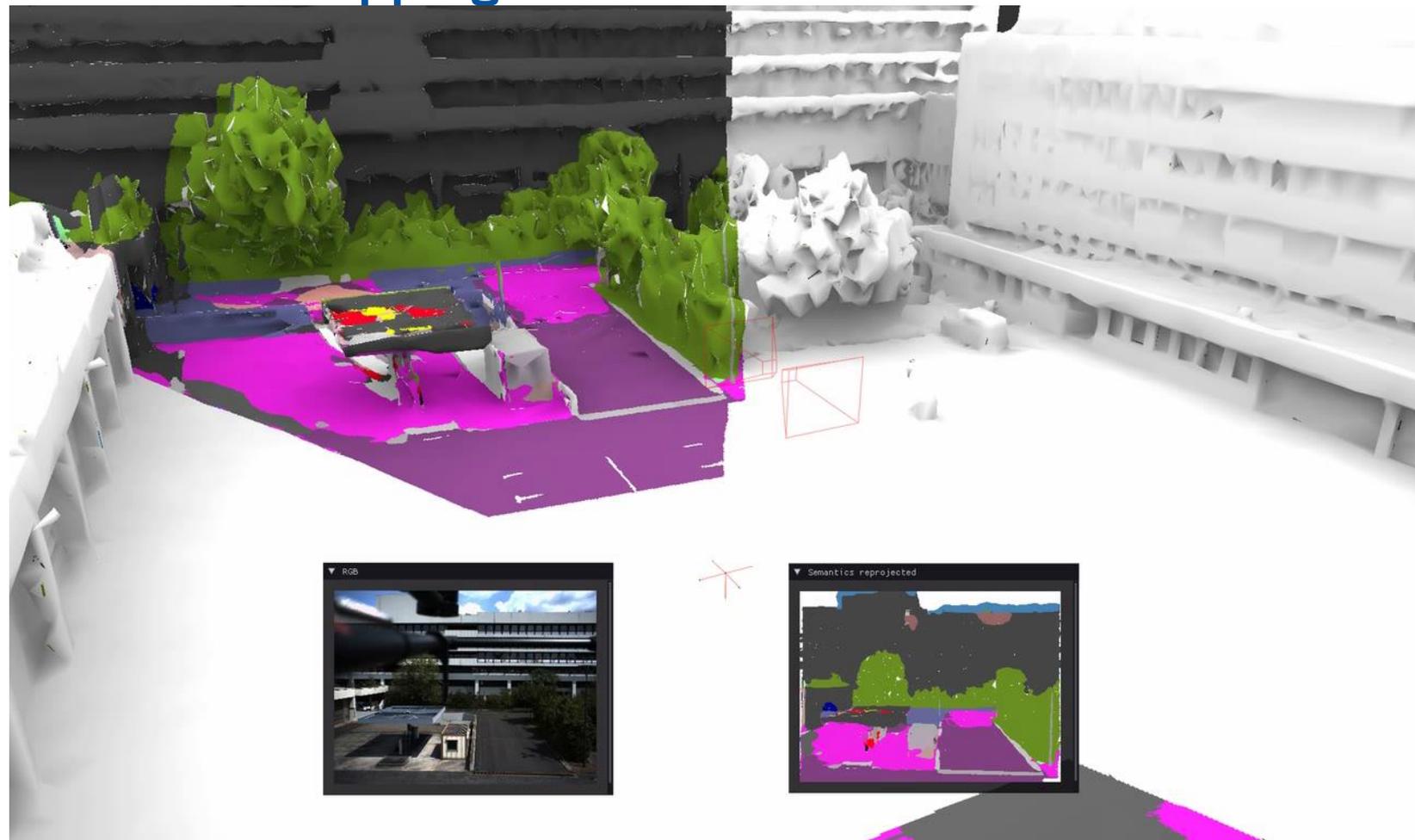


# 3D Semantic Mapping

- Image-based semantic categorization, trained with Mapillary data set
- 3D fusion in semantic texture
- Backprojection of labels to other views



# 3D Semantic Mapping



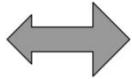
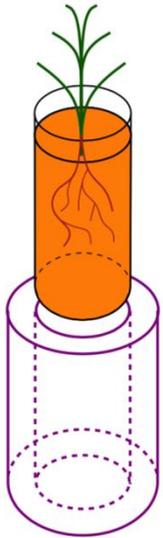
# 3D Semantic Map



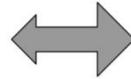
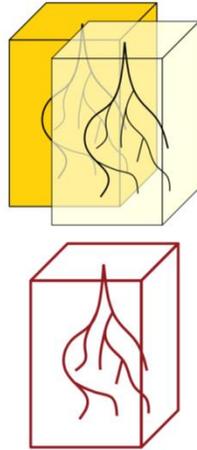
# Reconstruction of Plant Roots from MRI

- DFG project with Andrea Schnepf (FZJ)

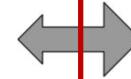
Measurements



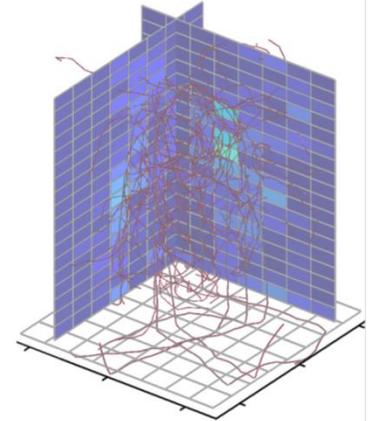
Segmentation



Structural Modeling

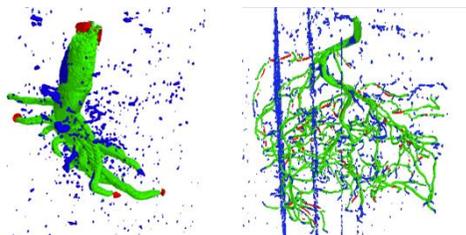
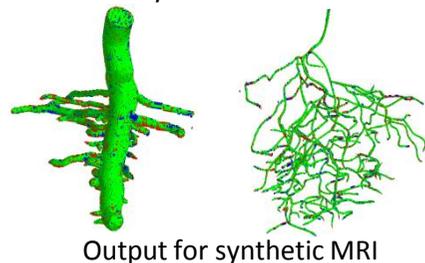
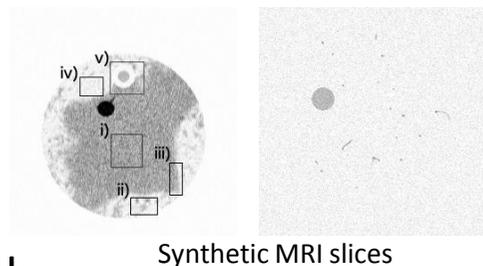
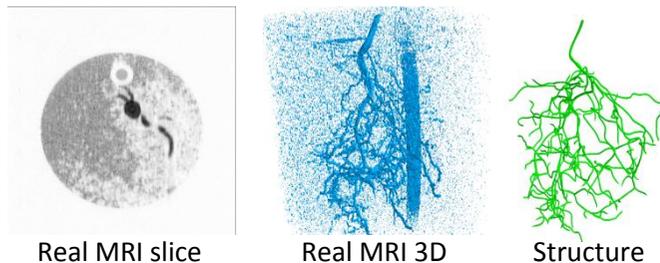


RWU Modeling



# Learning Root vs. Soil Segmentation and Superresolution

- Input: MRI, manual root structure reconstructions
- Desired output: Increased MRI contrast & resolution
- Issues: Few data, reconstructions not well aligned
- Generate synthetic MRI training data
  - Geometric transformations
  - Various noise
- Learn segmentation & superresolution with Deep NN
- Apply to real MRI

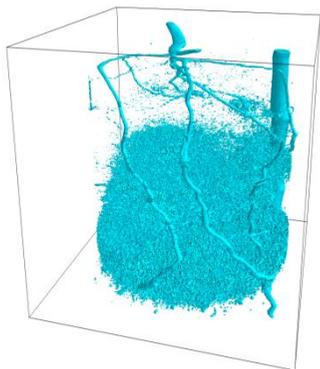


Output for real MRI

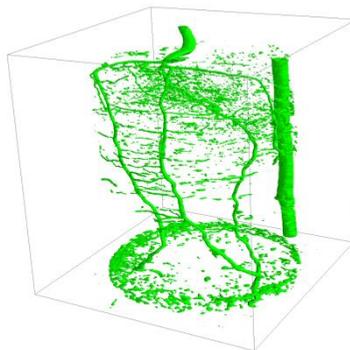
[Uzman et al. ESANN 2019]

# Using Learned Model for Root Structure Reconstruction

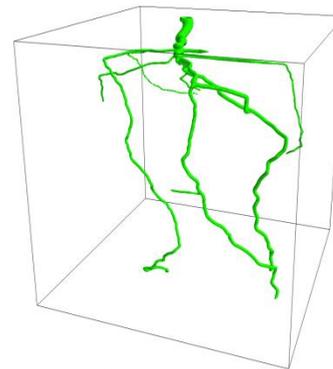
## ■ DAP17



MRI

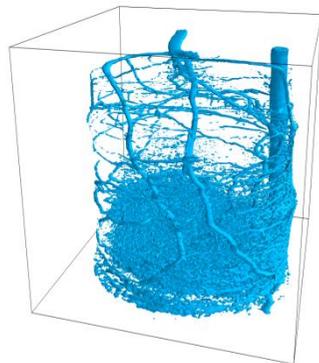


Model output

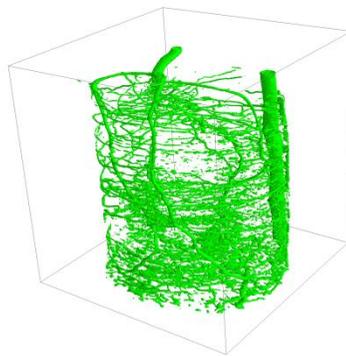


Manual reconstruction

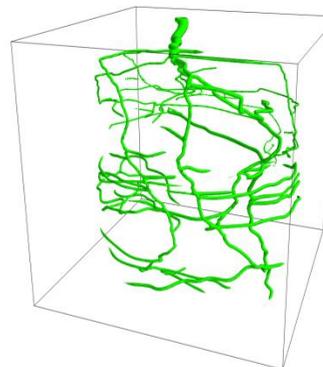
## ■ DAP24



MRI



Model output



Manual reconstruction

# Conclusions

- Developed capable robotic systems for challenging scenarios
  - Domestic service
  - Disaster response
  - Aerial inspection
- Autonomy for navigation and manipulation tasks
  - 3D semantic mapping
  - Navigation and manipulation planning
- Use as a tool in PhenoRob, e.g. in
  - CP1: 4D phenotyping of individual plants
  - CP4: Intervention
- Challenges include
  - Correspondences despite growth & deformations
  - Small and big data

