

# Perception and Planning for Humanoid Disaster-response Robots

**Sven Behnke**

University of Bonn  
Computer Science Institute VI  
Autonomous Intelligent Systems



# Some of our Cognitive Robots

- Equipped with numerous sensors and actuators
- Complex demonstration scenarios



Soccer



Domestic service



Mobile manipulation



Bin picking



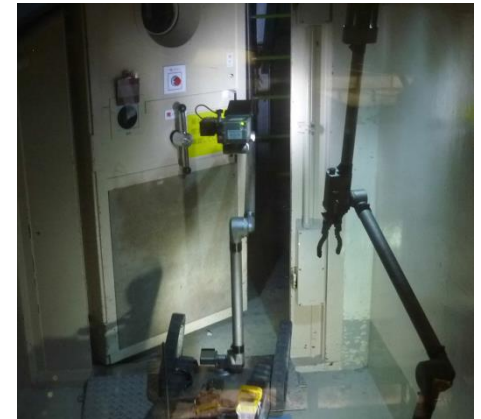
Aerial inspection

# Motivation

- Capabilities of disaster-response robots were insufficient for providing effective support to rescue workers.
  - Mobility: difficulties with uneven terrain, stairs, and debris
  - Manipulation: only a single actuator with simple end-effectors
  - User interface: requires extensive training, not intuitive, situation awareness problematic
- Complexity of achievable tasks and execution speed are low



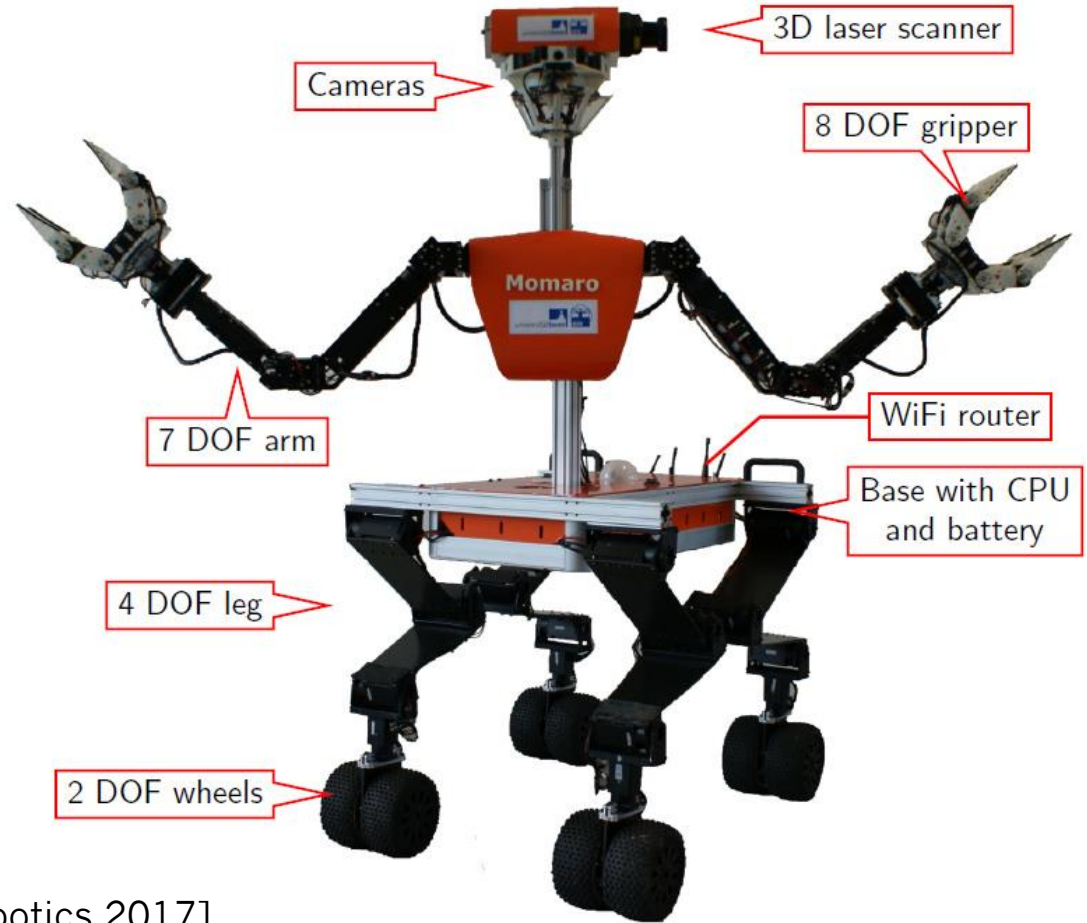
Fukushima disaster 2011, Image: Digital Globe CC 3.0.



iRobot PackBot in Plant, Image: Tepco.

# 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



CAUTION

POLARIS

4x4

PACIFIC TRAFFIC  
122-888

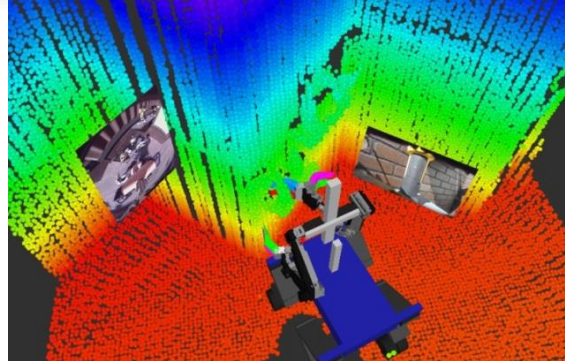
23:16:59 05/06/2015 UTC

4x



# Manipulation Operator Interface

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



[Rodehuts Kors et al., Humanoids 2015]





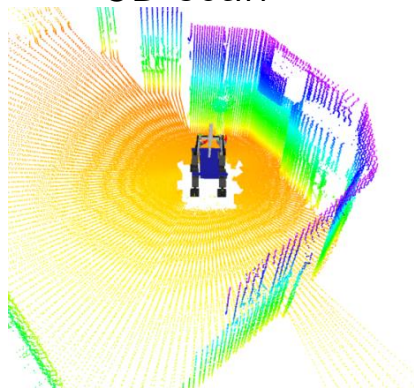
23:20:32 05/06/2015 UTC

4x

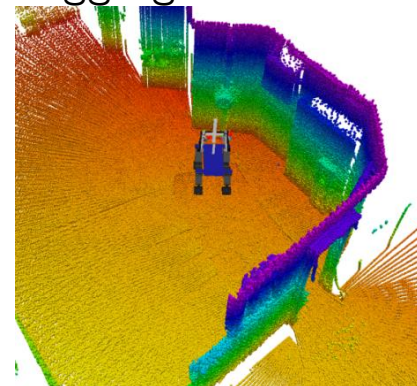
# Local Multiresolution Surfel Map

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

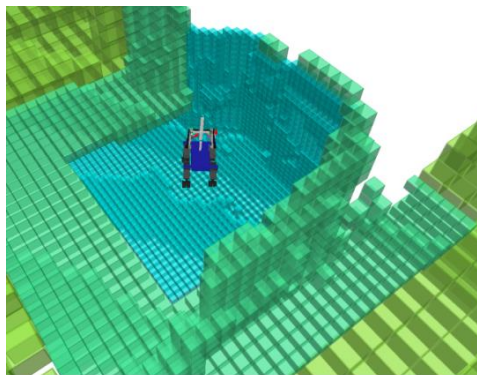
3D scan



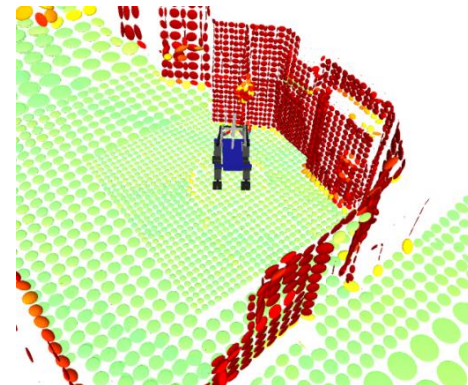
Aggregated scans



Multiresolution grid



Surfels

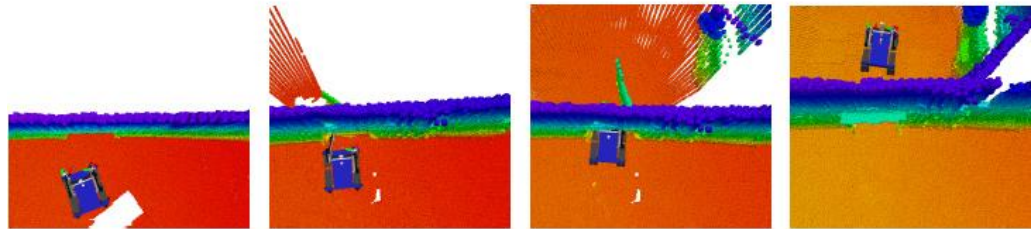
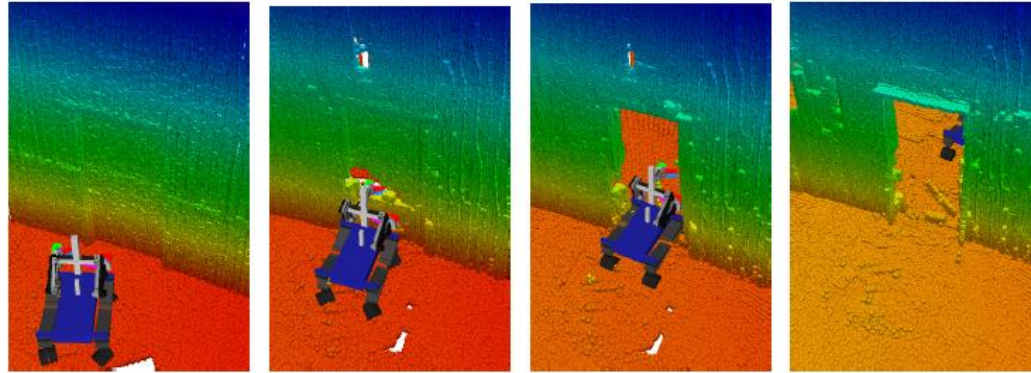


[Droeschel et al., Robotics and Autonomous Systems 2017]



# Filtering Dynamic Objects

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



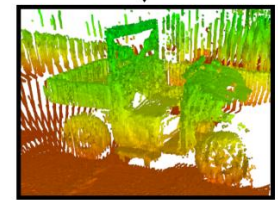
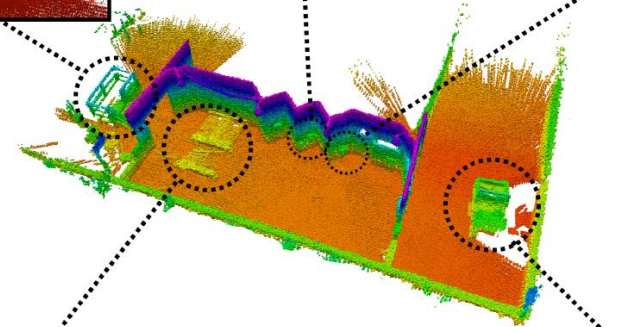
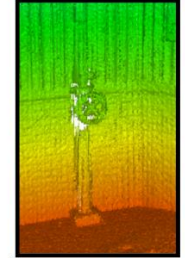
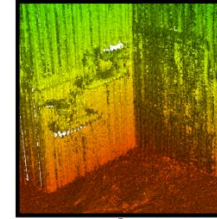
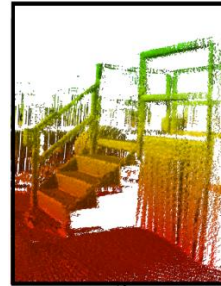
1 scan (5 s)

2 scans (10 s)

5 scans (25 s)

# Allocentric 3D Mapping

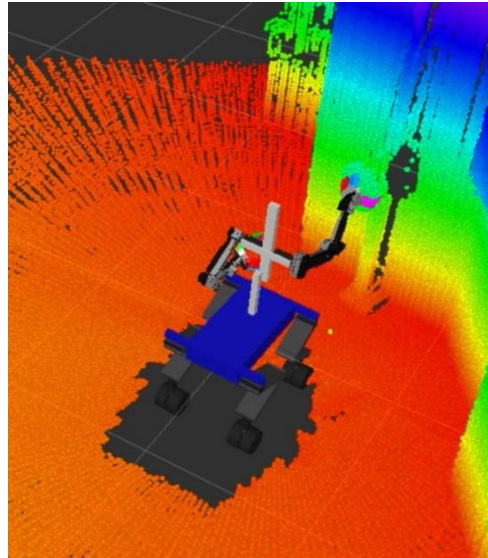
- Registration of egocentric maps by graph optimization



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

# Valve Turning Interface

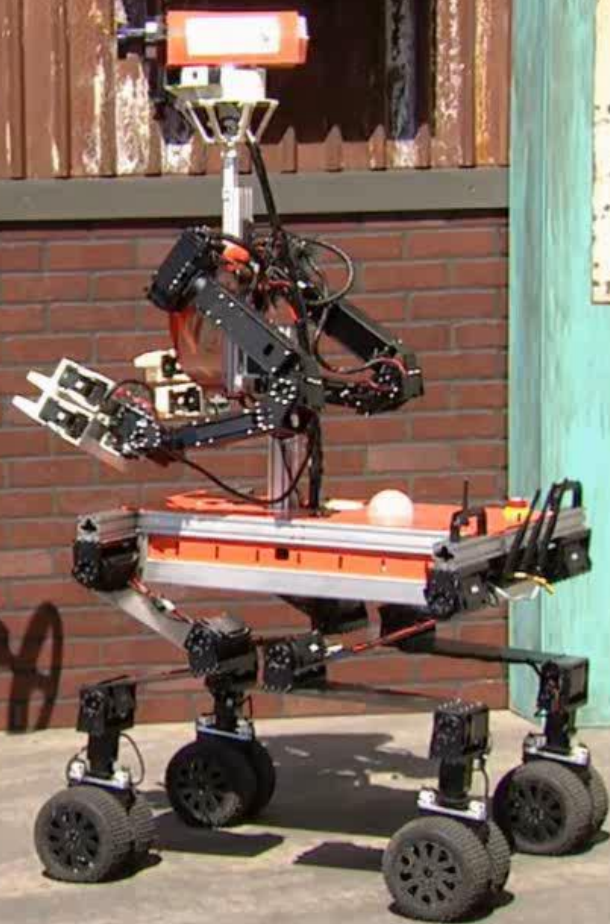
- Align wheel model with 3D points using interactive marker



[Schwarz et al. Journal of Field Robotics 2017]



23:25:56 05/06/2015 UTC



4x



23:28:21 05/06/2015 UTC

4x

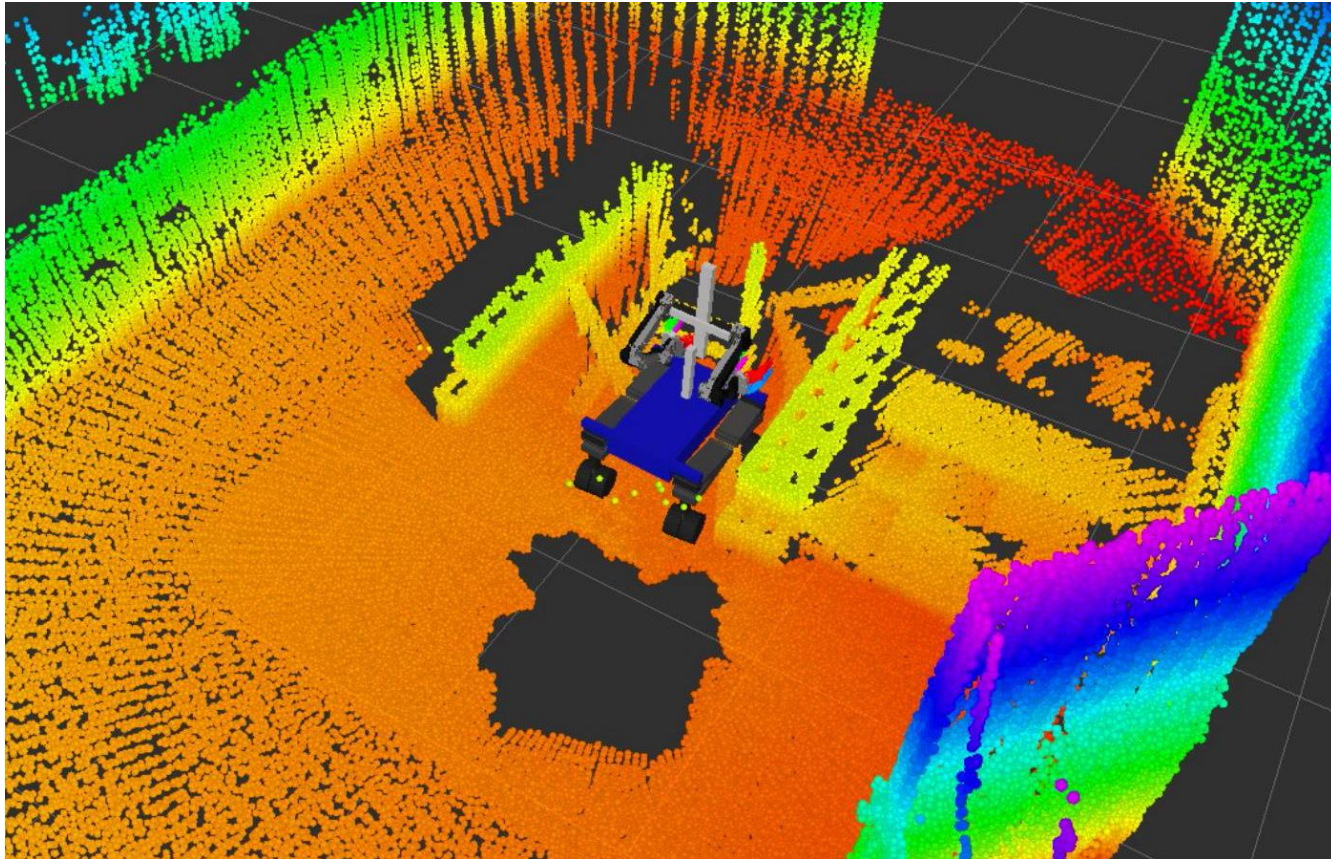




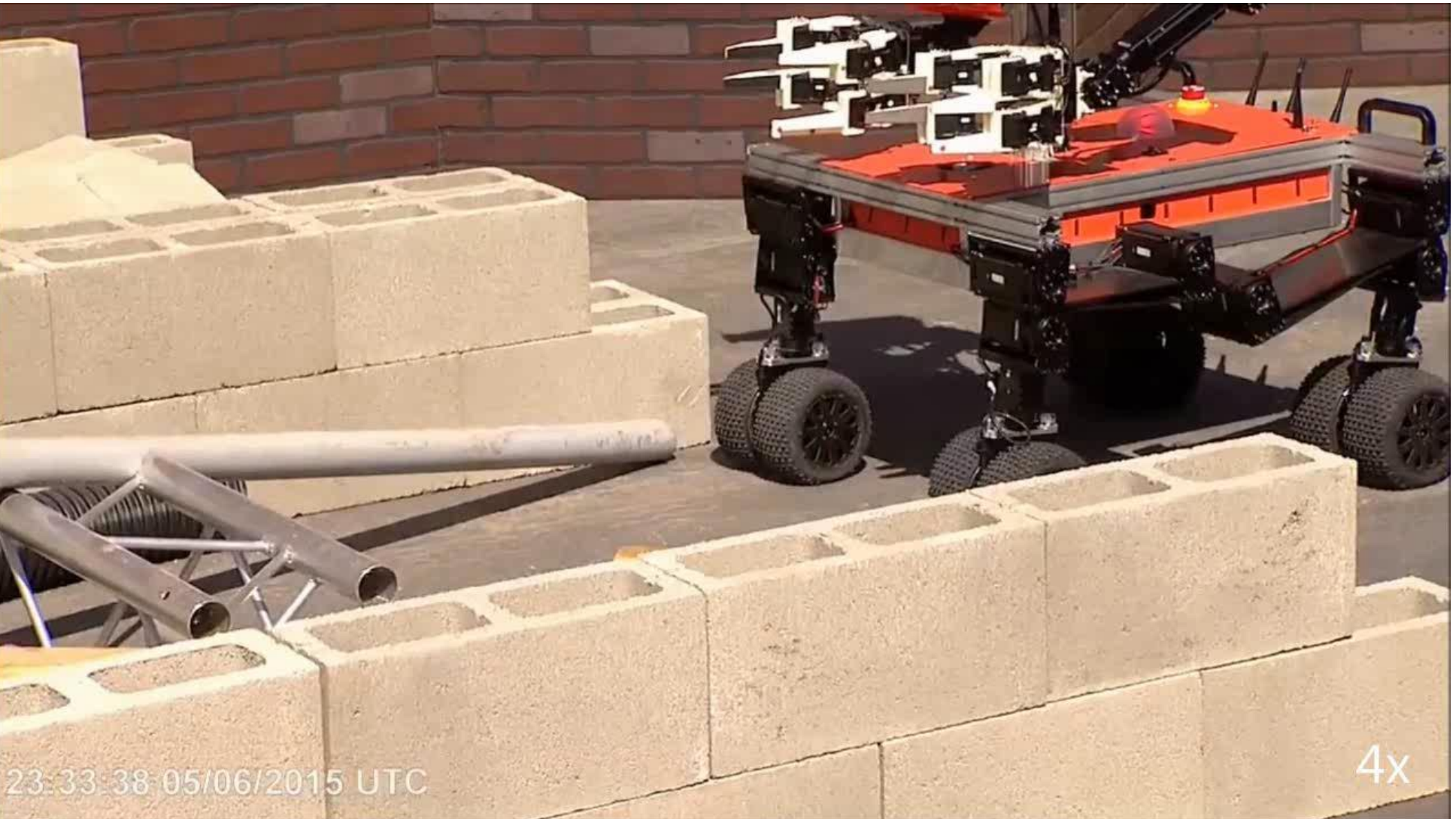
02:23:20 07/06/2015 UTC

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



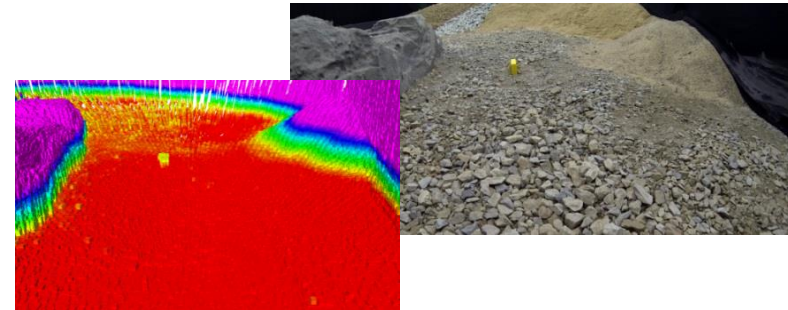
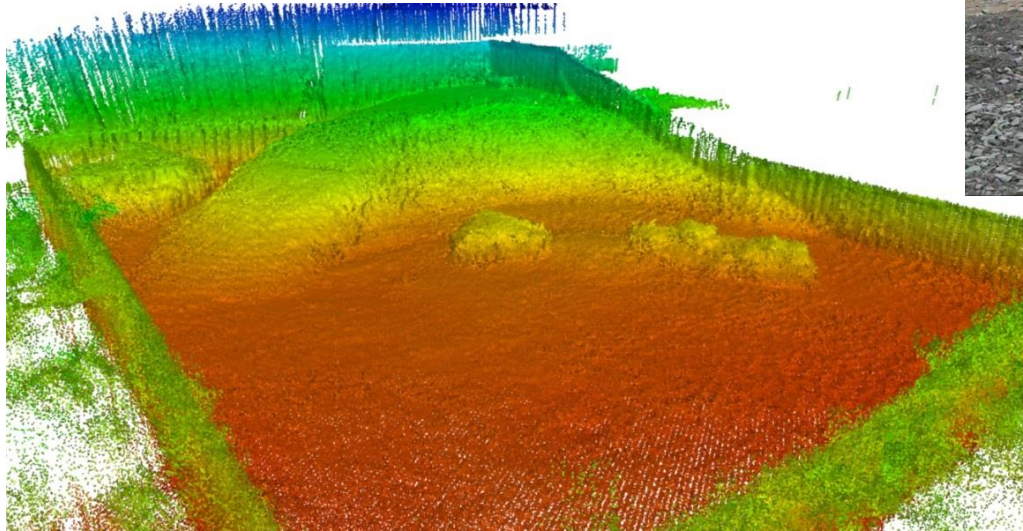
**Best European Team (4<sup>th</sup> place overall),  
solved seven of eight tasks in 34 minutes**



# DLR SpaceBot Cup 2015

- Mobile manipulation in rough terrain

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



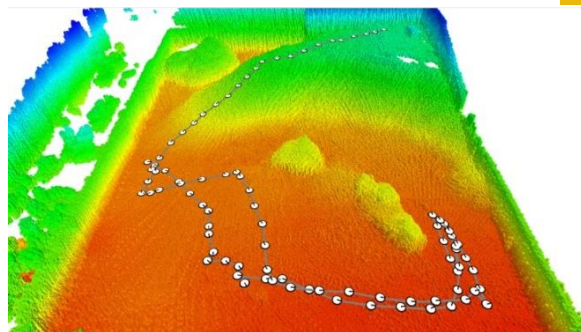


8X

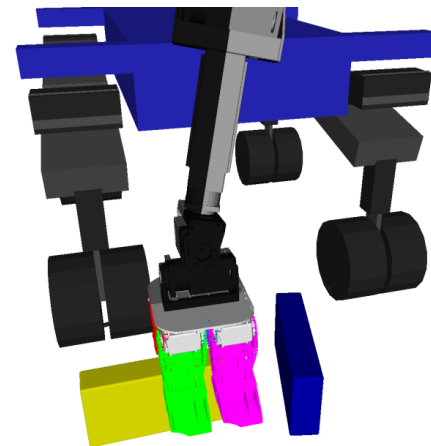
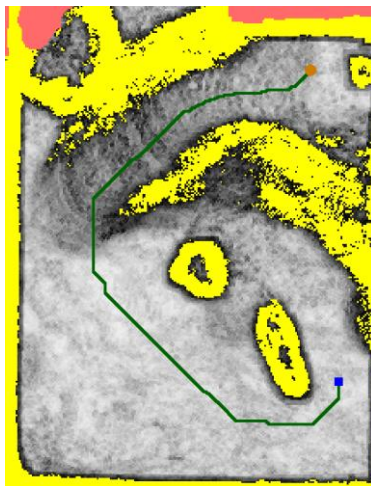
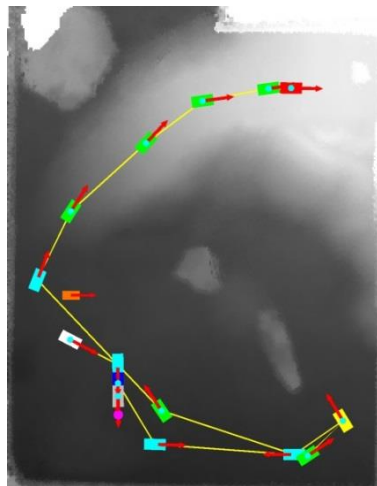
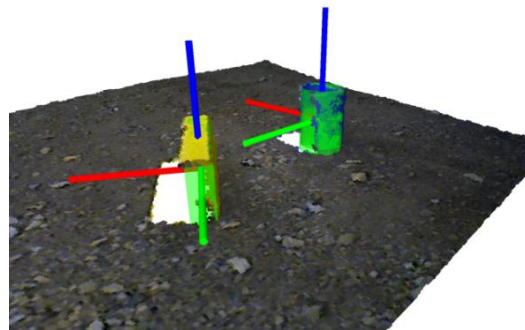


# Autonomous Mission Execution

- 3D mapping, localization, mission and navigation planning



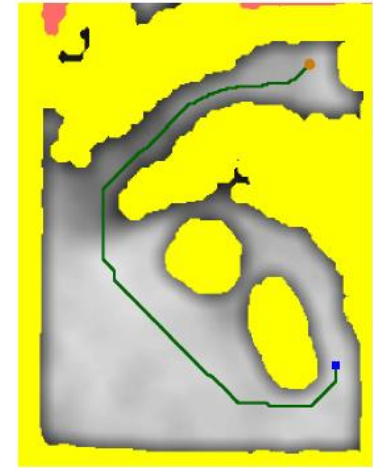
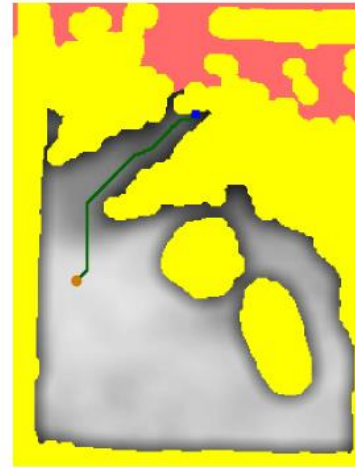
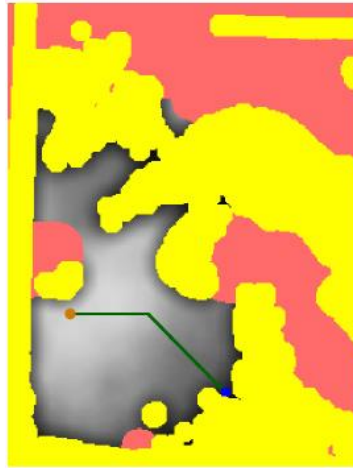
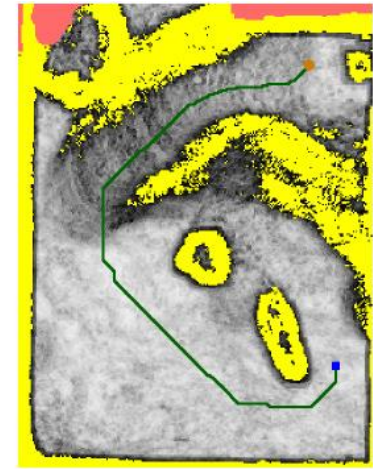
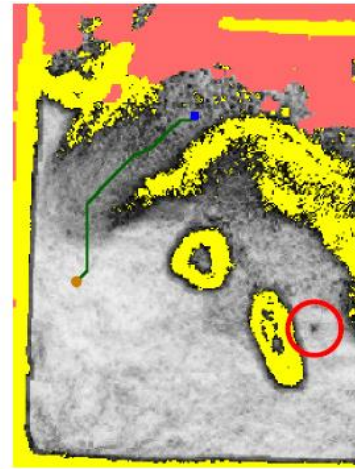
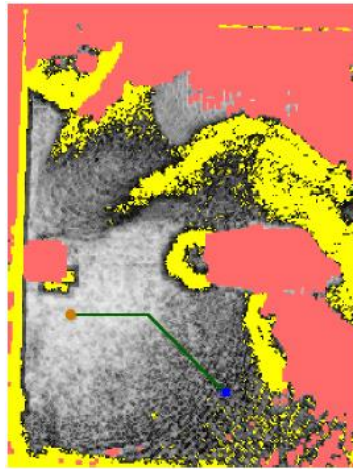
- 3D object perception and grasping



[Schwarz et al. Frontiers 2016]

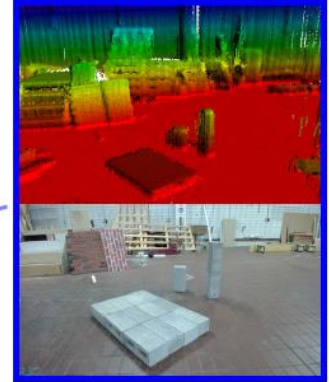
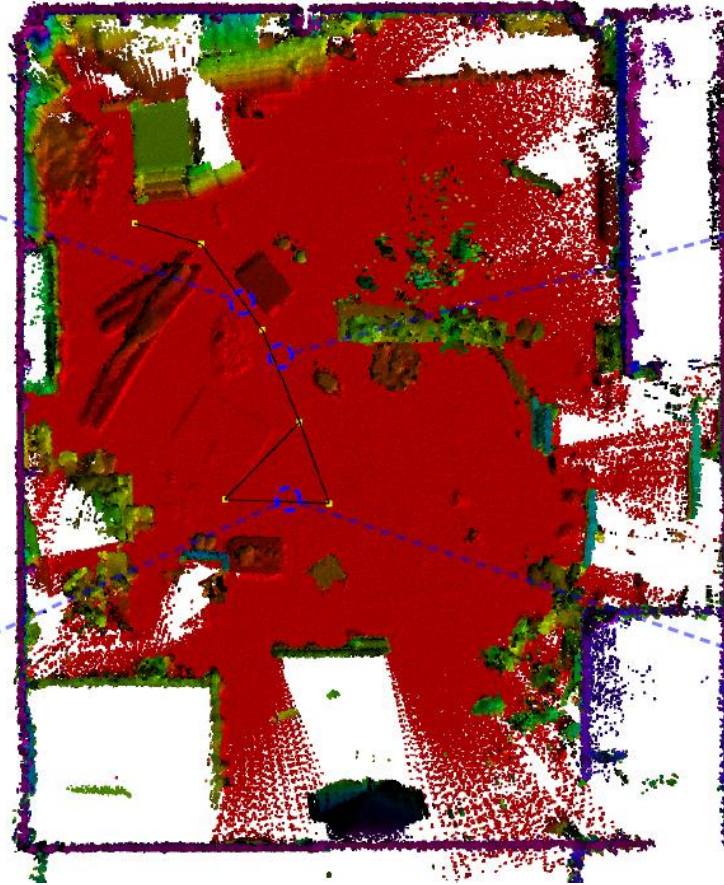
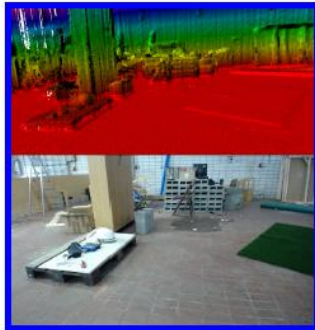
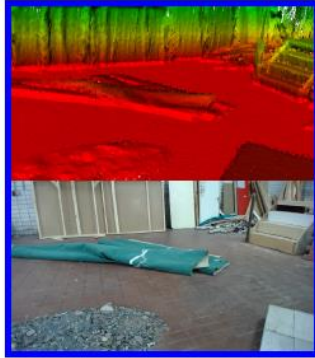
# Navigation Planning

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



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

# 3D Map



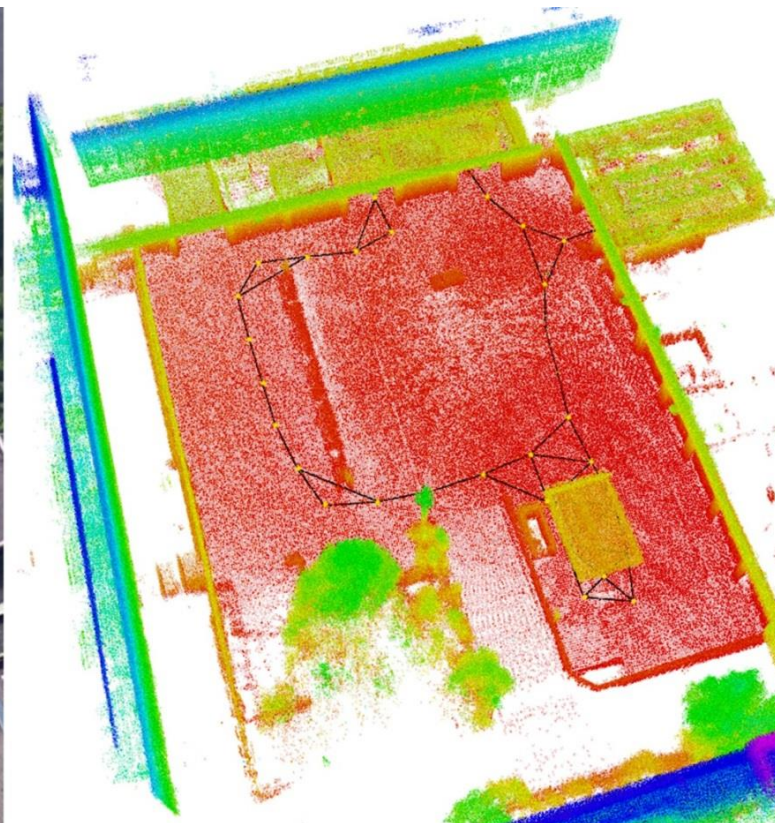


# Improved Sensor Head

- 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



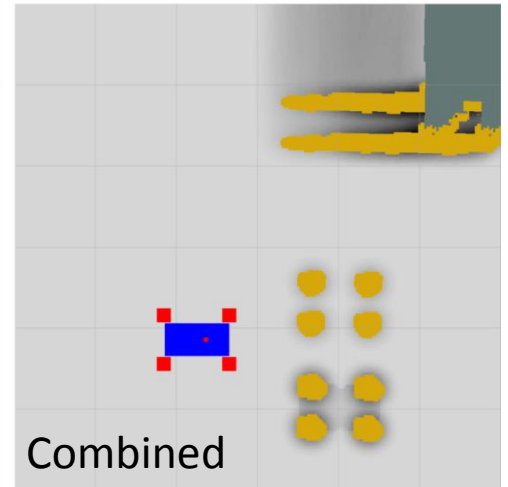
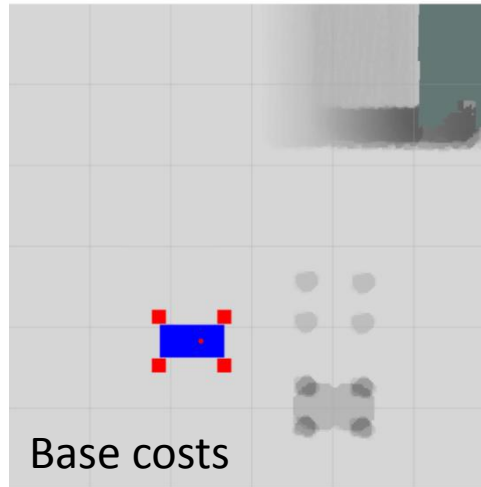
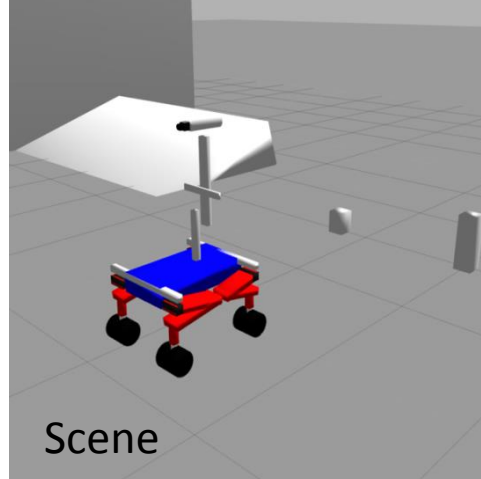
# 3D Map of Indoor+Outdoor Scene



[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

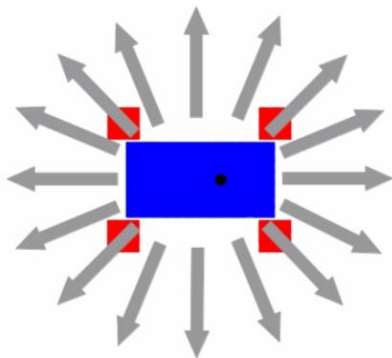


[Klamt and Behnke, IROS 2017]

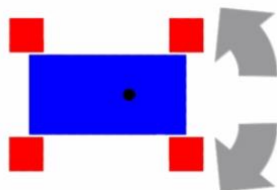


# 3D Driving Planning ( $x, y, \theta$ ): A\*

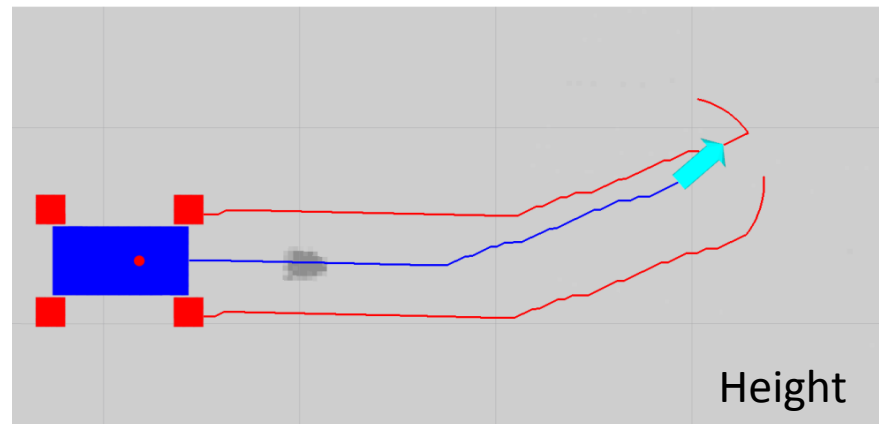
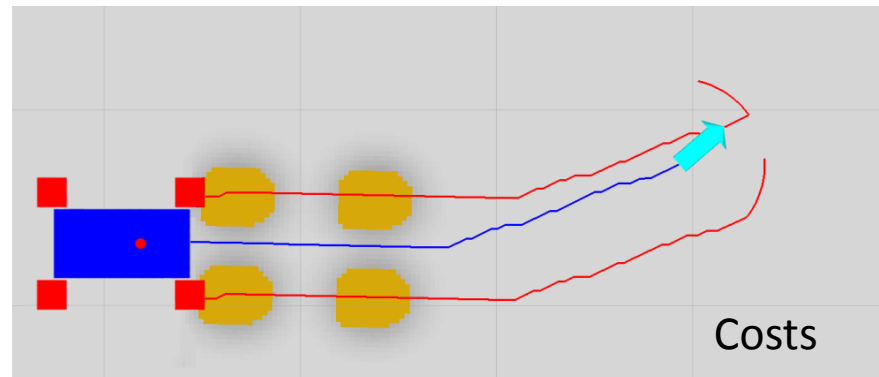
- 16 driving directions



- Orientation changes



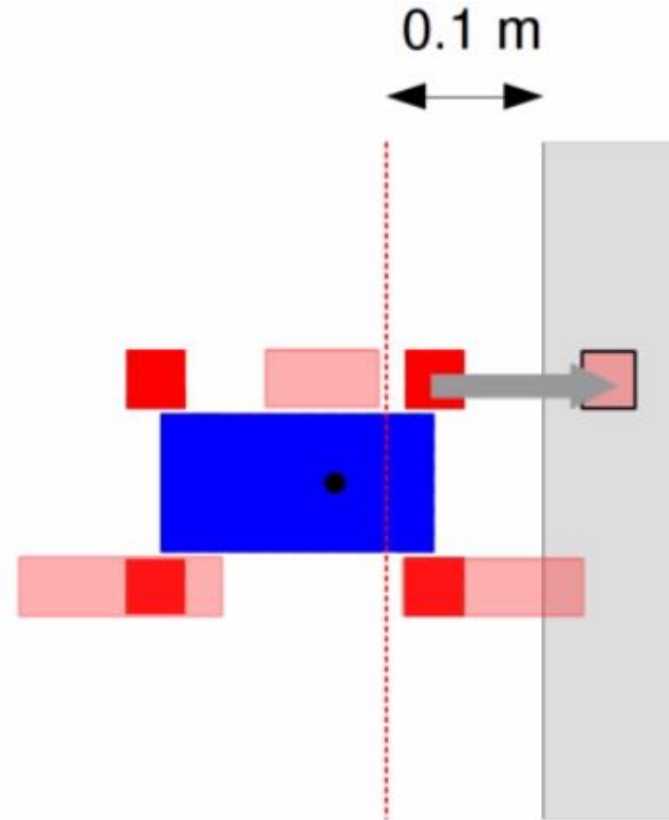
**=> Obstacle between wheels**



[Klamt and Behnke, IROS 2017]

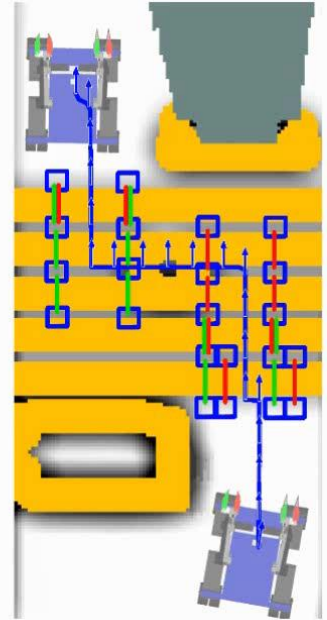
# Making Steps

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



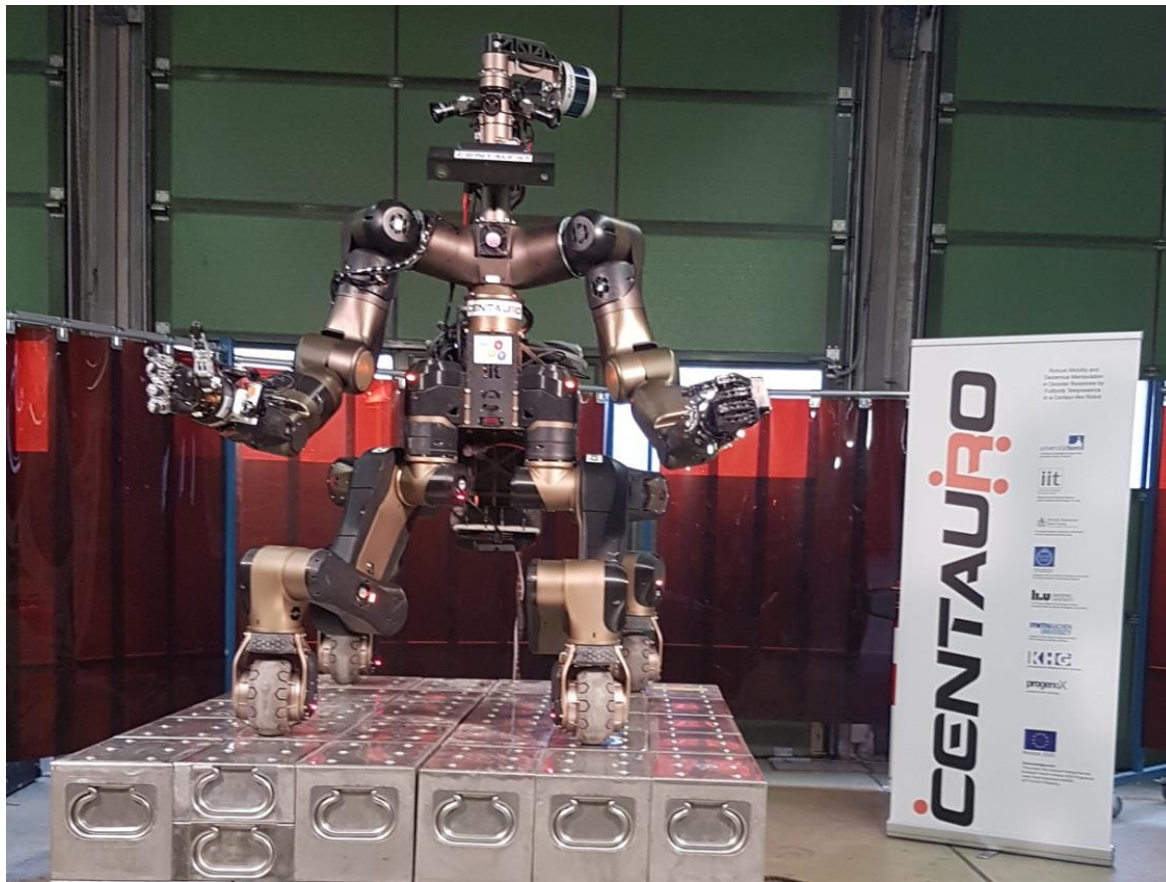
[Klamt and Behnke: IROS 2017]

# Planning for Challenging Scenarios





# Centauro Robot



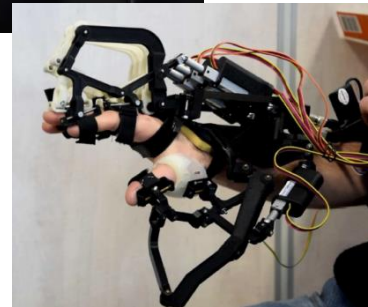
# CENTAURO

- 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



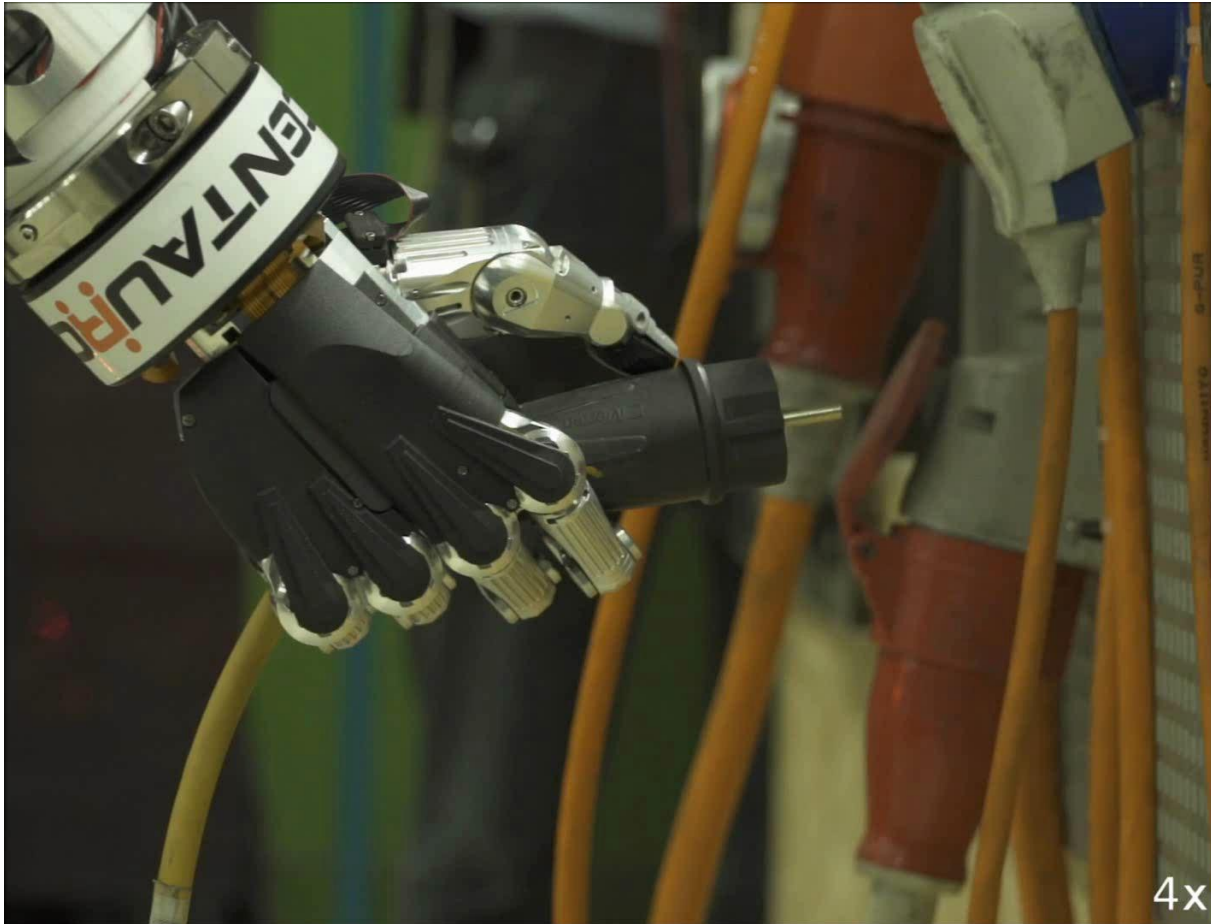
Autonomous



# 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



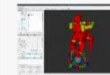
Joystick



Exus



6D



Keyframes



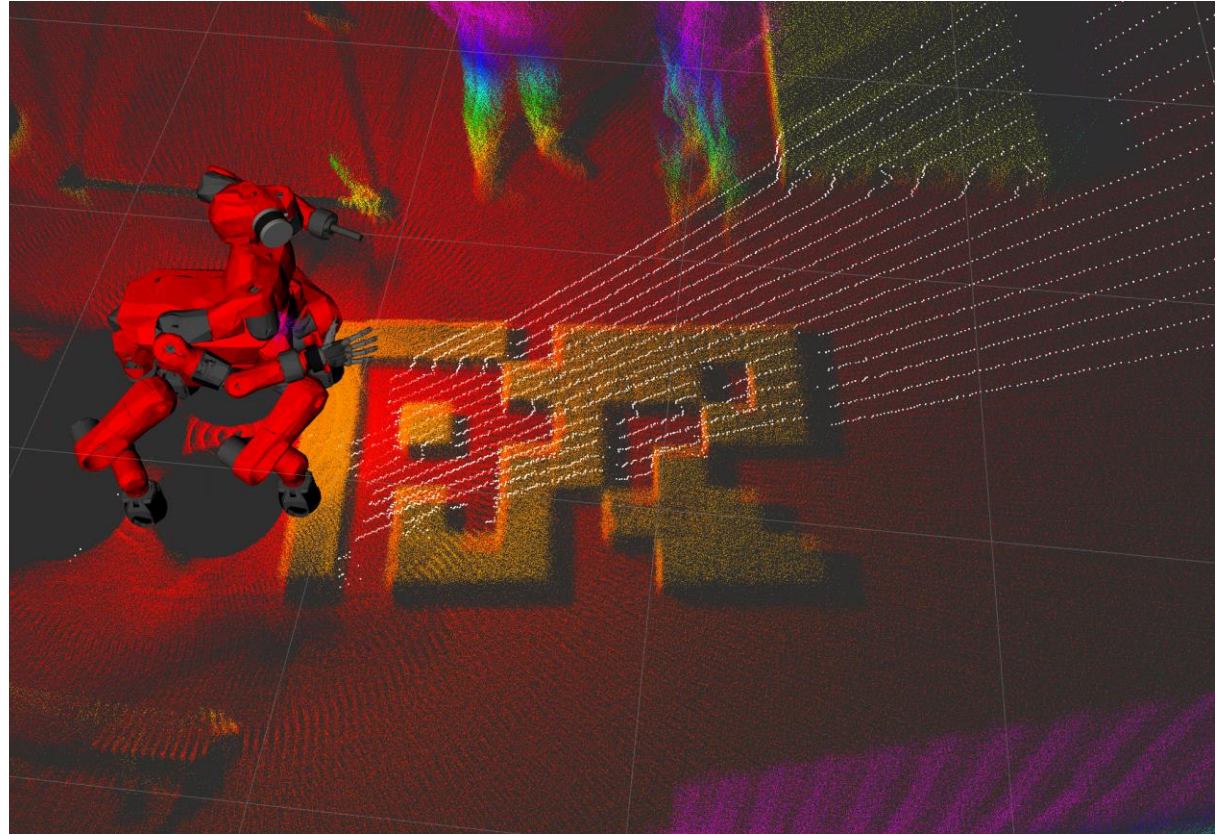
Stepping



Autonomous



# 3D Mapping and Localization

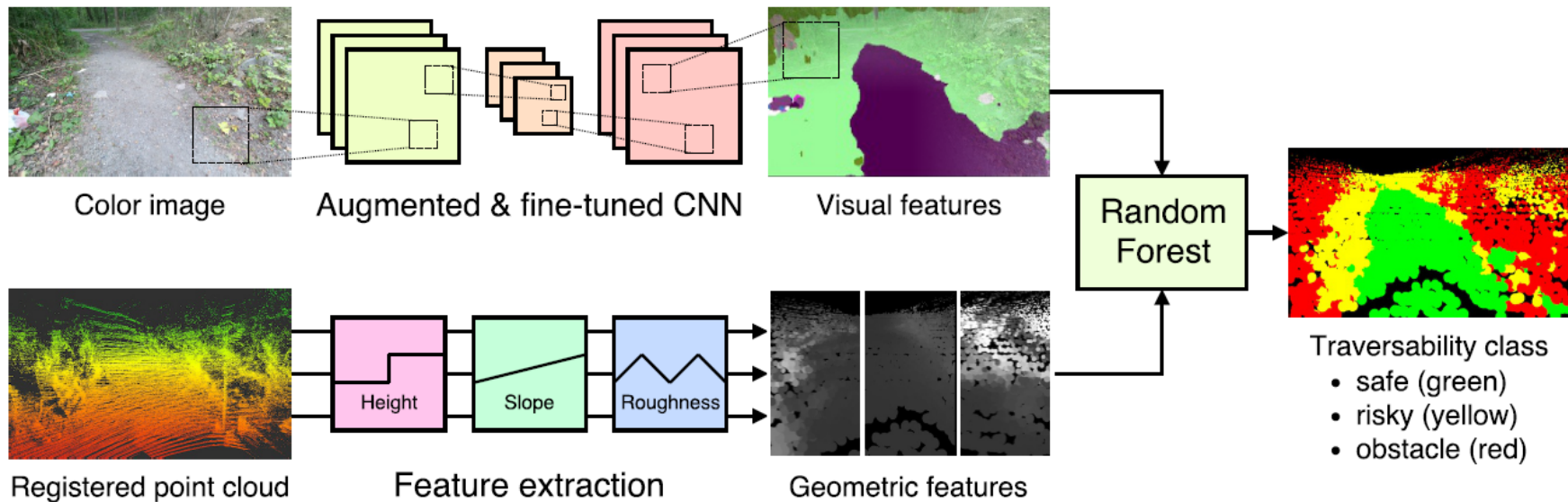




# Walking over a Step Field

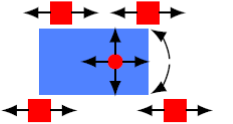
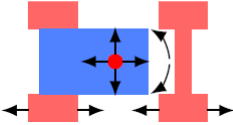
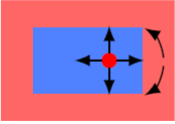


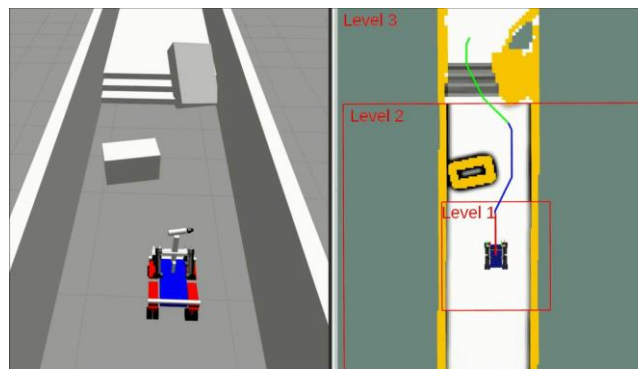
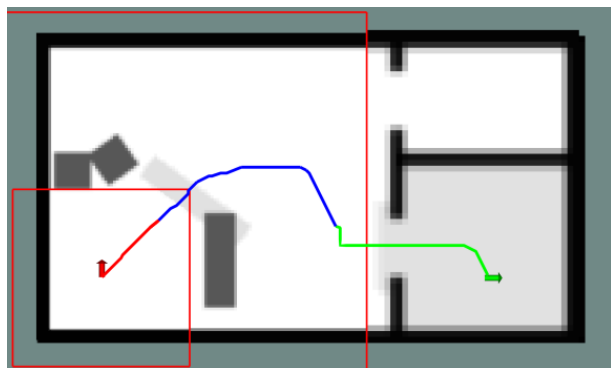
# Terrain Classification



[Schilling et al., IROS 2017]

# Hybrid Driving-Stepping Locomotion Planning: Abstraction

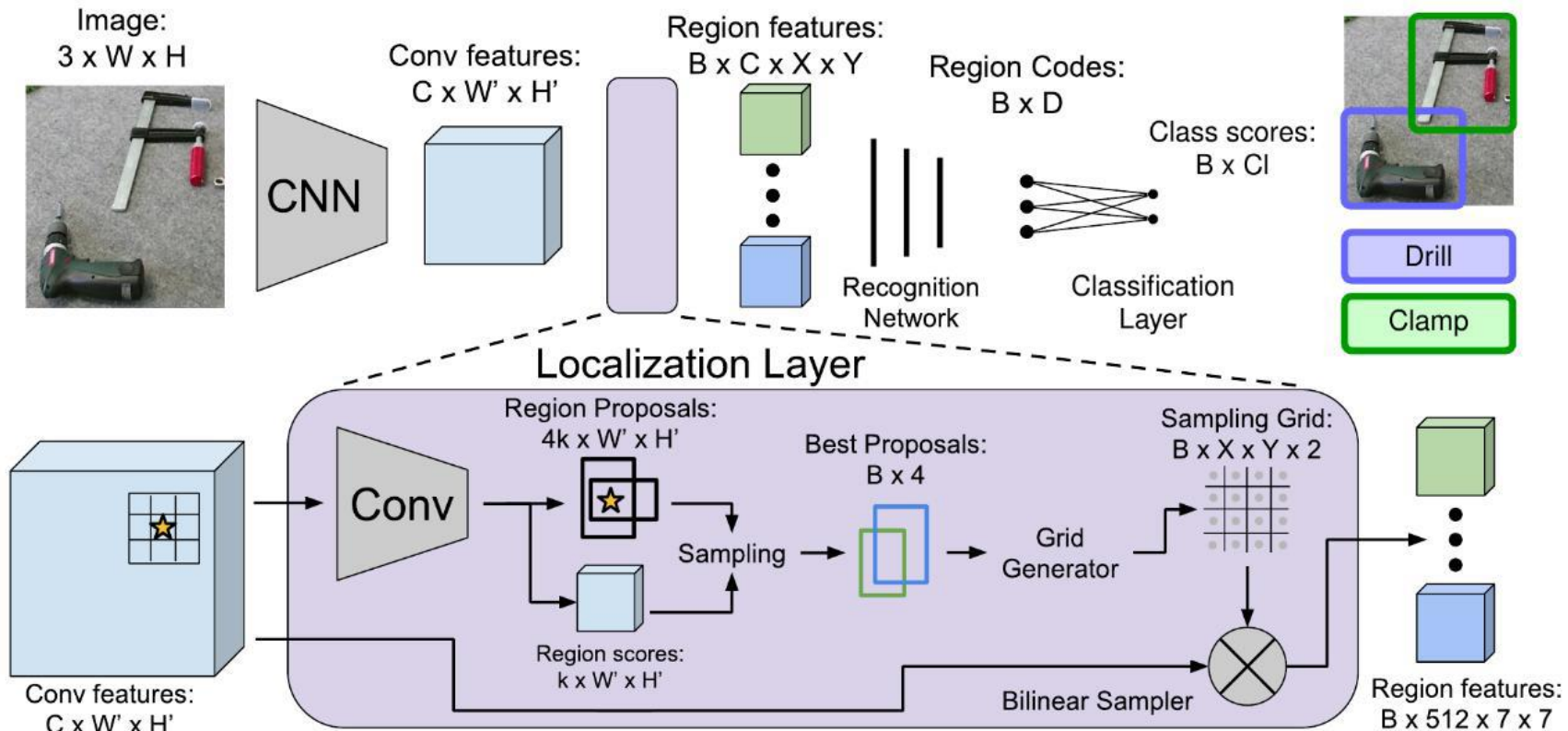
Level	Map Resolution	Map Features	Robot Representation	Action Semantics
1	<ul style="list-style-type: none"> <li>• 2.5 cm</li> <li>• 64 orient.</li> </ul>	<ul style="list-style-type: none"> <li>• Height</li> </ul>		<ul style="list-style-type: none"> <li>• Individual Foot Actions</li> </ul>
2	<ul style="list-style-type: 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]

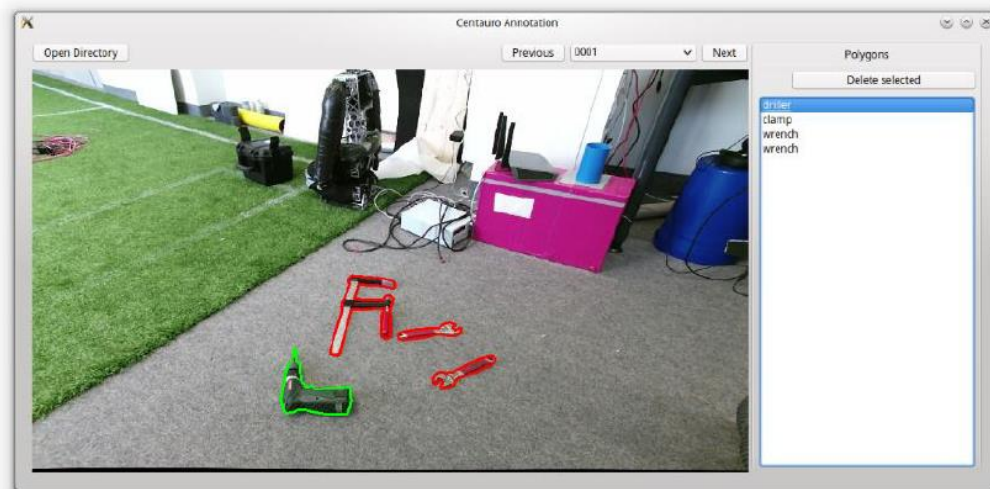


# Deep Learning Object Detection

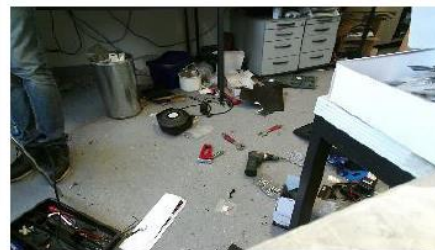


[Johnson et al. 2015]

# 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



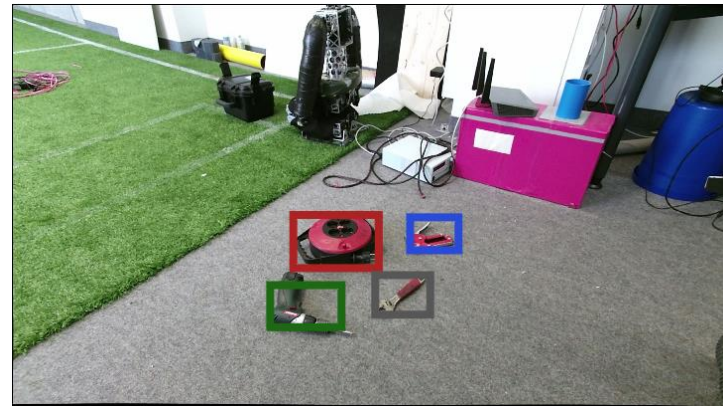
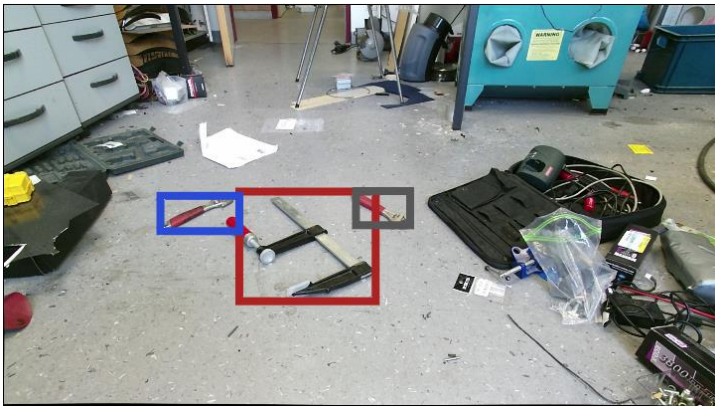
[Schwarz et al. IJRR 2017]

extension\_box stapler driller clamp [background]

Resolution	Clamp	Door handle	Driller	Extension	Stapler	Wrench	Mean
	AP / F1	AP / F1	AP / F1	AP / F1	AP / F1	AP / F1	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



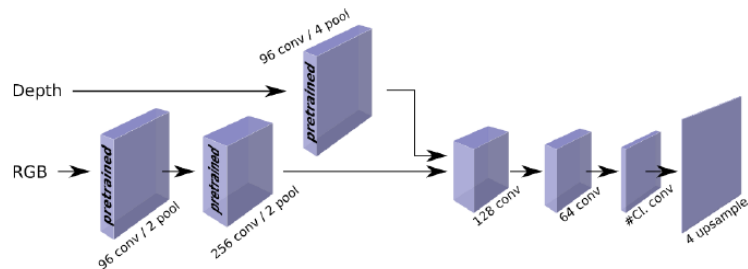
# Tools Detection Examples



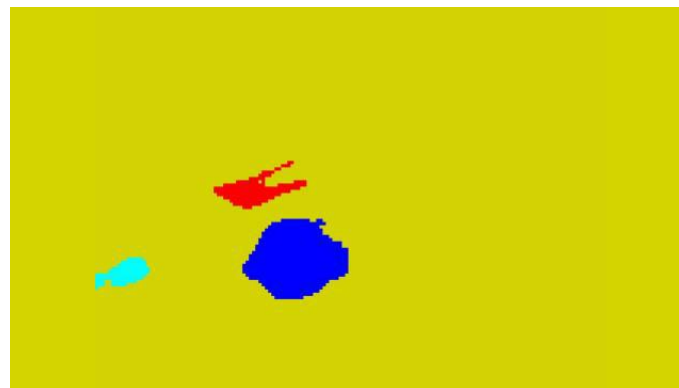
[Schwarz et al. IJRR 2017]

# Semantic Segmentation

## ■ Deep CNN



[Husain et al. RA-L 2016]

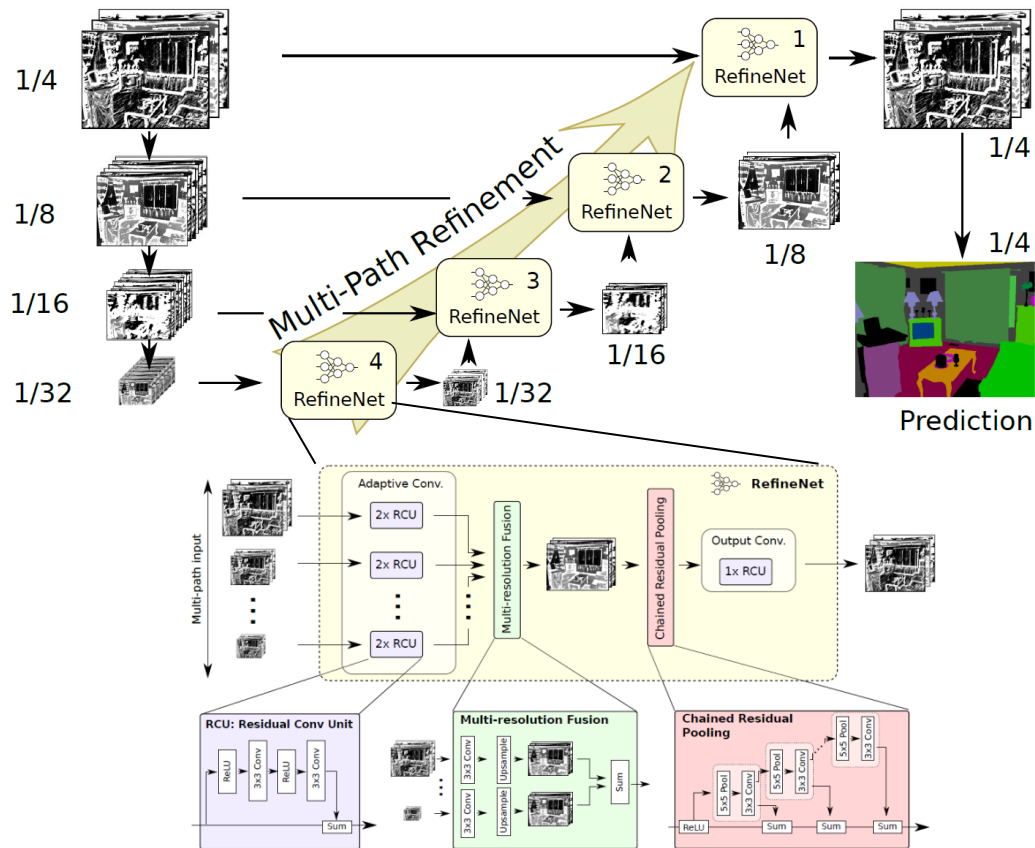


Pixel-wise accuracy:

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

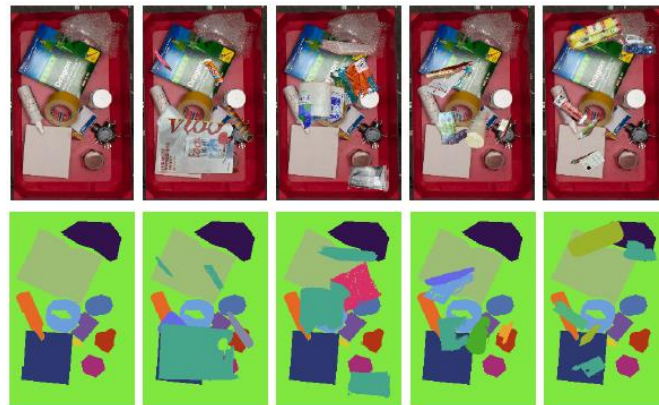
- Deep Learning in robotics (still) suffers from shortage of available examples
- We address this problem in two ways:

## 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

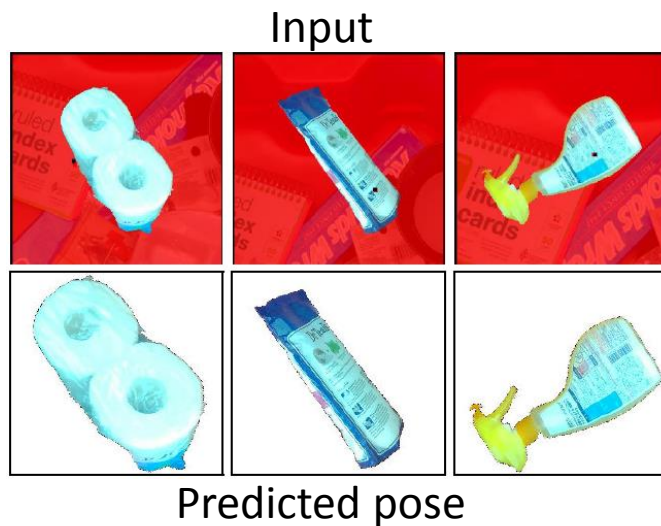
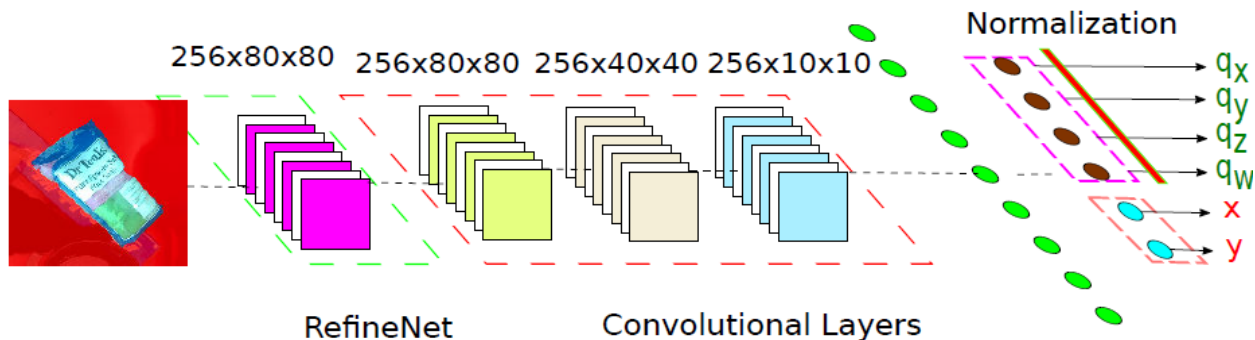


- mouse\_traps  
conf: 0.921731
- windex  
conf: 0.861246
- q-tips\_500  
conf: 0.475015
- fiskars\_scissors  
conf: 0.831069
- ice\_cube\_tray  
conf: 0.976856



# 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

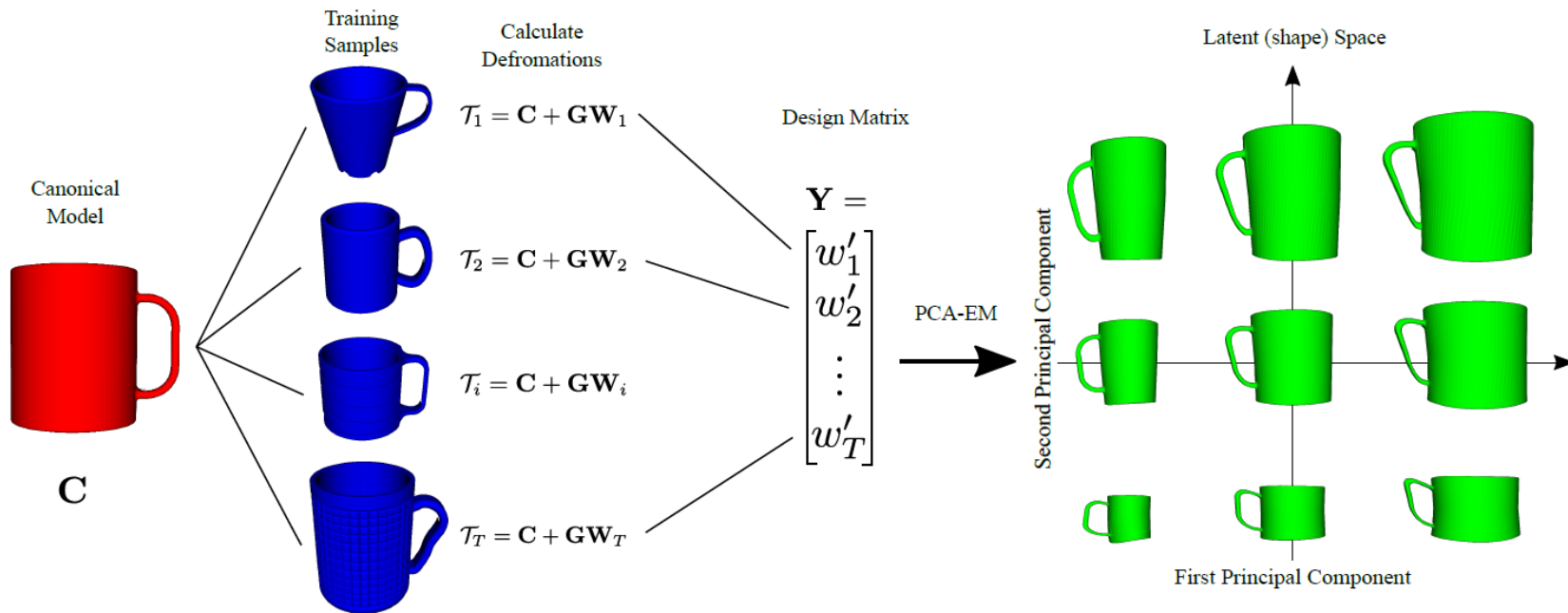


Knowledge  
Transfer

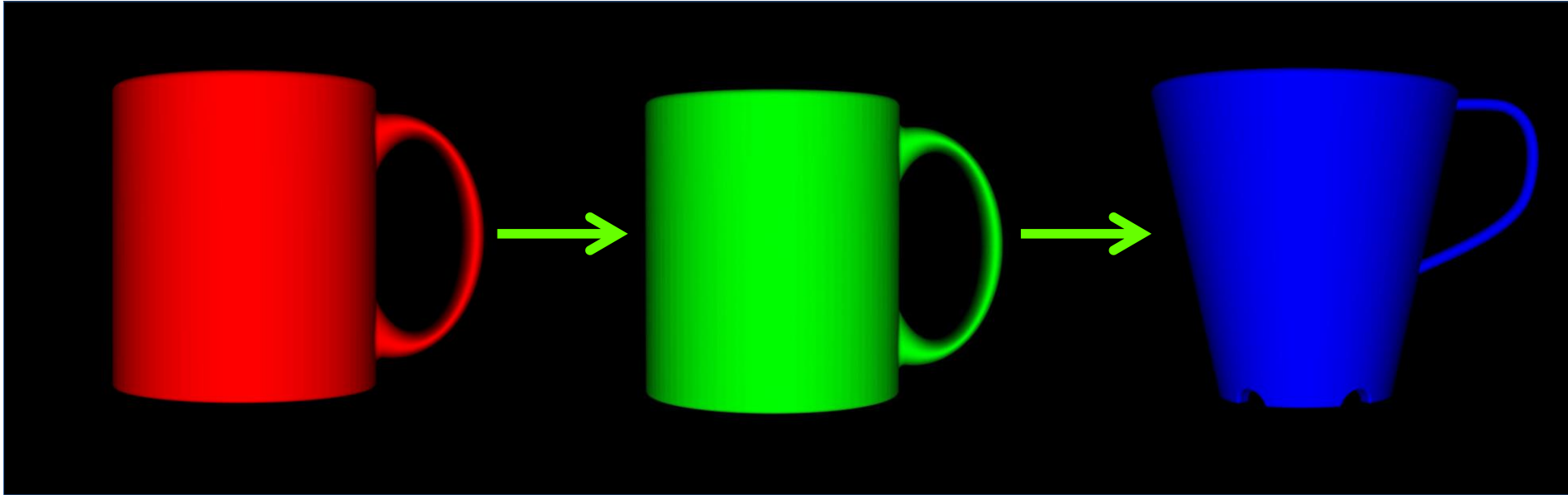


# Learning a Latent Shape Space

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



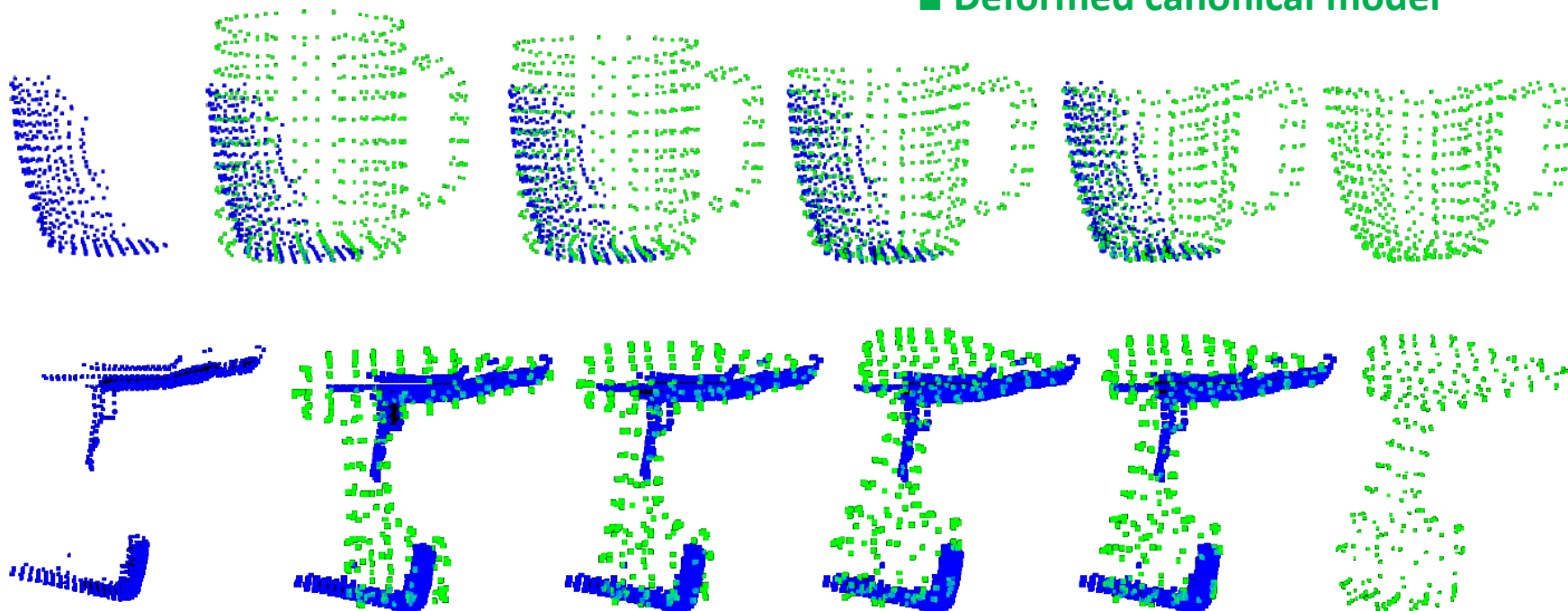
# Interpolation in Shape Space





# Shape-aware Non-rigid Registration

- Partial view of novel instance
- Deformed canonical model

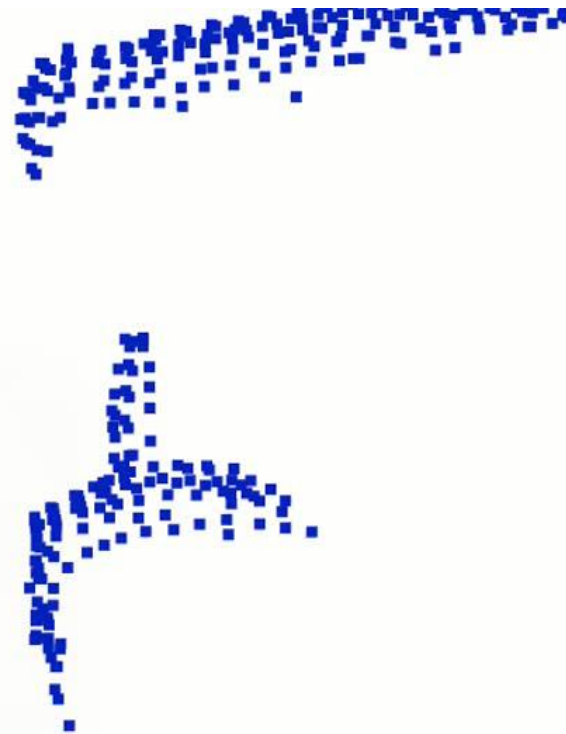


# Shape-aware Registration for Grasp Transfer

■ Full point cloud



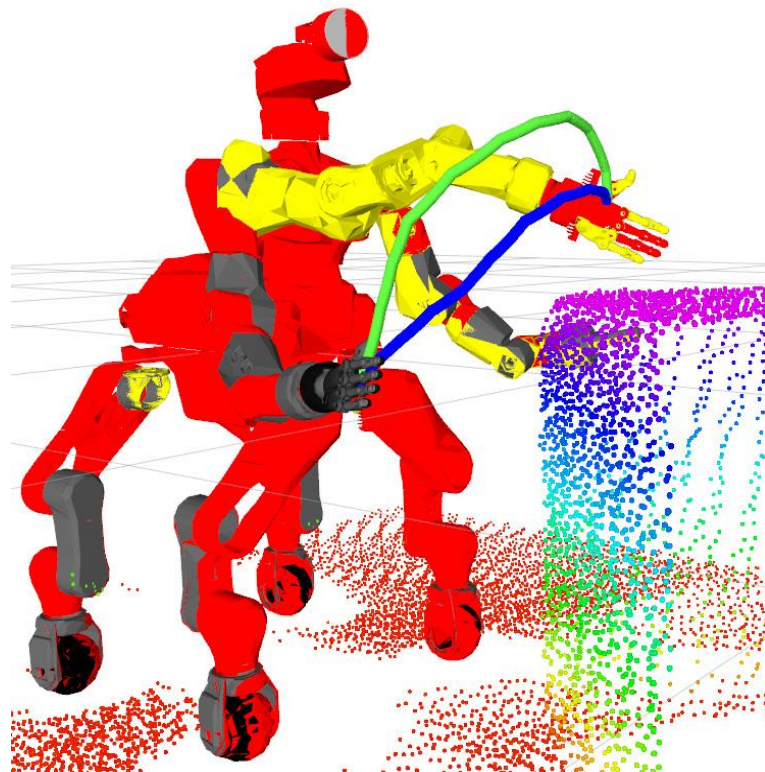
■ Partial view



# Collision-aware Motion Generation

Constrained Trajectory Optimization:

- Collision avoidance
- Joint limits
- Time minimization
- Torque optimization



[Pavlichenko et al., IROS 2017]



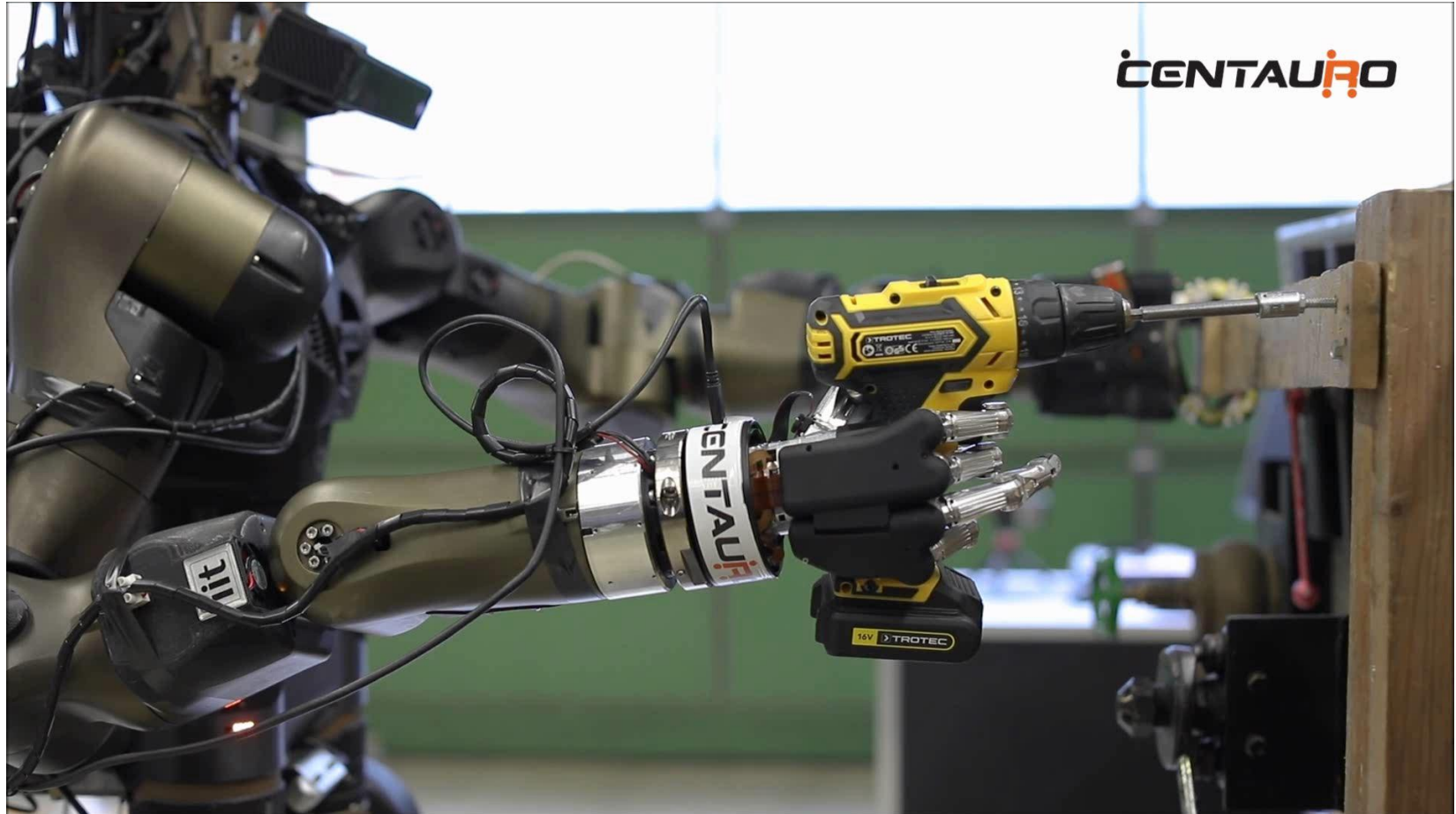
# Grasping an Unknown Power Drill



# Fastening a Screw



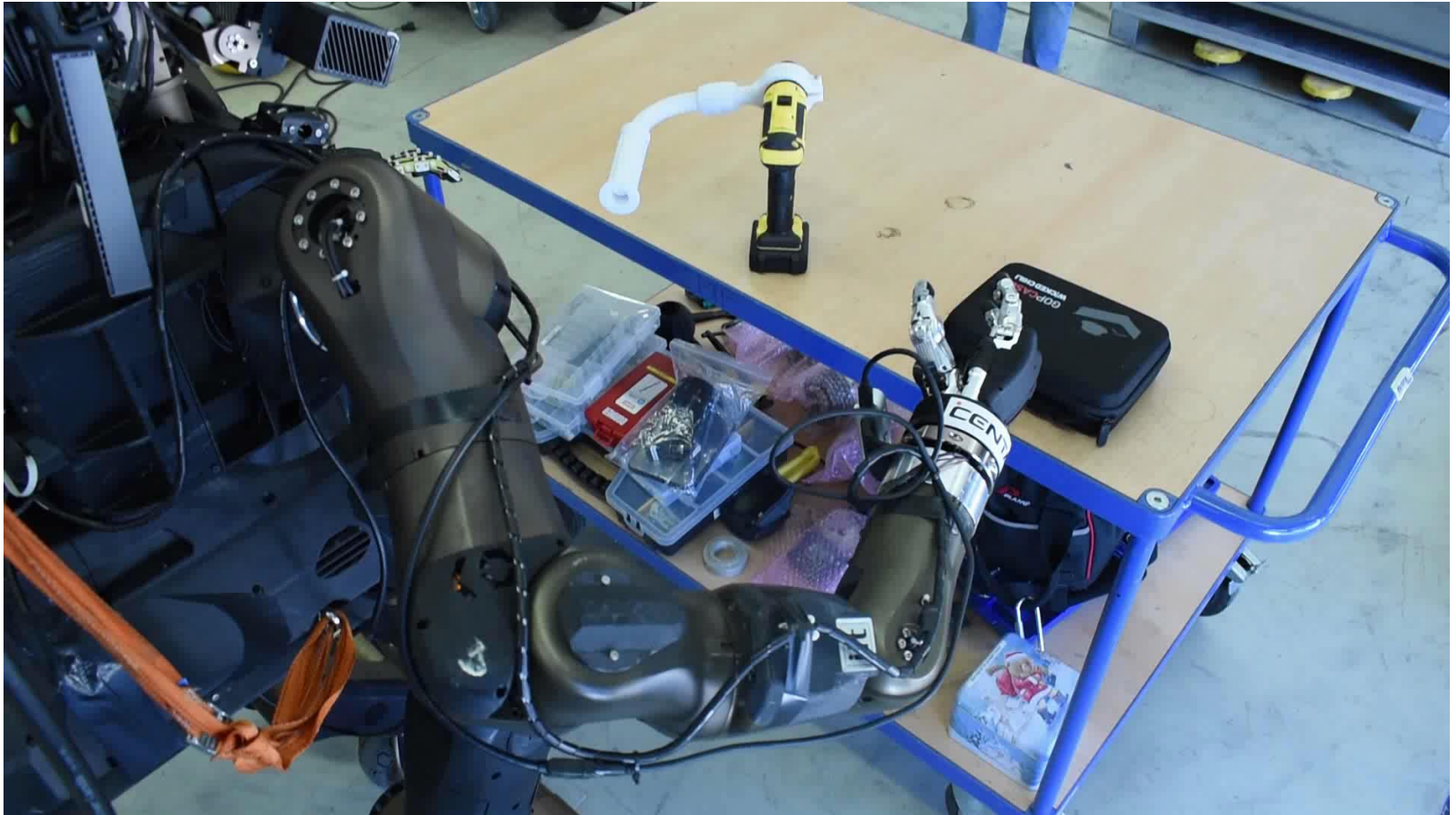
# Bimanual Fastening Task



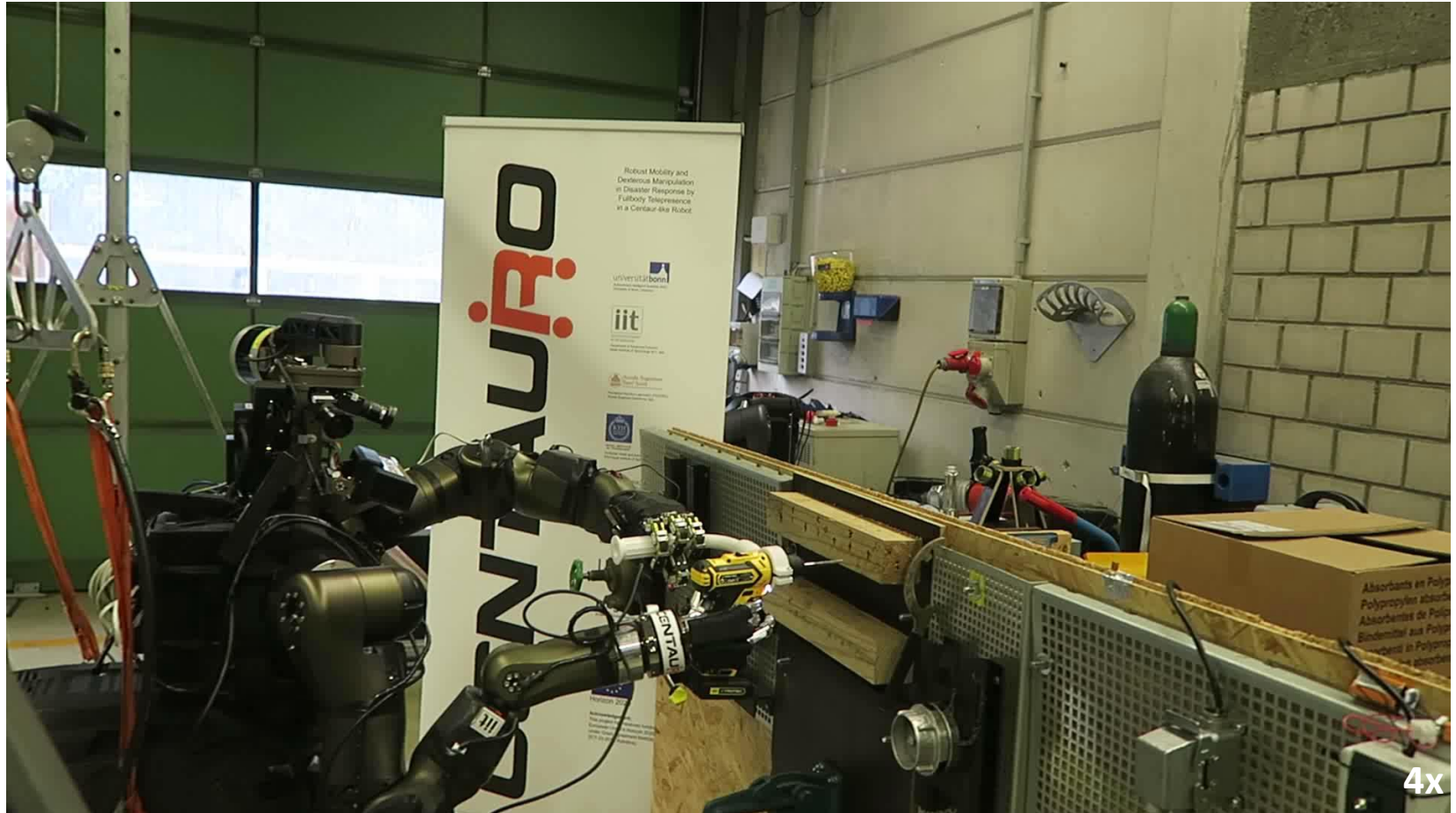
CENTAURO



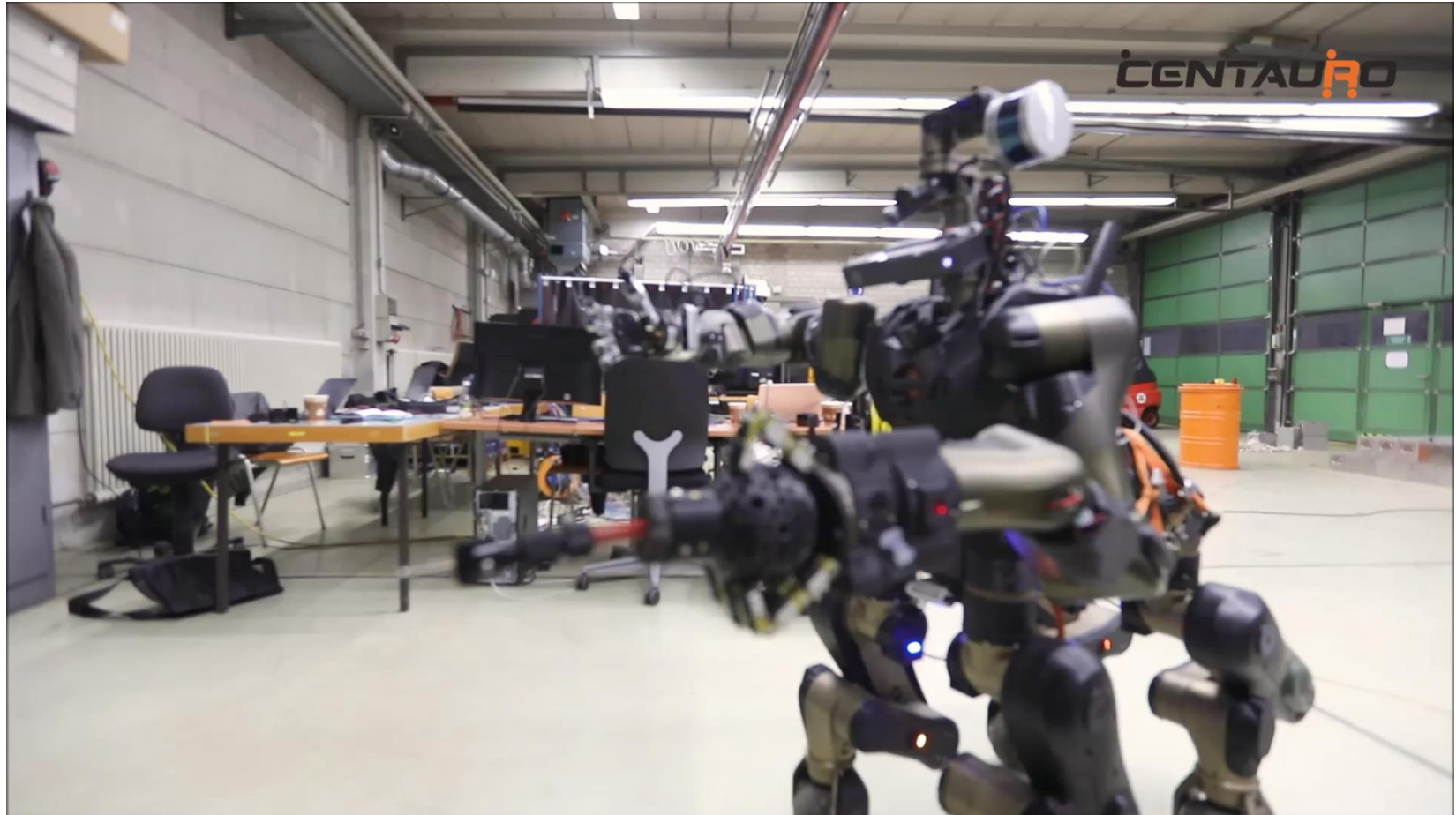
# Bimanual Grasping



# Bimanual Drilling

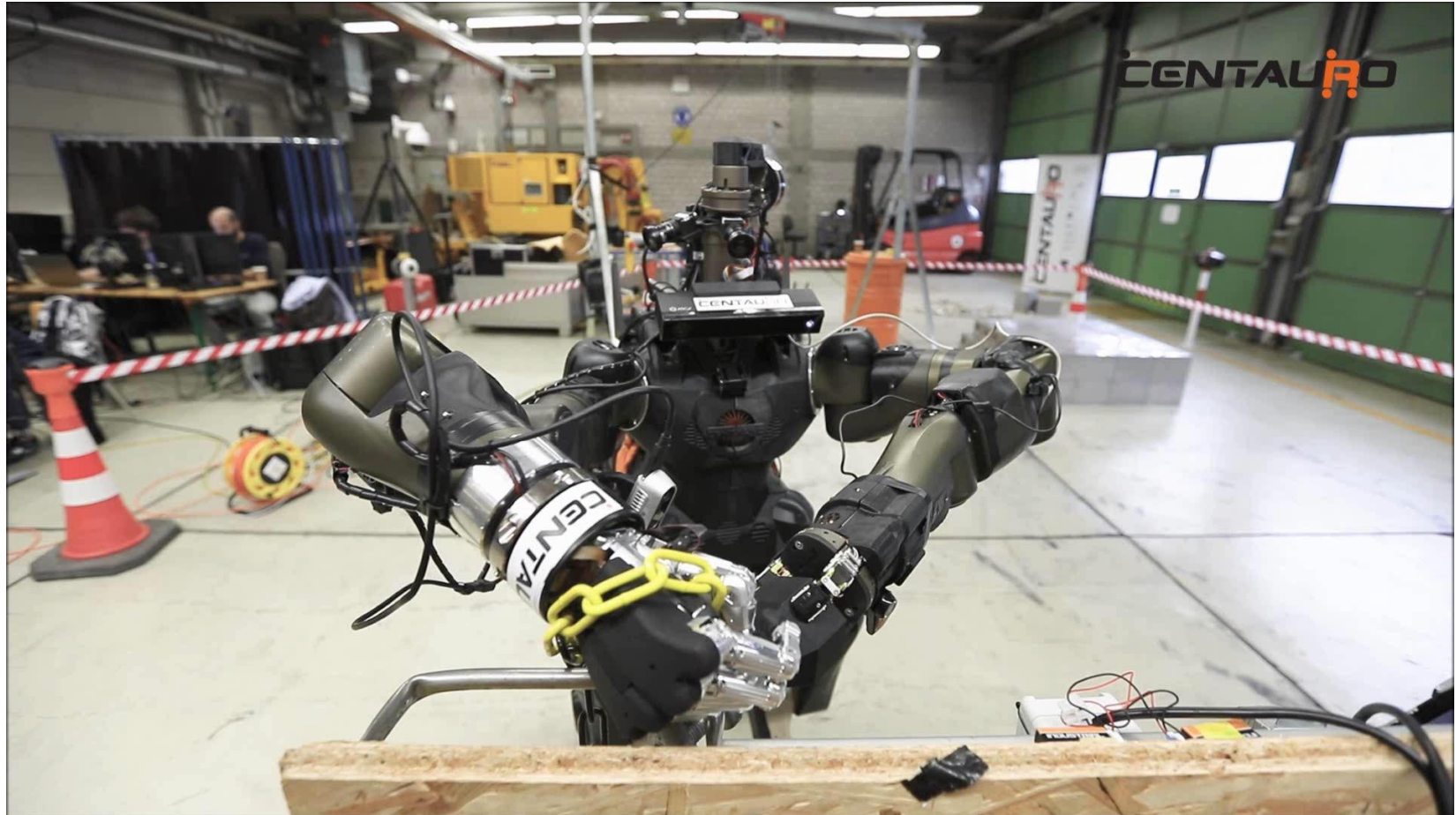


# Opening a Door with a Key

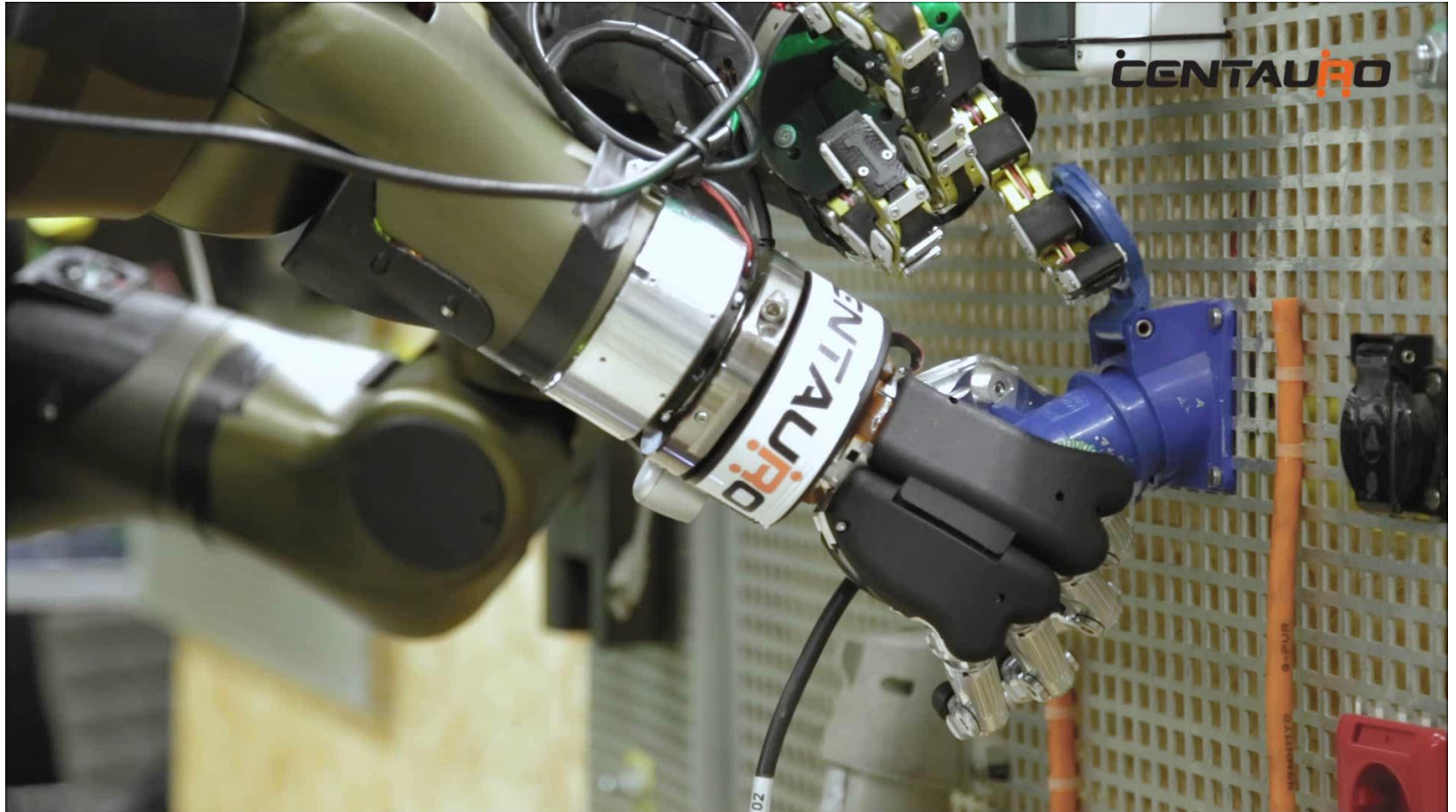




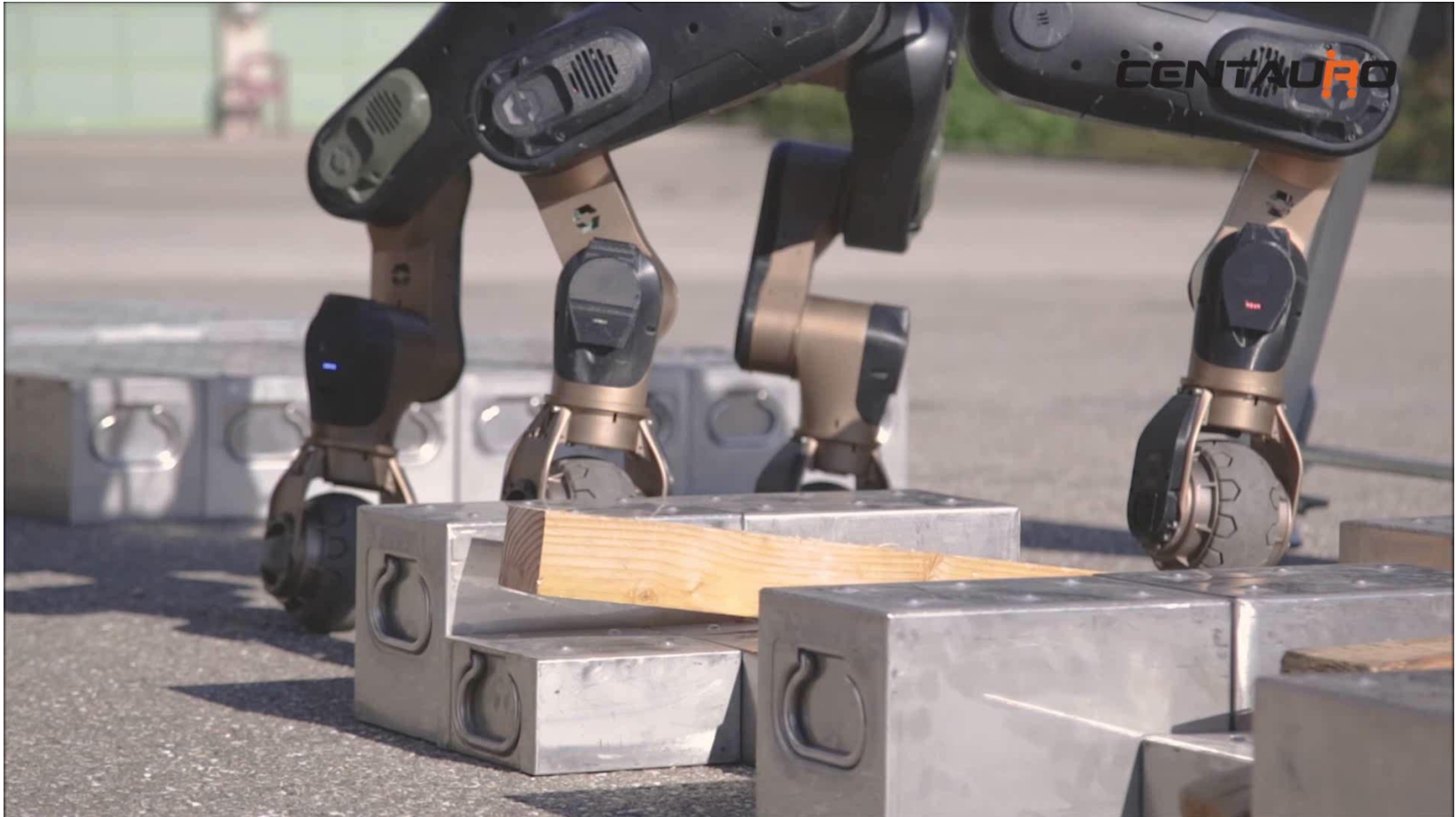
# Closing a Shackle



# Bimanual Plug Tasks



# Step Field with Debris





# Autonomous Navigation



# CENTAURO Team



# Conclusions

- Developed capable humanoid robot systems for disaster-response scenarios
- Teleoperation is flexible, but demanding and error-prone
- Autonomy for common navigation and manipulation tasks needed
- Challenges include
  - Capable and affordable robot platforms
  - 4D semantic perception
  - High-dimensional motion planning
- Promising approaches
  - Shared autonomy
  - Structured learning

