3D Perception for Transport and Inspection Robots

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1. AASS MR&O Lab – Profile
2. Field Robotics and 3D Perception Projects at AASS
3. Rich 3D for Industrial Applications
4. 3D-NDT Representation
5. Rich 3D Perception – Recent and Ongoing Work
   - NDT-to-NDT Registration
   - Real Time Registration of RGB-D Data using Local Visual Features and 3D-NDT Registration
   - iMAC Occupancy Grid Maps for Representation of Dynamic Environments
   - 3D-NDT in Dynamic Environments (A First Glimpse)

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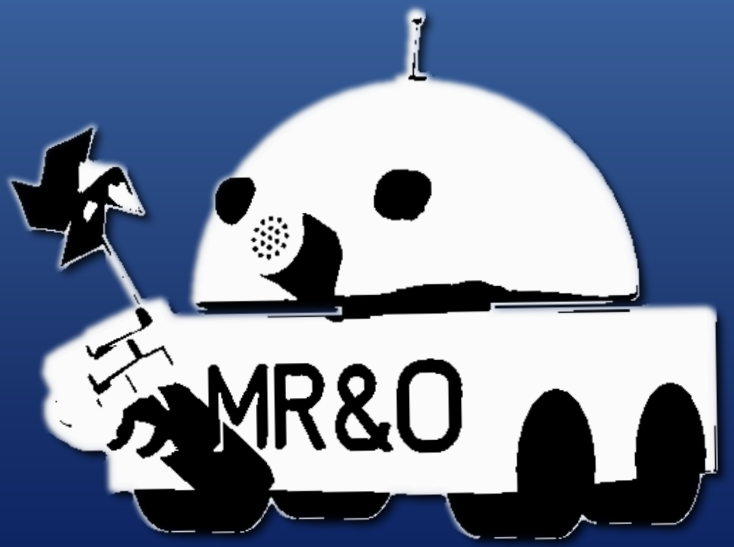
AASS MR&O Lab – Profile



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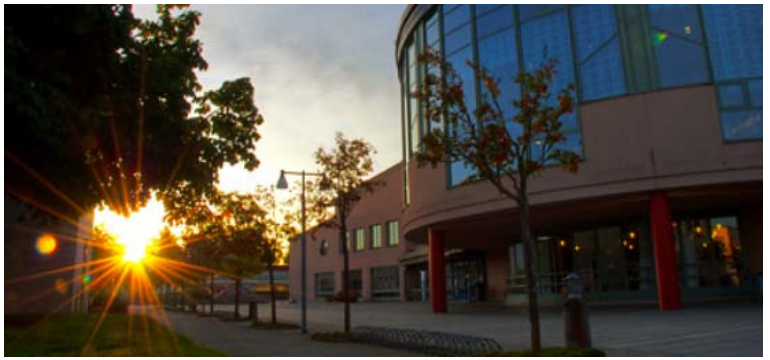
  - 7 schools, 15 research centers



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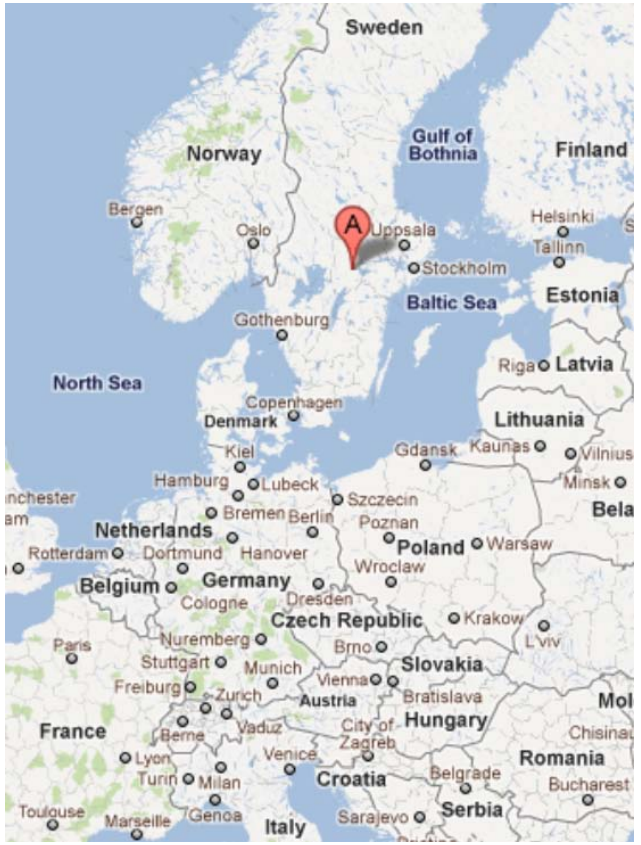

- **Center for Applied Autonomous Sensor Systems**
  - established in 1998
  - largest Swedish research center in robotics
  - two research labs
    - » Cognitive Robotic Systems lab (CRS)
    - » Mobile Robotics and Olfaction lab (MRO)

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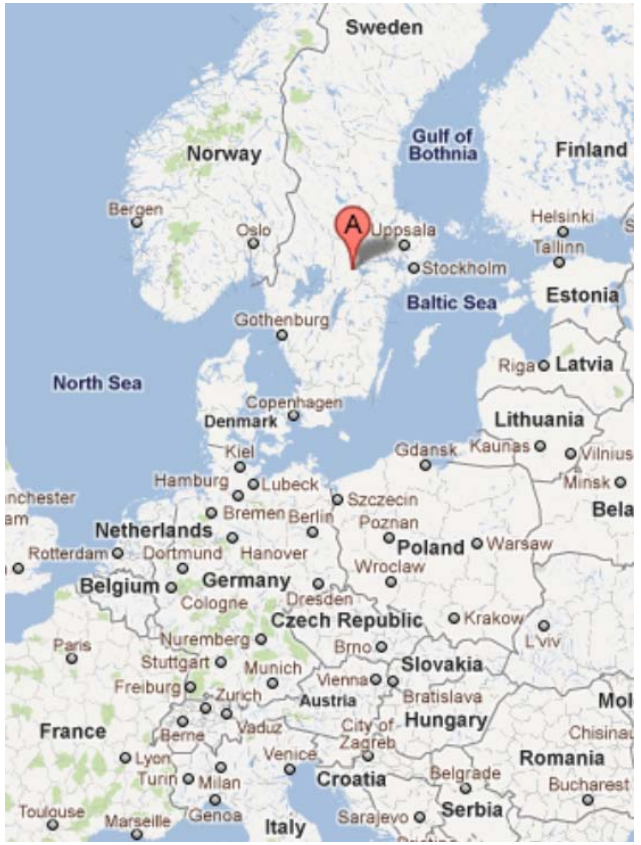

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MR&O MOBILE ROBOTICS & OLFACTION

http://aass.oru.se/Research/mro/

- **General Focus ...**
  - perception systems for mobile robots (fundamentals for autonomous and safe operation)
- **Objective ...**
  - advance theoretical and practical foundations that allow mobile robots to operate in an unconstrained, dynamic environment
- **Approaches are Characterized by ...**
  - fusion of different sensor modalities
  - timely integration into industrial demonstrators

Achim J. Lilienthal
Since Jul 2005 (Ass. Professor)

Henrik Andreasson
Since Sep 2005 (Lecturer)

Abdelbaki Bouguerra
Since Apr 2008 (Lecturer)

Marcello Cirillo
Since Feb 2011 (Postdoc)

Martin Magnusson
Since 2004 (Lecturer)

Dr. Jari Saarinen
Since Aug 2012 (Researcher, Aalto)

Todor Stoyanov
Since Sep 2008 (Postdoc)

Marco Trincavelli
Since Feb 2011 (Postdoc)

Anani Ananiev
Since 1999 (Ass. Professor)

Ivan Kalaykov
Since 1998 (Professor)

Houssam Albitar
Since 2011 (Ph.D. Student)

Mohamad Aldanmad
Since 2011 (Ph.D. Student)

Håkan Almqvist
Since Sep 2009 (Ph.D. Student)

Muhammad Asif Arain
Since Oct 2012 (Ph.D. Student)

Sahar Asadi
Since Jan 2009 (Ph.D. Student)

Victor Hernandez Bennetts
Since Jan 2011 (Ph.D. Student)

Daniel Canelhas
From Jun 2012 (Ph.D. Student)

Krzysztof Charusta
Since Oct 2012 (Ph.D. Student)

Kinan Dandan
Since 2011 (Ph.D. Student)

Robert Krug
since Sep, 2009 (Ph.D. Student)

Tomasz P. Kucner (ALLO)
Since Oct 2012 (Ph.D. Student)

Rasoul Mojtahedzadeh
Since Sep 2011 (Ph.D. Student)

- **D1 – Mobile Robotics**
  - for autonomous and safe long-term operation in the real world
  - technology transfer through collaborative projects with industrial partners in the area of logistics robots
  - examples: autonomous forklifts and autonomous wheel loaders

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- **Forklift Trucks** (Danaher Motion, Linde MH, Stora Enso)

speed x 2

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  - environment with a dynamic "background"

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  - environment with a dynamic "background"
  - requires 3D sensing

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speed **x 1**

MR&O Lab Profile – Two Major Research Directions

- **Forklift Trucks** (Danaher Motion, Linde MH, Stora Enso)
- **Wheel Loaders** (VolvoCE, VolvoTech, NCC)

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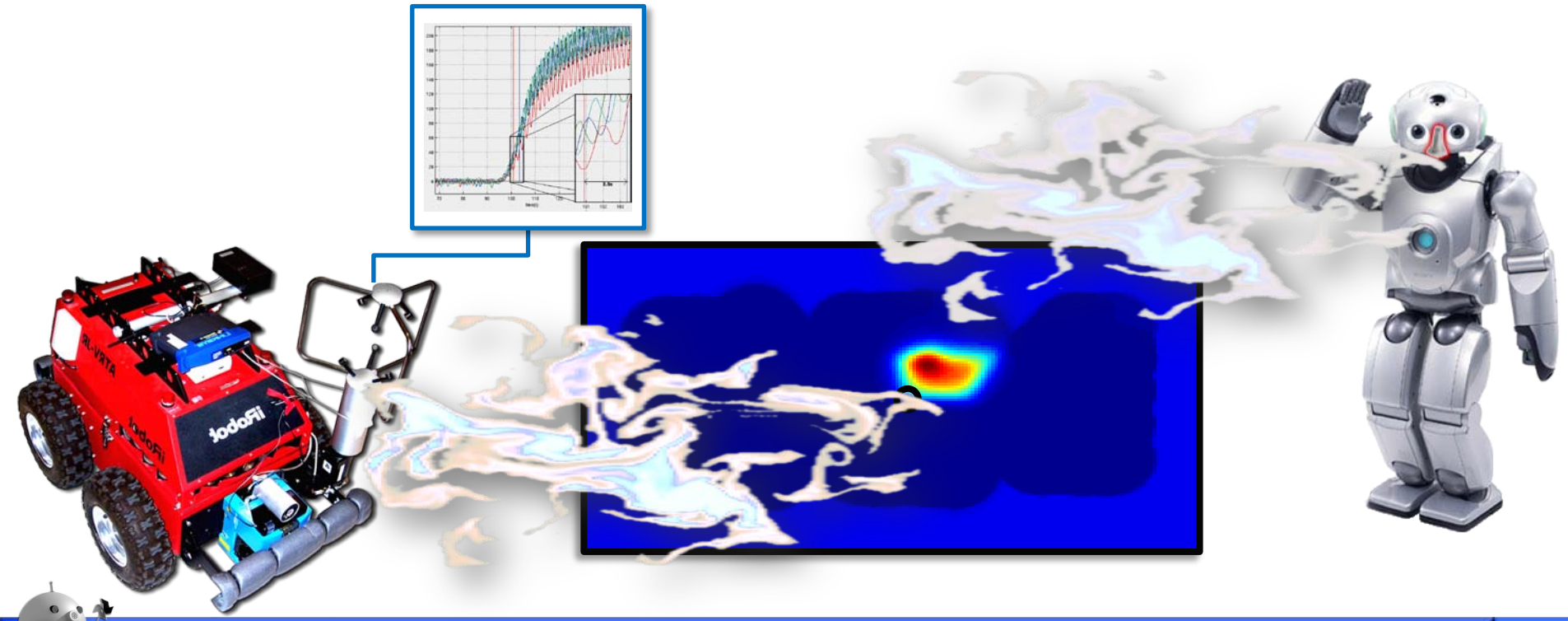
- **Forklift Trucks** (Danaher Motion
- **Wheel Loaders** (VolvoCE, Volvo
- **Mining Vehicles** (Atlas Copco, F
- **Hospital Transport Vehicles** (Ro
- **Garbage Bin Collection and Cleaning** (RoboTech)

- **D2 – Artificial and Mobile Robot Olfaction**
  - Artificial Olfaction = gas sensing with artificial sensor systems
  - we study particularly open sampling systems def
  - develop "electronic nose" towards a "mobile nose"
  - examples: gas sensor networks (air pollution monitoring), inspection robots (landfill site surveillance, gas leak localization)



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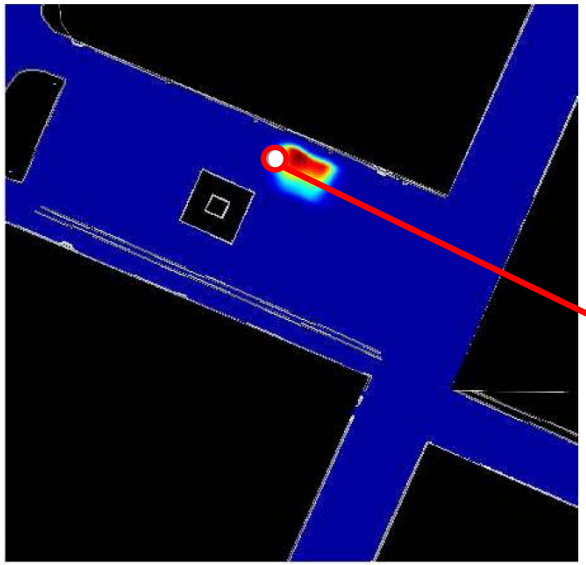
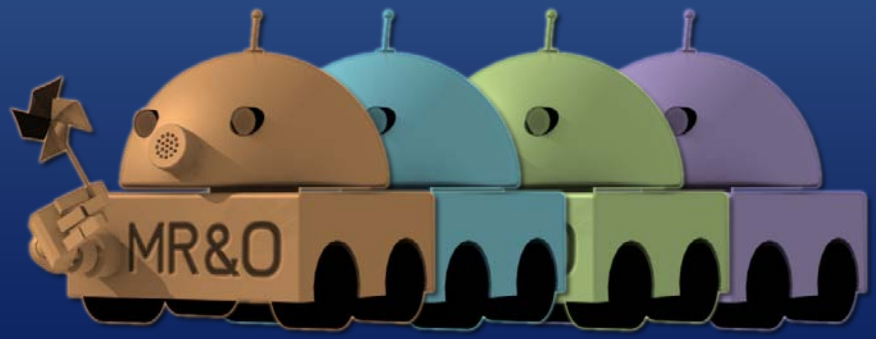
- **Hospital Transport Vehicles** (RobCab)
- **Garbage Bin Collection and Cleaning** (RoboTech)
  - … and pollution monitoring



Mobile Work Machines

- **Forklift Trucks** (Danaher M
- **Wheel Loaders** (VolvoCE, V
- **Mining Vehicles** (Atlas Cop
- **Hospital Transport Vehicle**
- **Garbage Bin Collection an**
- **Landfill Site Inspection** (Atleverket)

Field Robotics and 3D Perception Projects at AASS



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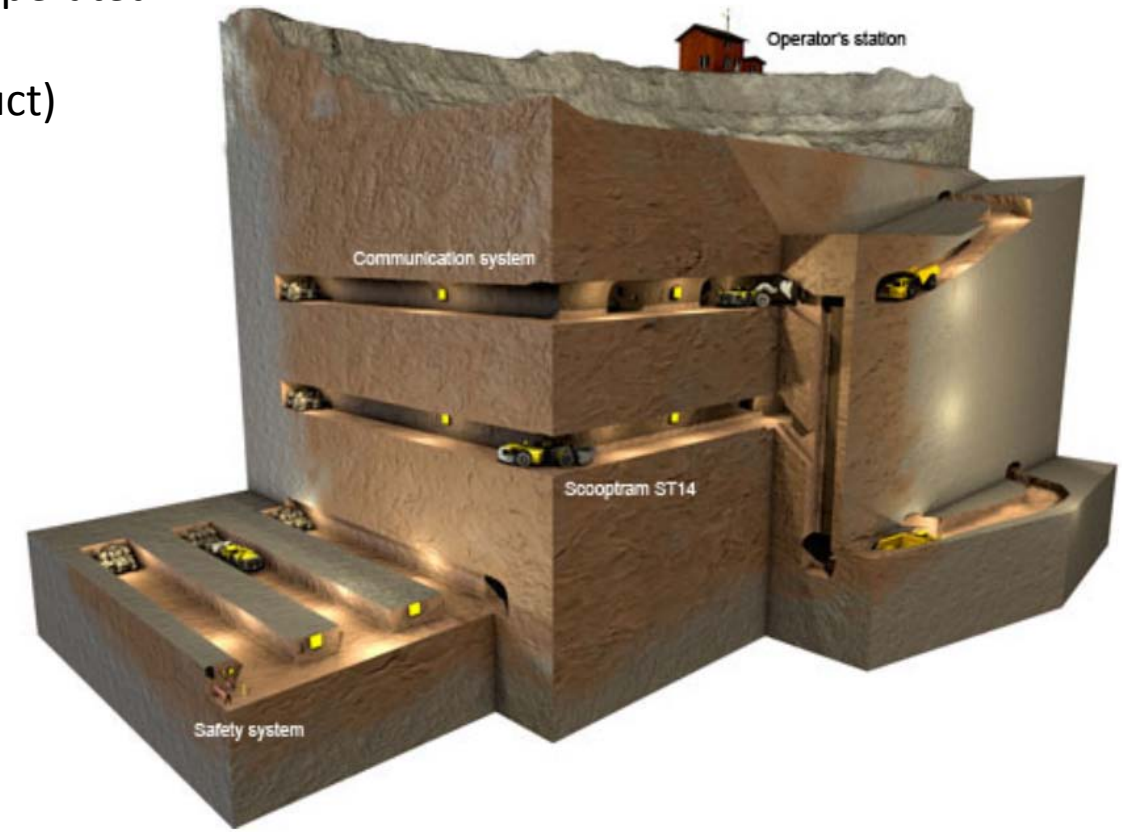
History of "Field Robotics" Projects

- NSAL (2005–2012) AASS (CRS Lab), Atlas Copco
  - behavior-based autonomous LHD vehicle navigation in mines
  - main contribution
    - mixed autonomous/teleoperated control
      (now a commercial product)



History of "Field Robotics" Projects

- NSAL (2005–2012)
- MALTA (2008–2011) AASS, HiH, Kollmorgen, Linde Material Handling, Stora Enso Logistics
  - Multiple autonomous forklifts for loading and transportation applications
  - main contribution
    - navigation without reflectors
    - autonomous paper reel handling

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- NSAL (2005–2012)
- MALTA (2008–2011) → SAVIE (2011–2014) AASS, Kollmorgen, Linde MH
  - Multiple autonomous forklifts for loading and transportation applications
  - Safe autonomous industrial vehicles for industrial environments
  - topics
    - localization w minimum infrastructure (single fish-eye camera, 2D LRF)
    - obstacle detection/avoidance at "high speed"

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  - Safe autonomous industrial vehicles for industrial environments
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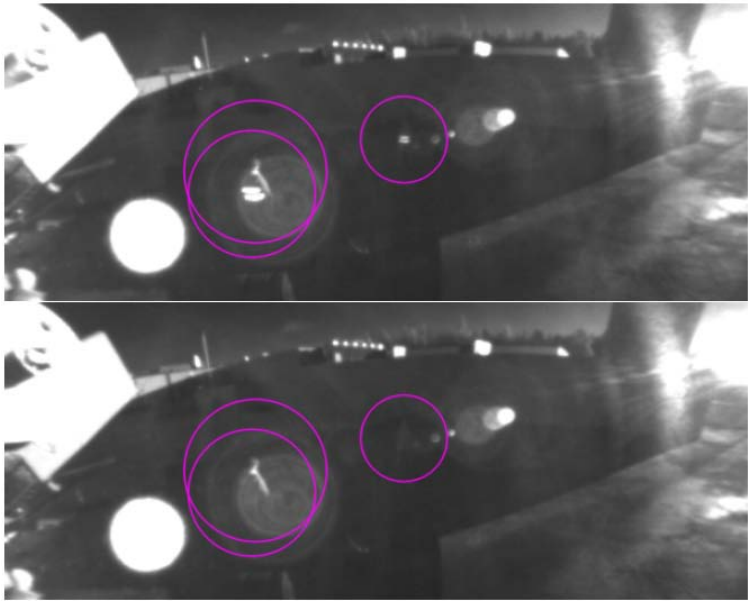
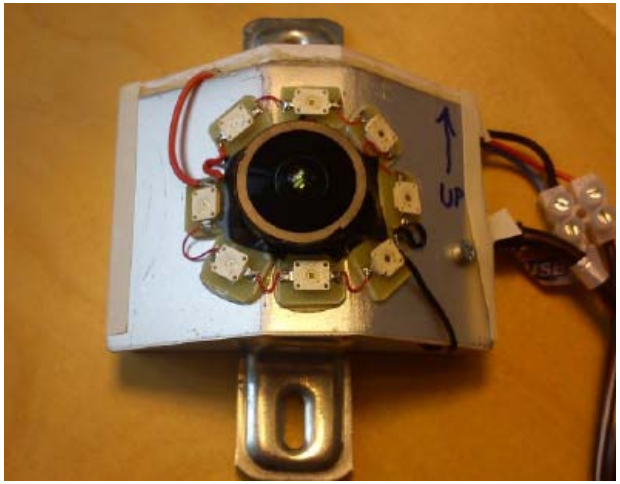
    - localization w minimum infrastructure (single fish-eye camera, 2D LRF)
    - detection and distance prediction of humans with reflective vest





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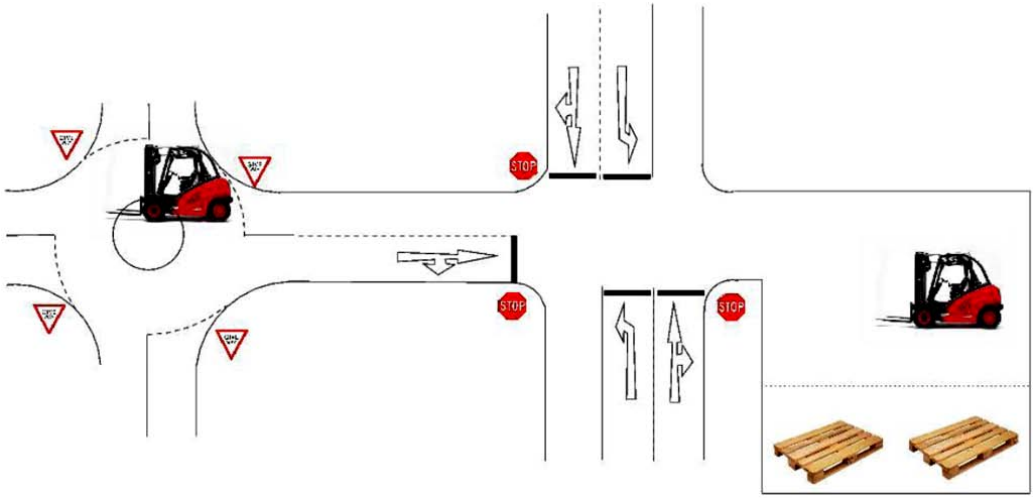
    - localization w minimum infrastructure (single fish-eye camera, 2D LRF)
    - obstacle detection/avoidance at "high speed"
    - trajectory prediction / path planning, with traffic rules (→ flexibility + predictability)



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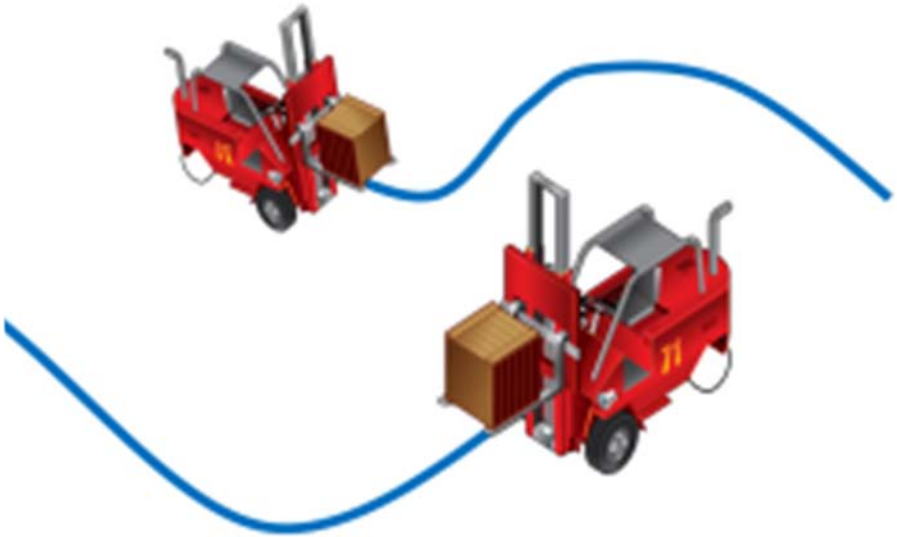

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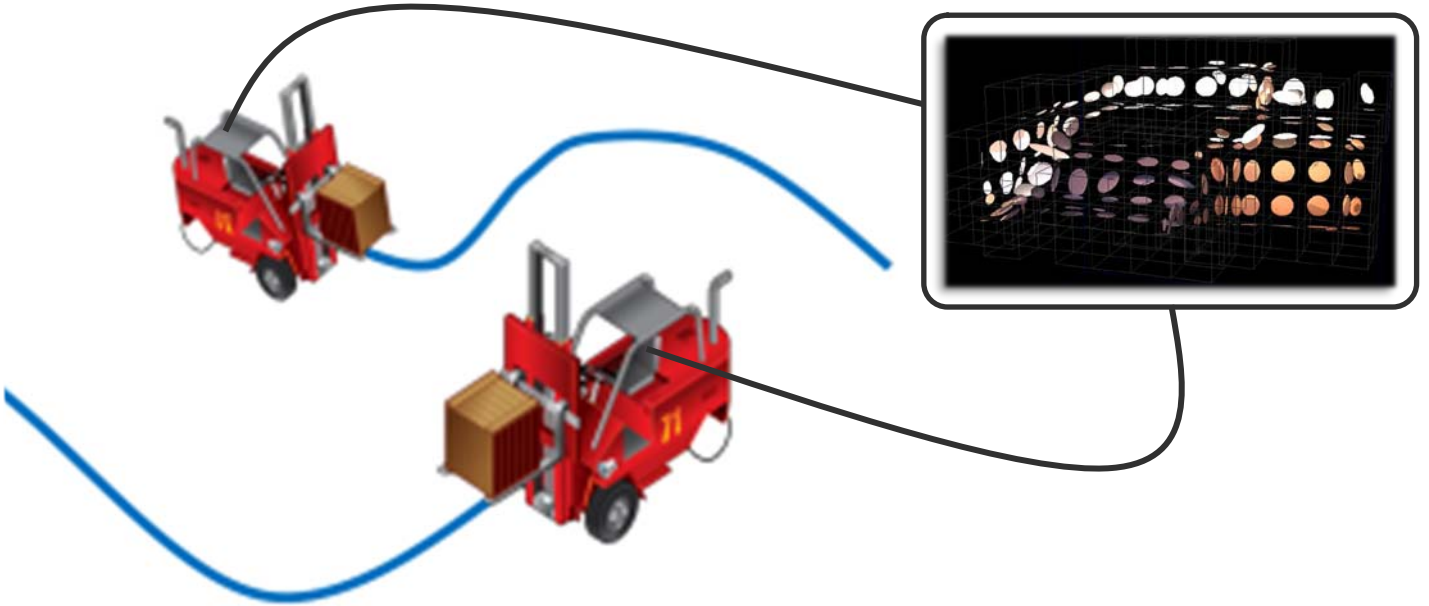
  - » logistics + safe autonomous vehicle navigation in dynamic environments
    - Objective 2 – Rich 3D Perception
      - compact 3D representation, registration on compact 3D representations (localization), mapping in dynamic environments, identification of drivable areas, 3D HMT SLAM



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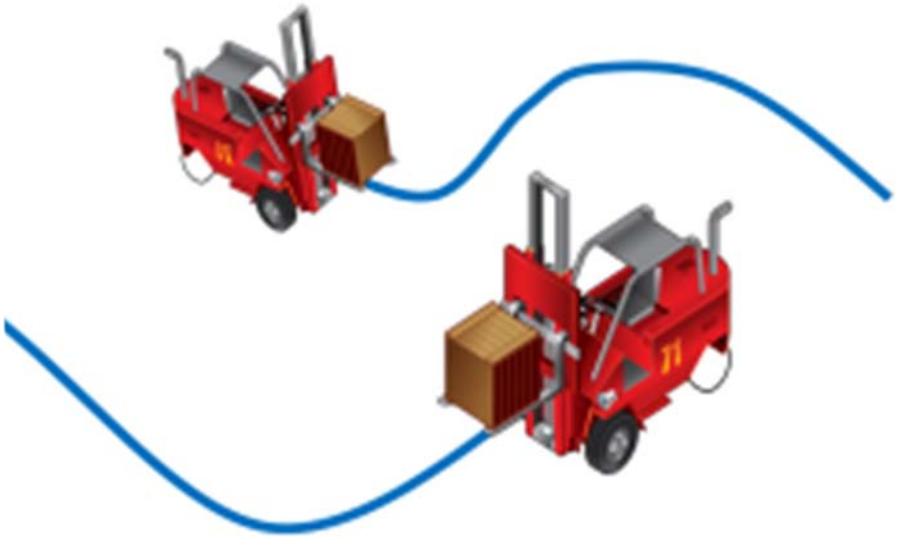
    - Objective 2 – Rich 3D Perception
    - Objective 1 – Safe Motion
      - collision avoidance, trajectory modification, tracking of vehicles/humans, real-time response



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    - Objective 2 – Rich 3D Perception
    - Objective 1 – Safe Motion
    - Objective 3 – Hybrid Planning
      - automate mission planning process (mission + motion planning), take into account multiple types of requirements/constraints, incomplete prior knowledge

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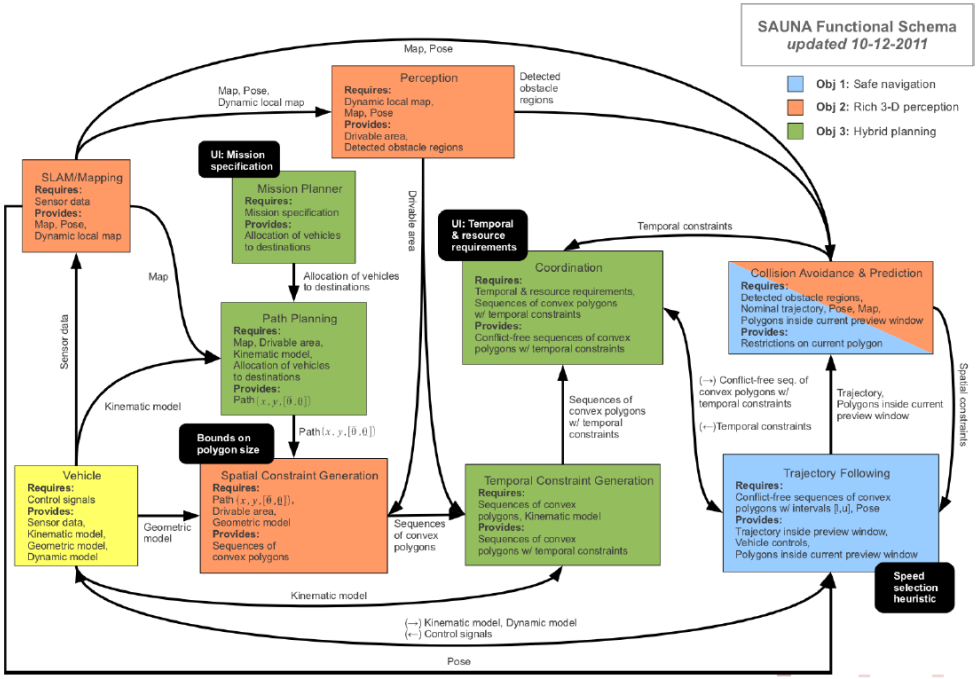
  - » logistics + safe autonomous vehicle navigation in dynamic environments
    - requirements elicited from industrial partners
    - → solutions integrated into a "SAUNA System"



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  - logistics + safe autonomous vehicle navigation in dynamic environments
  - challenges
    - fleets of mixed autonomous and human-operated vehicles
    - high speeds (up to 30-40 km/h)
    - rich 3-D perception for enhanced safety and performance
    - automated mission planning capabilities at several levels of abstraction
    - collision and deadlock avoidance throughout mission planning, trajectory computation and execution
    - flexible operation, accommodation of run-time changes

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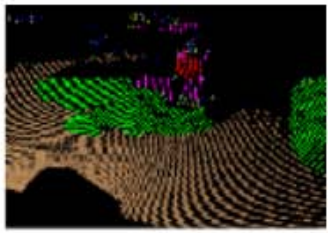
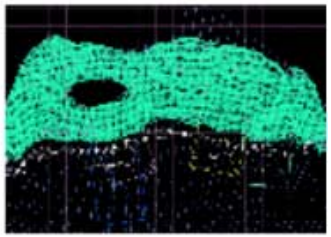
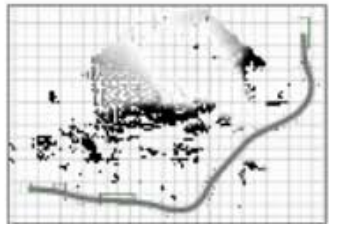
- SAUNA (2011–2014)
- All-4-eHAM (2009–2012) AASS, Volvo CE, NCC Roads
  - Autonomous wheel loaders for efficient handling of heterogeneous materials







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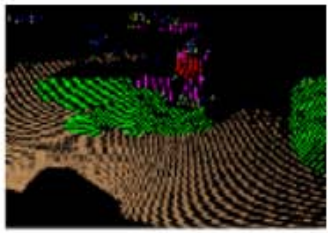
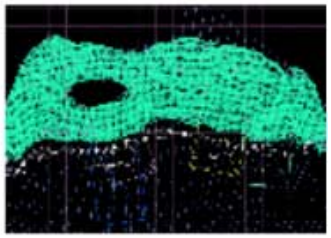
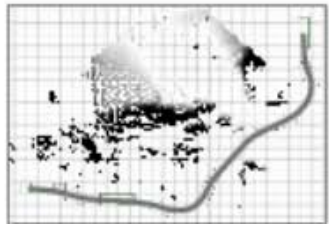
  - » Autonomous wheel loaders for efficient handling of heterogeneous materials
    - robust autonomous operation in 3D, slowly-changing terrain
      - pile detection and attack pose estimation
      - scanning while moving
      - obstacle and people detection in 3D data







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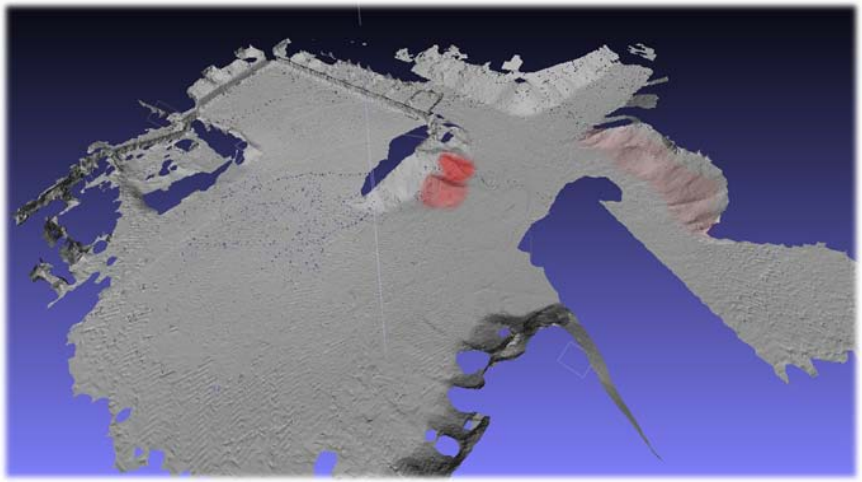
  - » Autonomous wheel loaders for efficient handling of heterogeneous materials
  - » Automomous Long-Term Load-Haul-Dump Operations
    - quantitative evaluation of pile handling and maintenance
    - long-term strategies for pile handling
    - task planning and scheduling (gravel recipes for asphalt production)
    - maintenance of 3D maps in dynamic environments
    - path planning and scheduling in dynamic environments
    - map quality assurance (certification)



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  - RobLog (2011–2015) AASS, Vollers, Qubica, BIBA, Jacobs, Pisa, HSRT
    - » Unloading Containers (Cognitive Robot for Automation of Logistic Processes)

Field Robotics and 3D Perception Projects at AASS

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    - » Unloading Containers
      - industrial scenario (coffee sacks)

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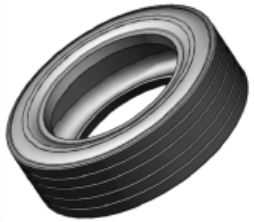
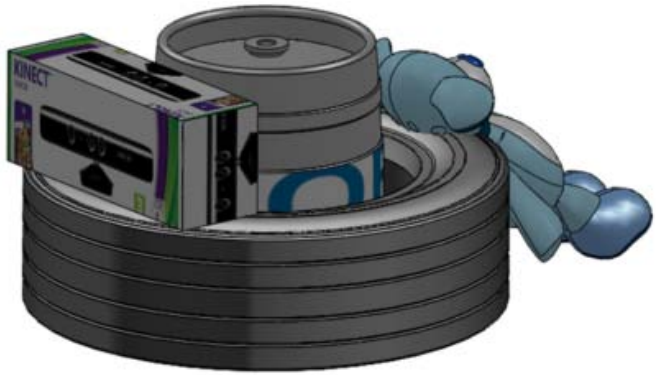
  - » Unloading Containers
    - industrial scenario (coffee sacks)
    - advanced scenario





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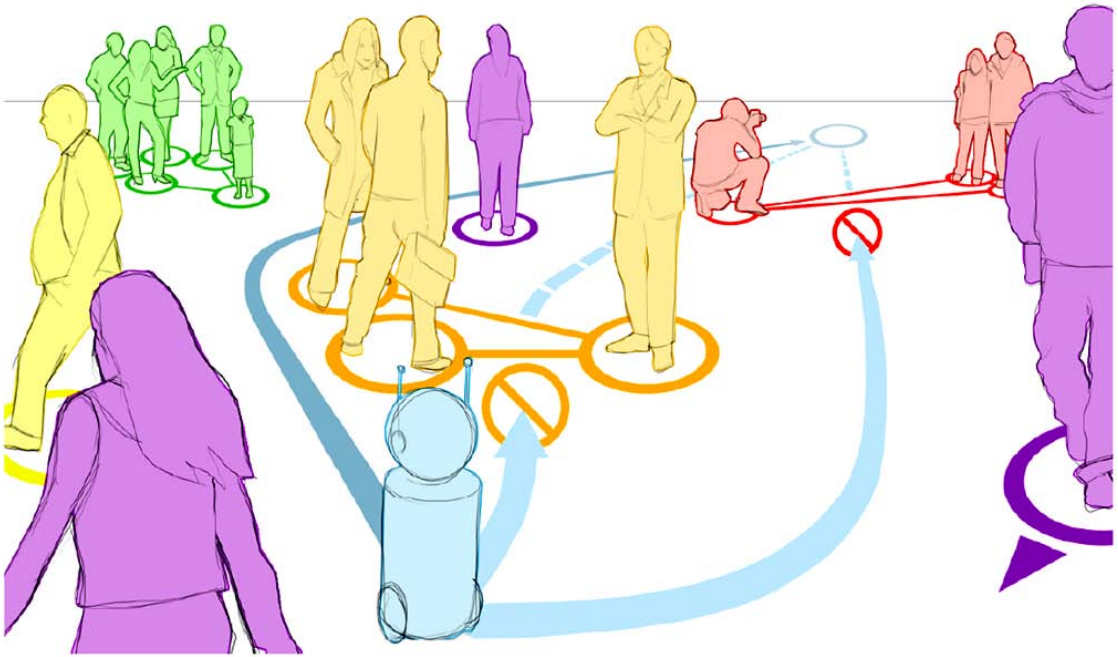
- SPENCER (2013–2016) AASS, TUM, Twente, CNRS, RWTH, BlueBotics, KLM, Freiburg
  - group-friendly navigation



History of "Field Robotics" Projects

- NSAL (2005–2012)
- MALTA (2008–2011) → SAVIE (2011–2014)
- SAUNA (2011–2014)
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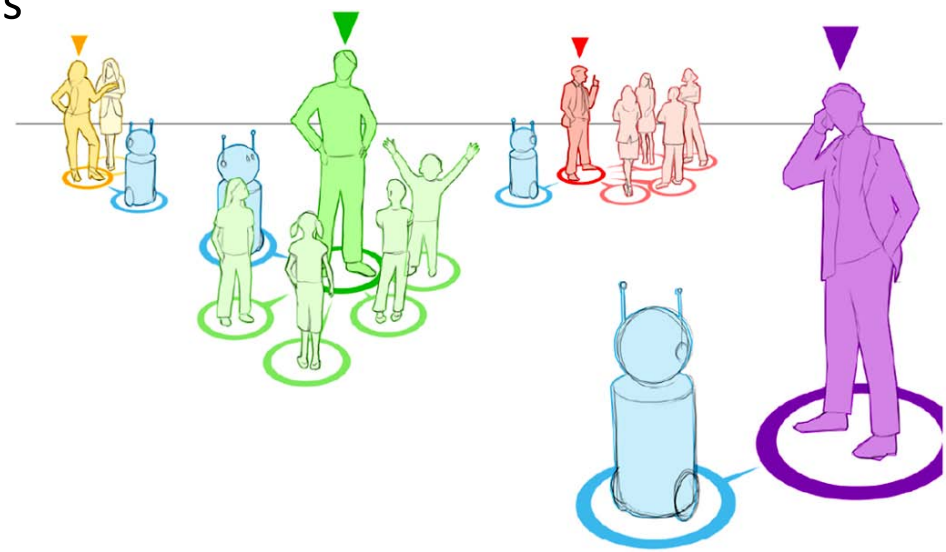
  - group-friendly navigation
  - identification of likely spokespersons



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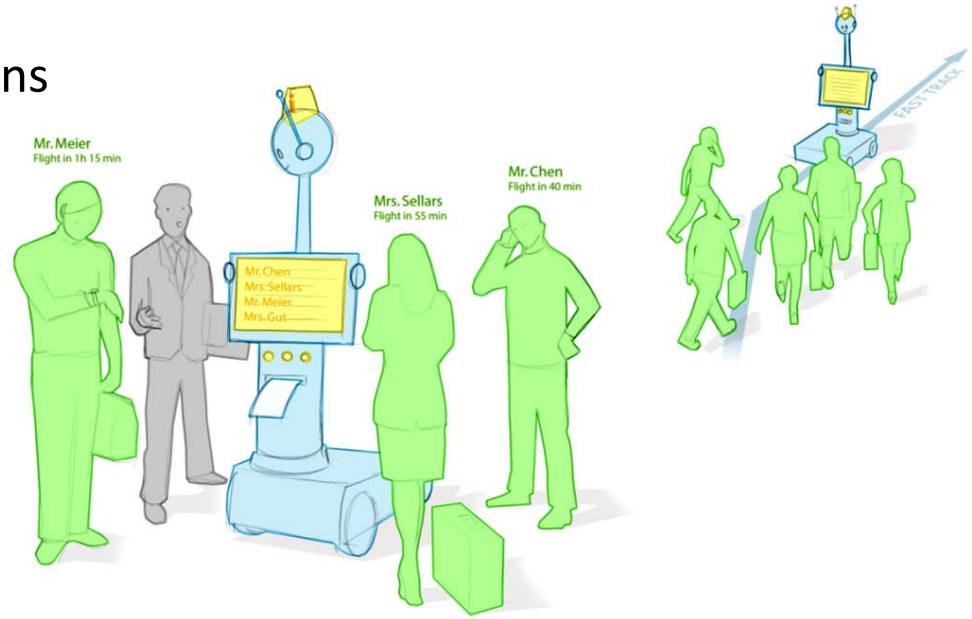
  - group-friendly navigation
  - identification of likely spokespersons
  - Schengen fast track scenario



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- SPENCER (2013–2016) AASS, TUM, Twente, CNRS, RWTH, BlueBotics, KLM, Freiburg
  - challenges
    - localization and mapping in dynamic and social environments
      - identify dynamics of objects
      - → robust and precise localization in highly dynamic environments
    - learning of socially annotated maps
      - related to spatial event distribution models

Rich 3D for Industrial Applications

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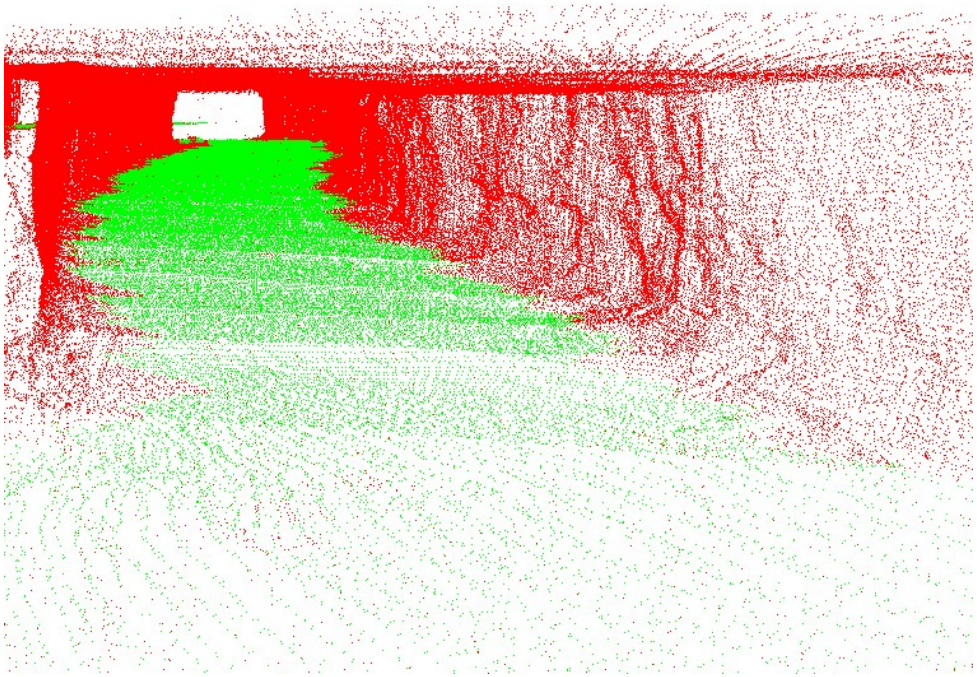
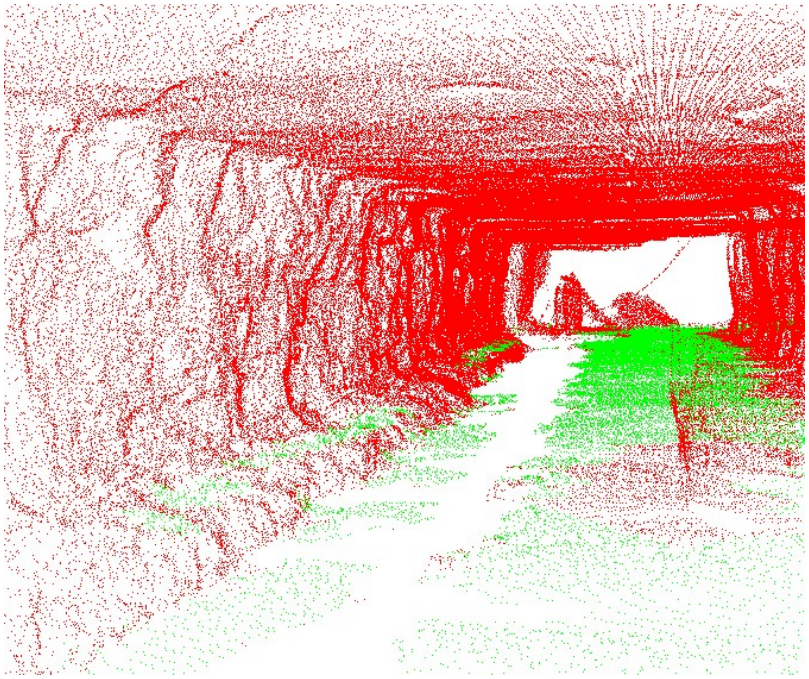
3D Perception Requirements

- ... depend heavily on the application scenario, e.g. SAUNA, RobLog
- → we consider also an inspection robot that senses
  - range
  - colour
  - temperature
  - gas
  - air flow
  - humidity

3D Perception Requirements

- detailed model (detailed "enough")
  - SAUNA: allows extraction of drivable area at reasonably high speeds





3D Perception Requirements

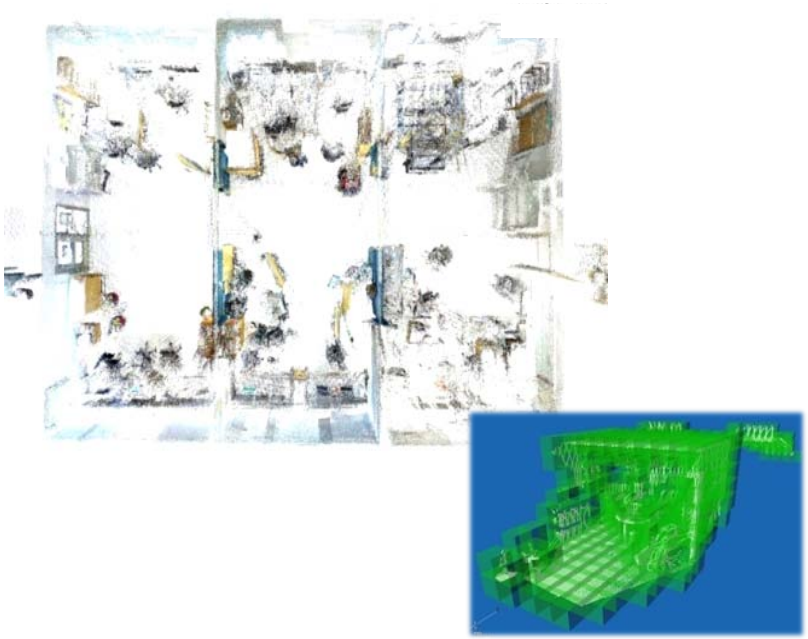
- detailed model (detailed "enough")
  - SAUNA: allows extraction of drivable area at reasonably high speeds
  - RobLog: allows identification of objects from partial views (occlusion)
    - → allows inference (predicting future states)

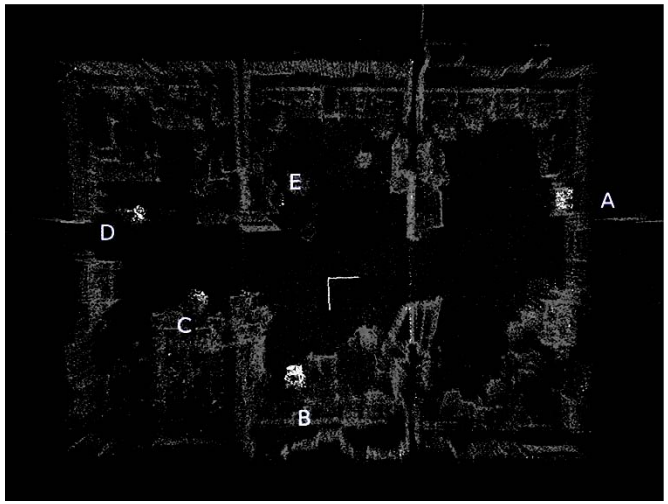
3D Perception Requirements

- detailed model (detailed "enough")
  - » SAUNA: allows extraction of drivable area at reasonably high speeds
  - » RobLog: allows identification of objects from partial views (occlusion)
    - → allows inference (predicting future states)
  - » Inspection Robot: allows for detection of changes that are of potential interest to human decision makers

3D Perception Requirements

- detailed model
- dense (quasi-continuous) model from sparse measurements
  - SAUNA: model uncertainty between distant measurements
  - RobLog: dense enough for object recognition
  - Inspection Robot: change detection for arbitrary points in space from non-aligned measurements



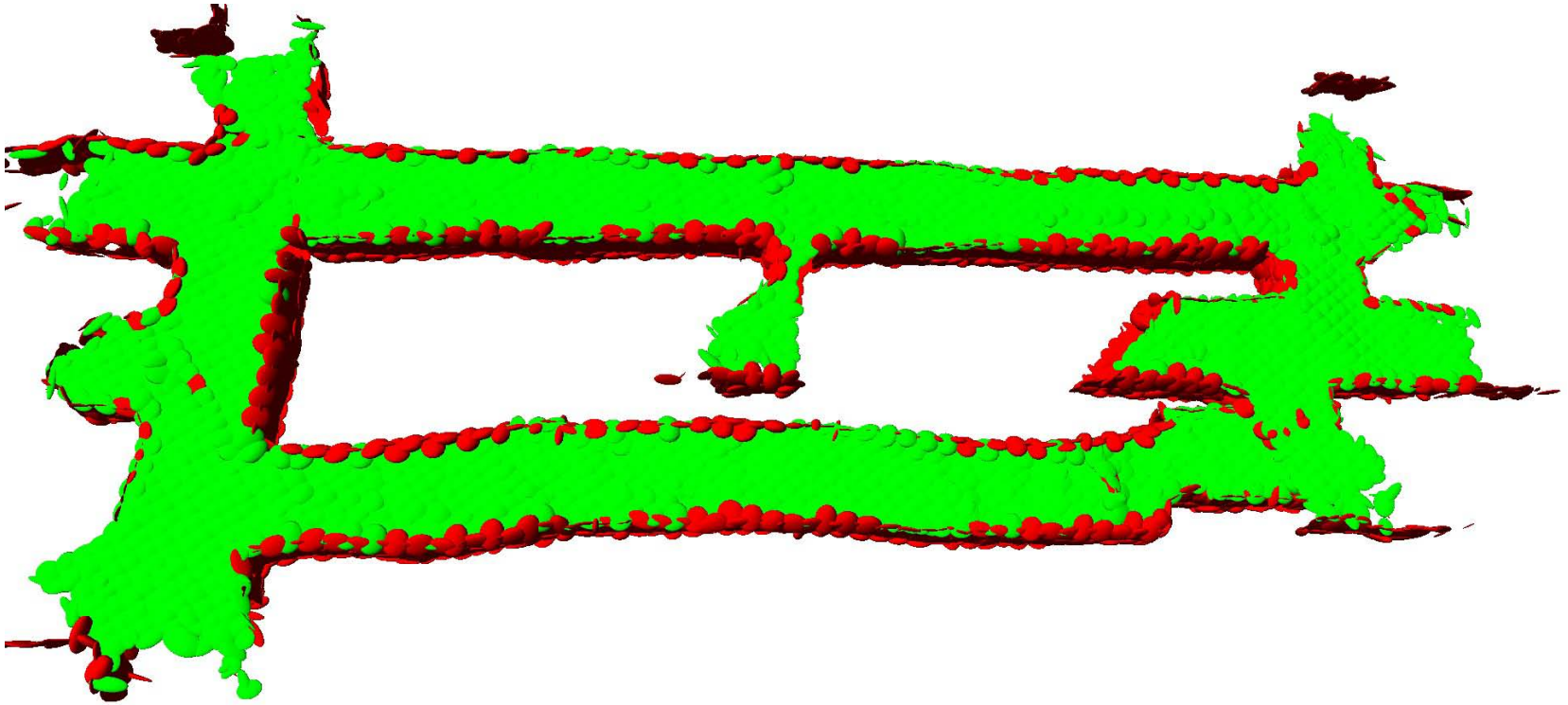


3D Perception Requirements

- detailed model
- dense (quasi-continuous) model from sparse measurements
- compact model
  - often large amount of data
  - compact ⇔ memory requirements do not scale with time but with the size of the environment
  - queries often faster in a compact model
  - → compact yet truthful and versatile representation required

3D Perception Requirements

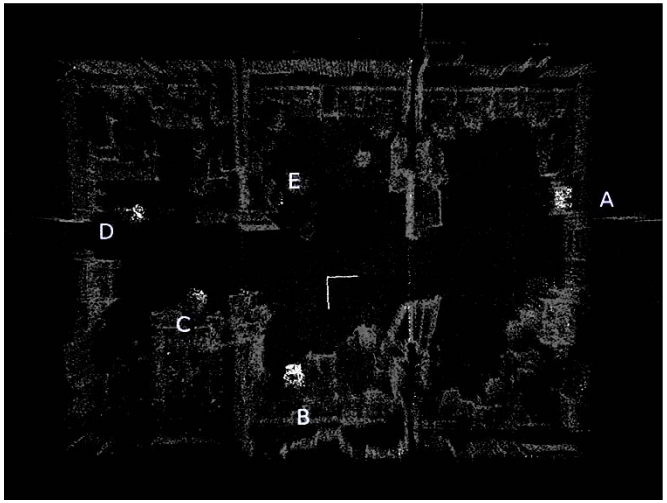
- detailed model
- dense (quasi-continuous) model from sparse measurements
- compact model
  - SAUNA: allows for real-time and long-term operation
  - SAUNA: all operations need to be carried out on the compact model



3D Perception Requirements

- detailed model
- dense (quasi-continuous) model from sparse measurements
- compact model
  - SAUNA: allows for real-time and long-term operation
  - SAUNA: all operations need to be carried out on the compact model
  - Inspection Robot: detect changes compared to old model

weeks or months



- **3D Perception Requirements**
  - detailed model
  - dense (quasi-continuous) model from sparse measurements
  - compact model
  - probabilistic model
    - » model should represent uncertainty about the state of the world
    - » can be in a separate layer

3D Perception Requirements

- detailed model
- dense (quasi-continuous) model from sparse measurements
- compact model
- probabilistic model
- layered model
  - layers carry most of the meaning
    - object labels + corresponding uncertainty
    - semantic categories + corresponding uncertainty
    - distribution of social behaviours, temperature, colour, gas, ...

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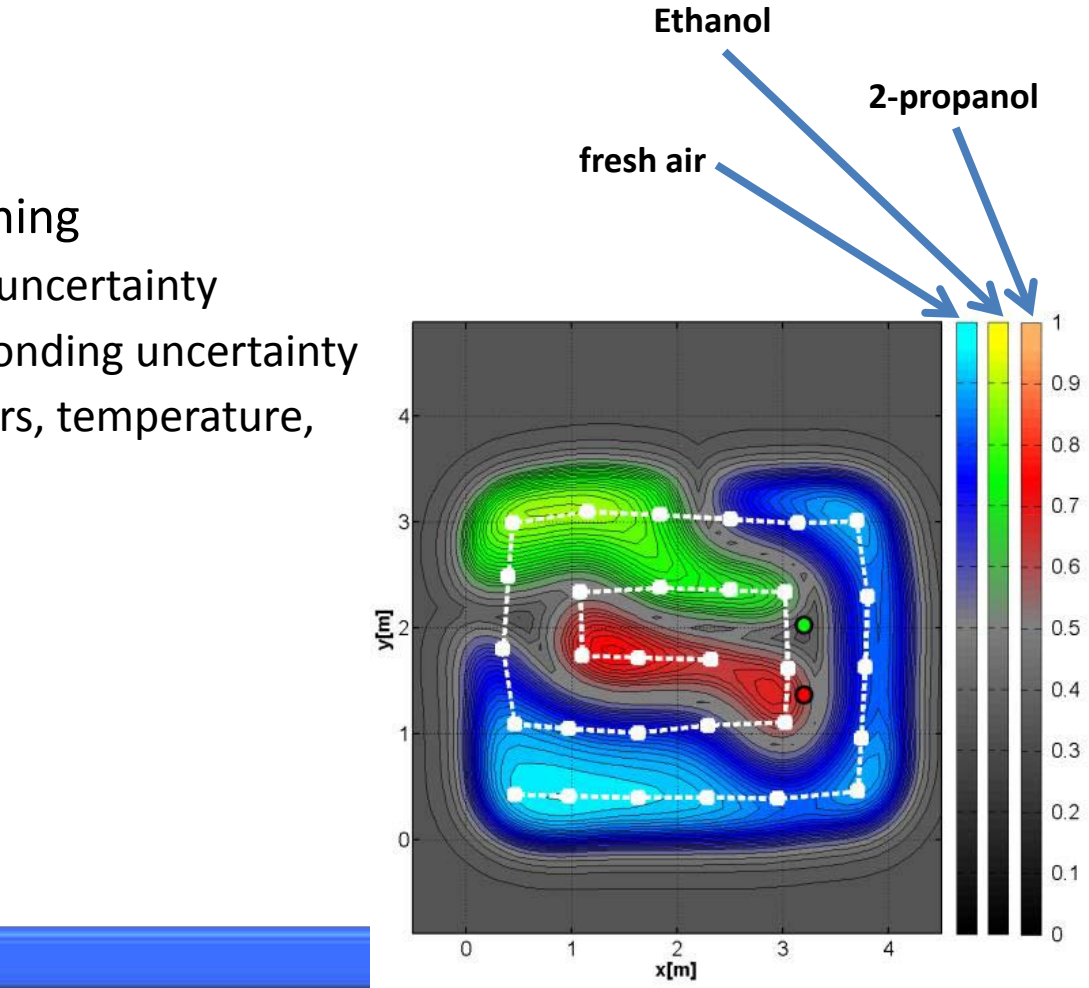

3D Perception Requirements

- detailed model
- dense (quasi-continuous) model from sparse measurements
- compact model
- probabilistic model
- layered model
- maintenance of model in a dynamic environment
  - online update
  - representation of changes over time
  - representation of different dynamics

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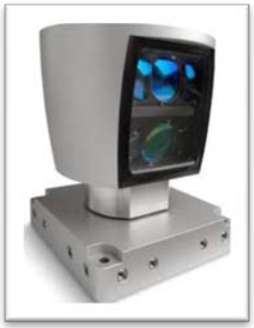
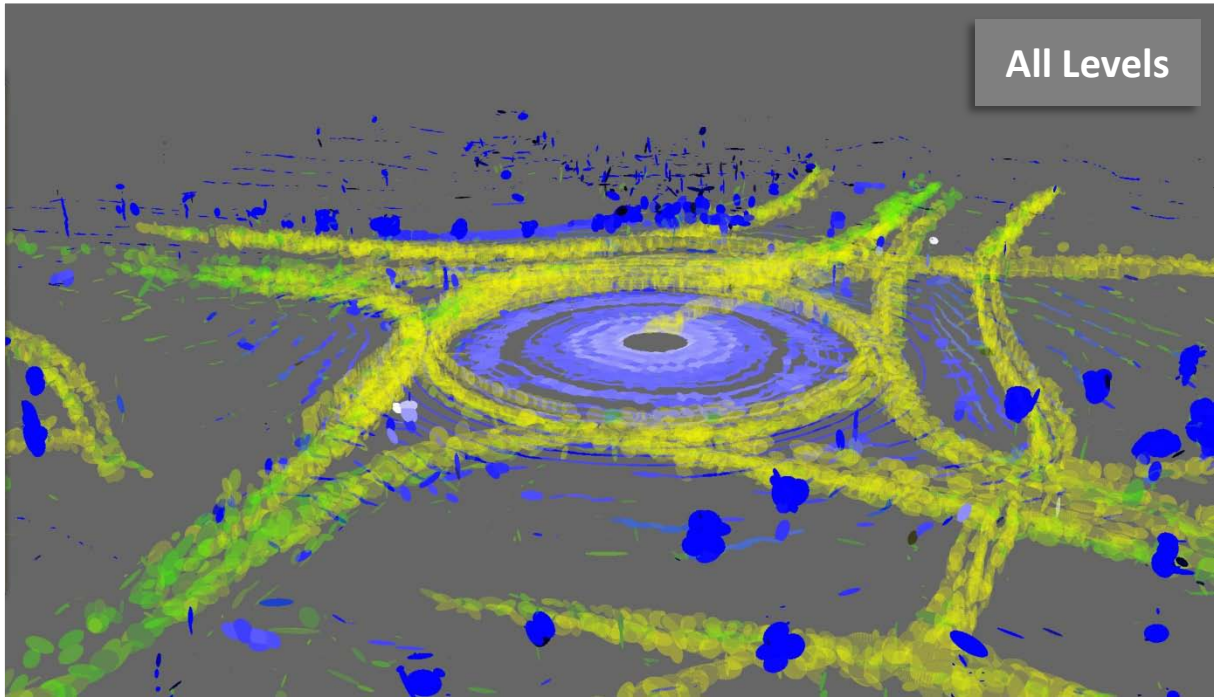
- layered model
- maintenance of model in a dynamic environment
  - » online update
  - » representation of changes over time
  - » representation of different dynamics
    - changes against different time scales





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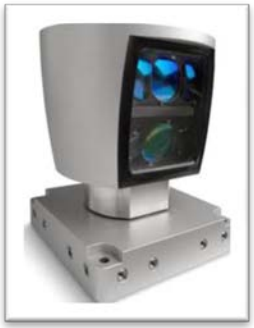

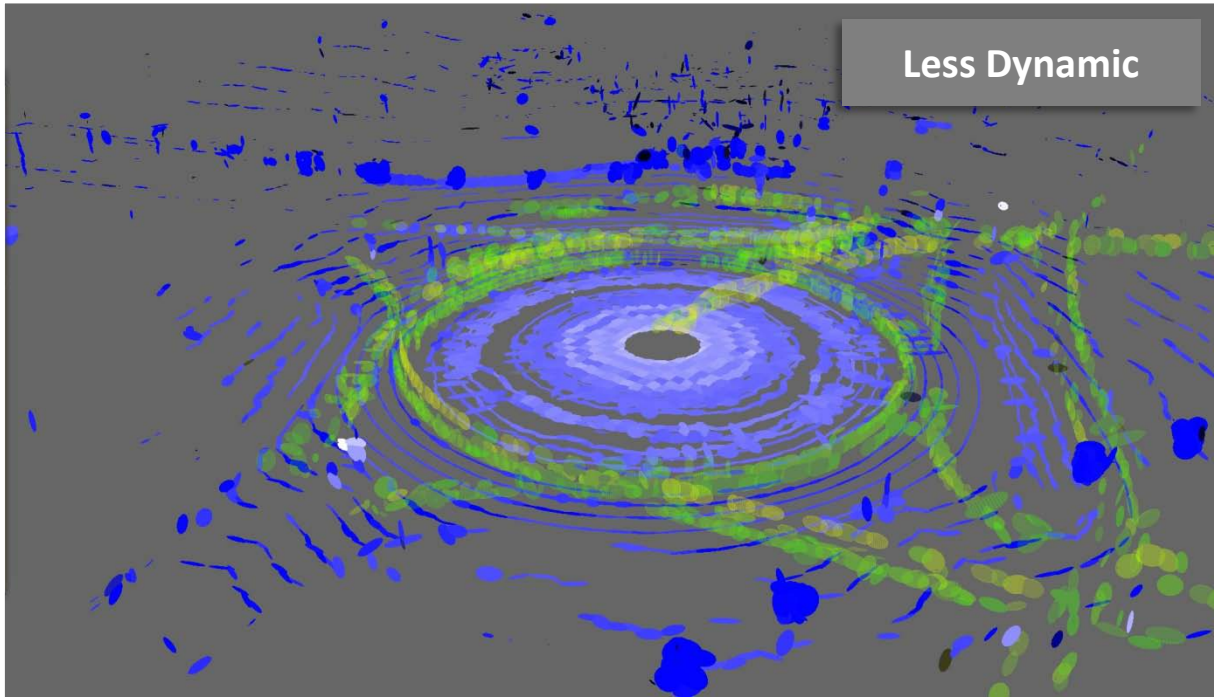

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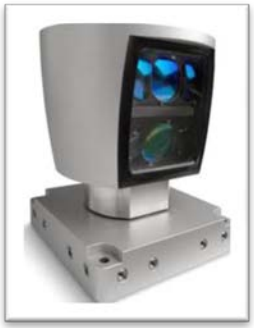

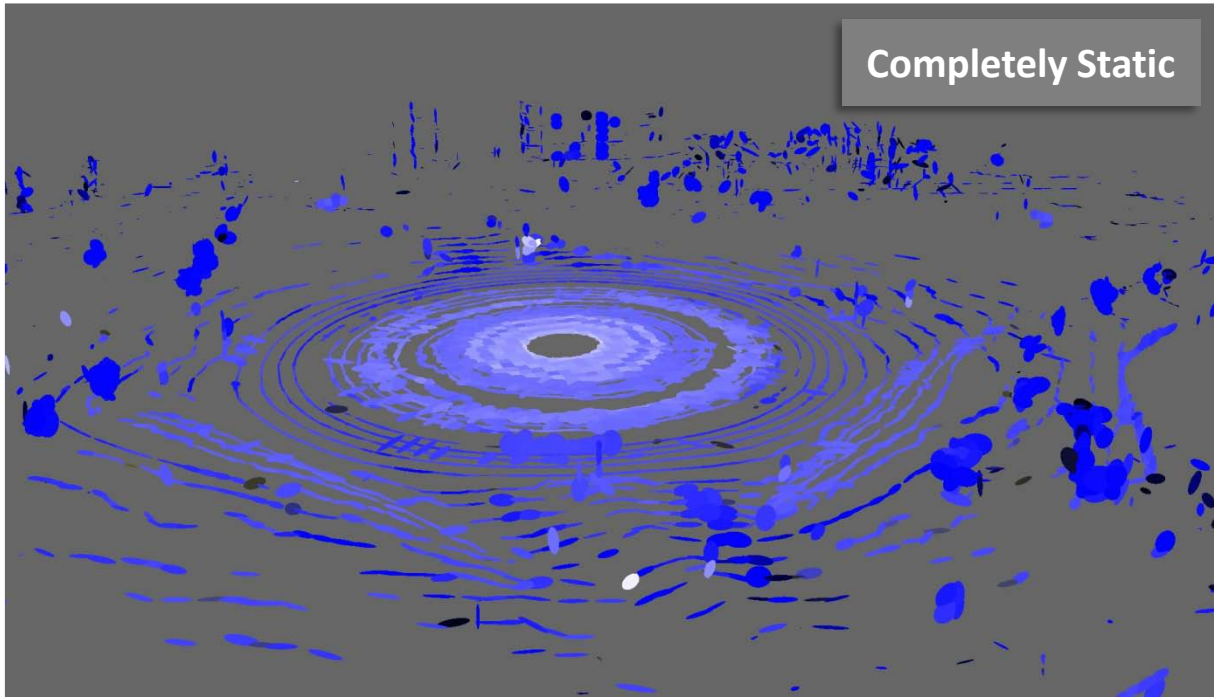

3D Perception Requirements

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- compact model
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- maintenance of model in a dynamic environment
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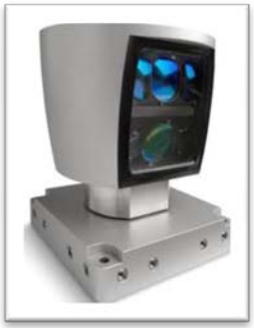
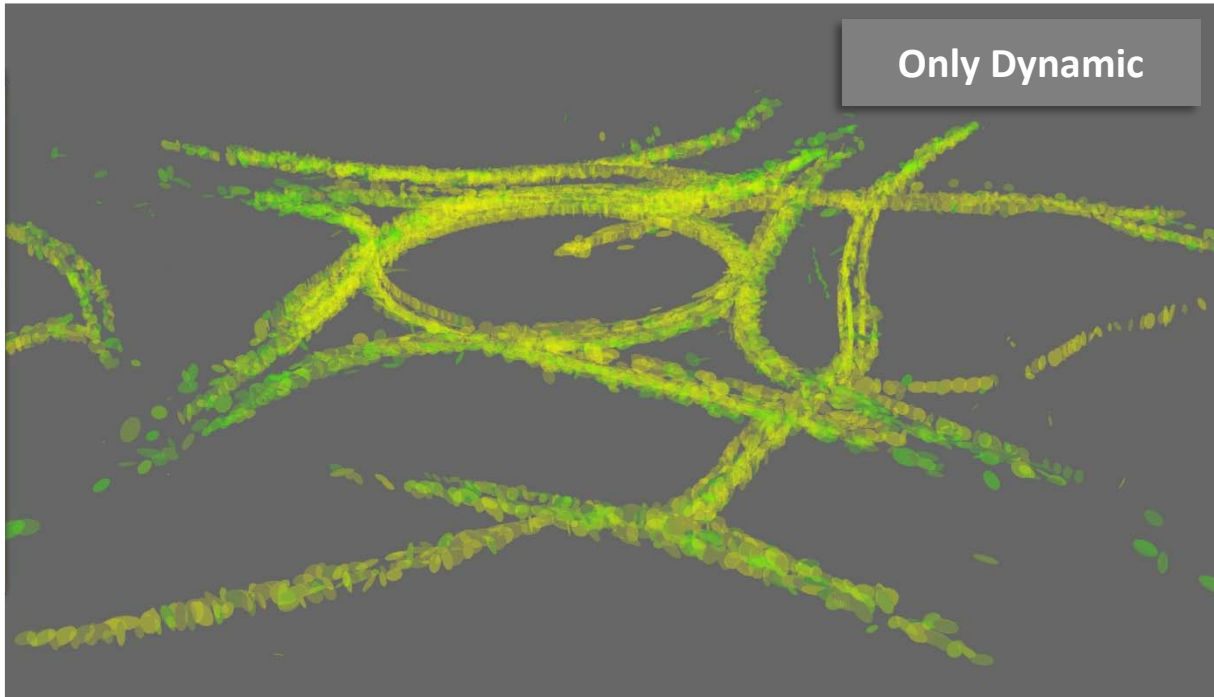




3D Perception Requirements

- detailed model
- dense (quasi-continuous) model from sparse measurements
- compact model
- probabilistic model
- layered model
- maintenance of model in a dynamic environment
  - online update
  - representation of changes over time
  - representation of different dynamics
    - changes against different time scales
    - model different dynamics explicitly (static, fully dynamic, alternating, semi-static, ...)

3D Perception Requirements

- detailed model
- dense (quasi-continuous) model from sparse measurements
- compact model
- probabilistic model
- layered model
- maintenance of model in a dynamic environment
  - online update
  - representation of changes over time
  - representation of different dynamics
- → use of dynamic map
  - discard dynamic areas for localization
    - assign lower weight depending on dynamics and last observation
  - take dynamics into account for planning and scheduling

3D Perception Requirements

- detailed model
- dense (quasi-continuous) model from sparse measurements
- compact model
- probabilistic model
- layered model
- maintenance and use of model in a dynamic environment
- sensor planning
  - Inspection Robot: build dense model that allows to detect changes at arbitrary points in space

3D Perception Requirements

- detailed model
- dense (quasi-continuous) model from sparse measurements
- compact model
- probabilistic model
- layered model
- maintenance and use of model in a dynamic environment
- sensor planning
- scanning-while-moving
  - » ALL-4-eHAM → necessary?

3D Perception Requirements

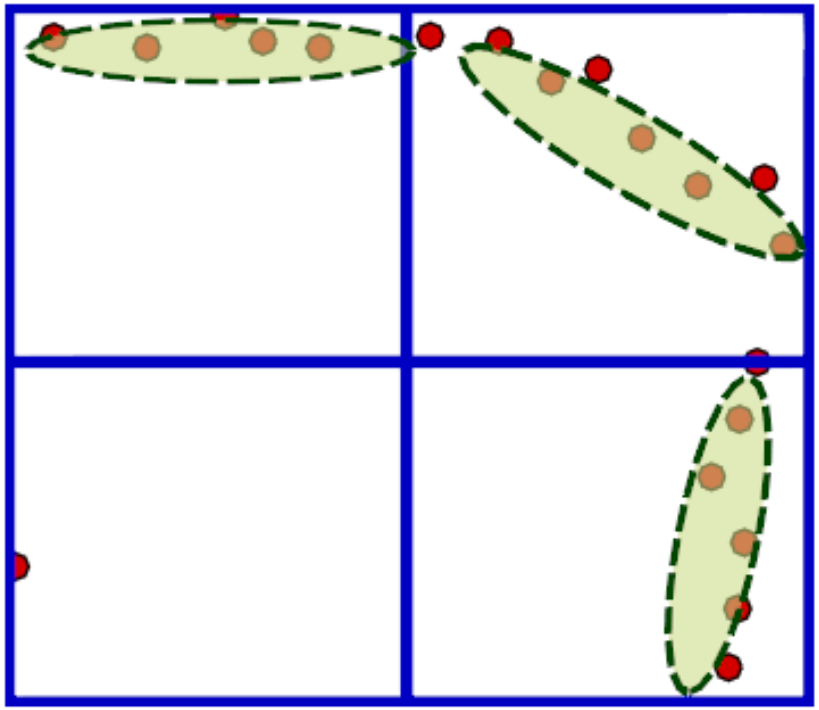
- detailed model
- dense (quasi-continuous) model from sparse measurements
- compact model
- probabilistic model
- layered model
- maintenance and use of model in a dynamic environment
- sensor planning
- scanning-while-moving
- robustness
  - outdoor conditions
  - graceful degradation wrt errors

- **3D Perception Requirements → Does Rich 3D Help?**
  - detailed model (detailed "enough")
    - » extraction of drivable area, object recognition, change detection
  - dense (quasi-continuous) model from sparse measurements
    - » change detection for arbitrary points in space
  - compact model
    - » compact yet truthful representation → real-time and long-term operation
  - probabilistic model
    - » represent uncertainty about the state of the world
  - layered model
    - » layers often carry most of map meaning
  - maintenance and use of model in a dynamic environment
    - » representation of changes and dynamics, use for localization and planning
  - sensor planning
  - robustness

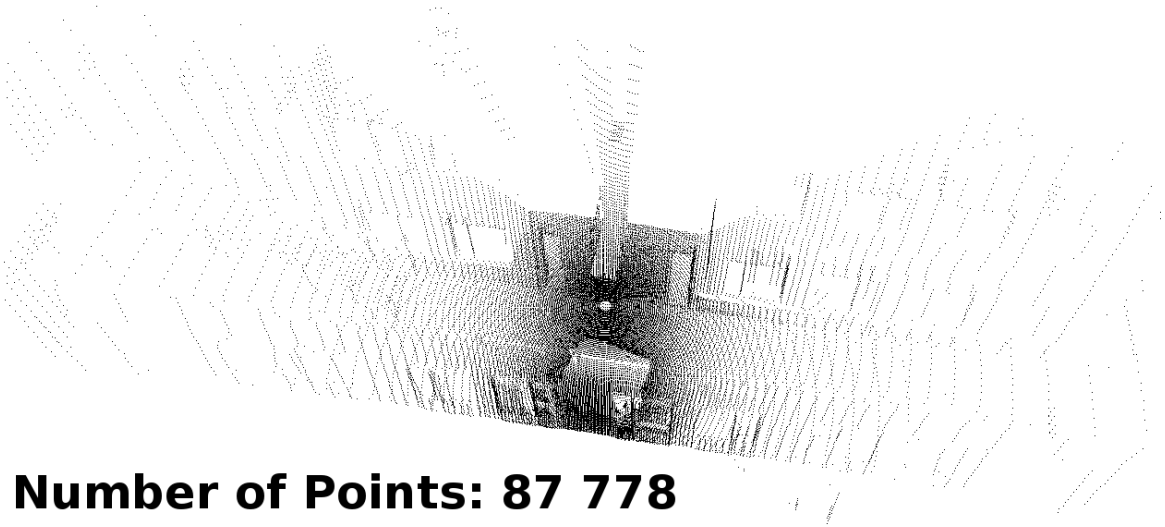
- **3D Perception Requirements → Does Rich 3D Help?**
  - detailed model (detailed "enough") — longer range, richer information
    - » extraction of drivable area, object recognition, change detection
  - dense (quasi-continuous) model from sparse measurements
    - » change detection for arbitrary points in space
  - compact model — better extrapolation on sparse measurements
    - » compact yet truthful representation → real-time and long-term operation
  - probabilistic model — additional information → key points
    - » represent uncertainty about the state of the world
  - layered model
    - » layers often carry most of map meaning — rich 3D models may often be layered maps
  - maintenance and use of model in a dynamic environment
    - » representation of changes and dynamics, use for localization and planning
  - sensor planning — also required for rich 3D
  - robustness — e.g. localization in feature-sparse areas

3D-NDT Representation

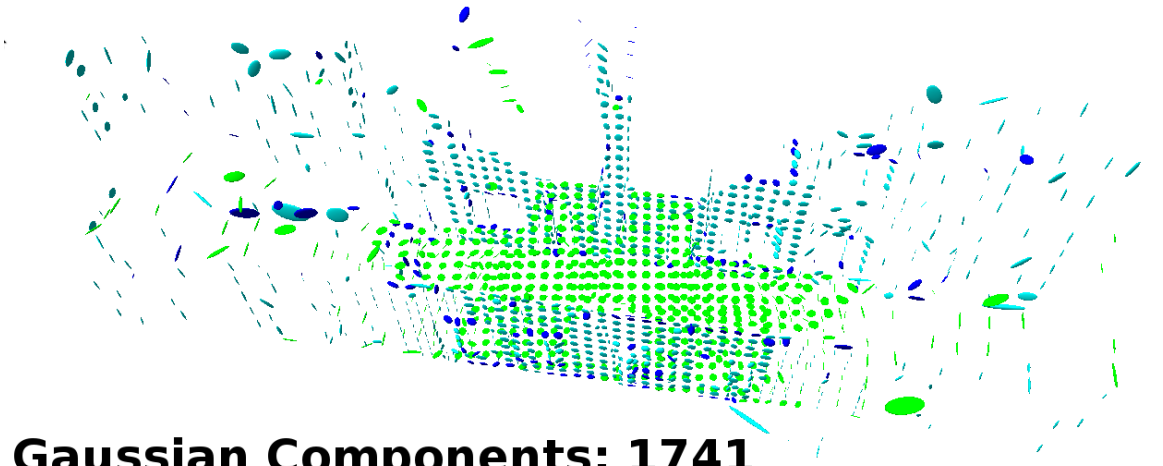
- **(2D) Normal Distributions Transform (NDT)**
  - originally developed for 2D scan registration [Biber et al., 2003]
  - sparse (grid-based) Gaussian mixture model
    - » space is partitioned in disjoint voxels (cells)
    - » Gaussian pdf, parametrized by a Covariance matrix and mean used to represent space in each cell



- **3D Normal Distributions Transform (3D-NDT)**
  - extension to 3D scan registration [Magnusson et al., 2007]
  - 3D-NDT is
    - » sparse



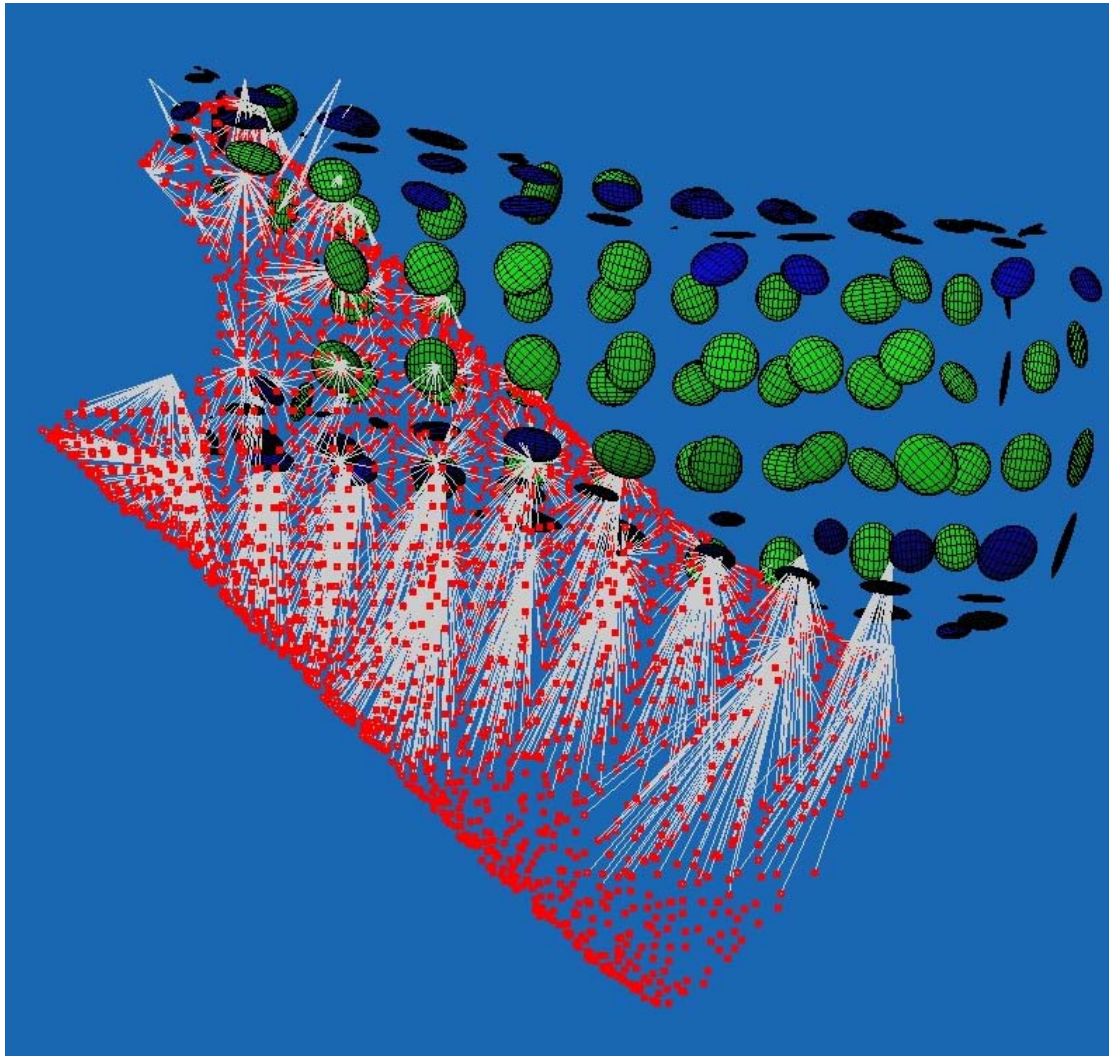
Number of Points: 87 778



Gaussian Components: 1741

3D Normal Distributions Transform (3D-NDT)

- extension to 3D scan registration [Magnusson et al., 2007]
- 3D-NDT is
  - sparse
  - useful for 3D registration
    - Point-to-NDT [Magnusson et al., 2007]



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      - Point-to-NDT [Magnusson et al., 2007]
      - NDT-to-NDT [Stoyanov et al., 2012]

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  - 3D-NDT is
    - sparse
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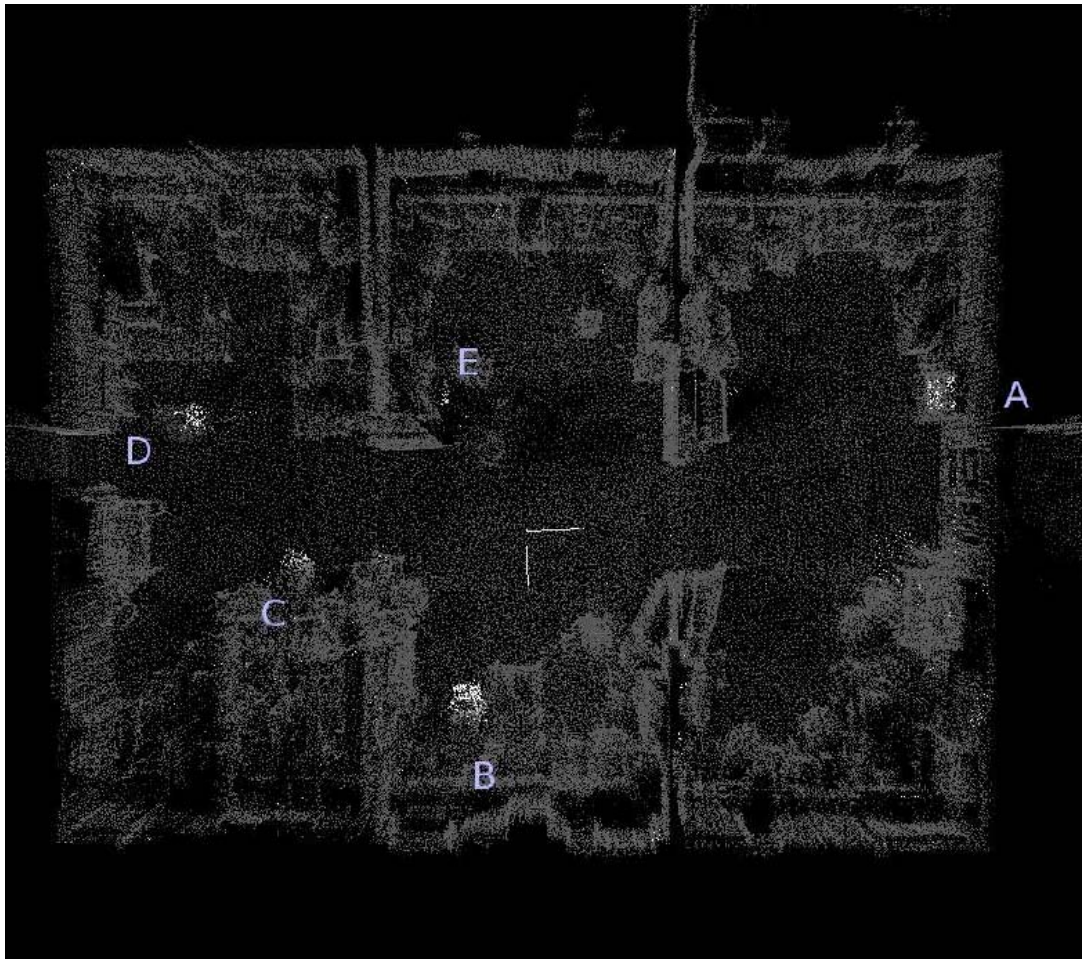
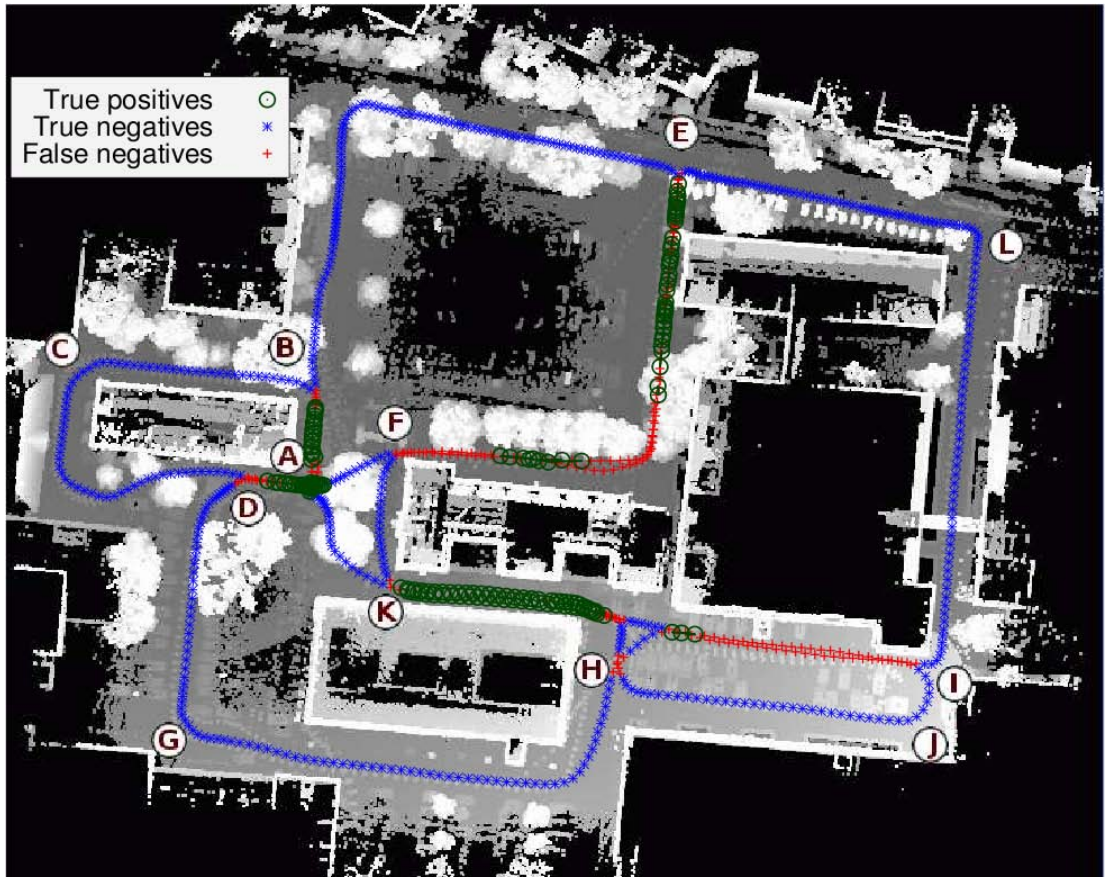
    - useful for change detection



3D Normal Distributions Transform (3D-NDT)

- extension to 3D scan registration [Magnusson et al., 2007]
- 3D-NDT is
  - sparse
  - useful for 3D registration
  - useful for change detection
  - useful for place recognition [Magnusson et al., 2009]



Rich 3D Perception – Recent and Ongoing Work

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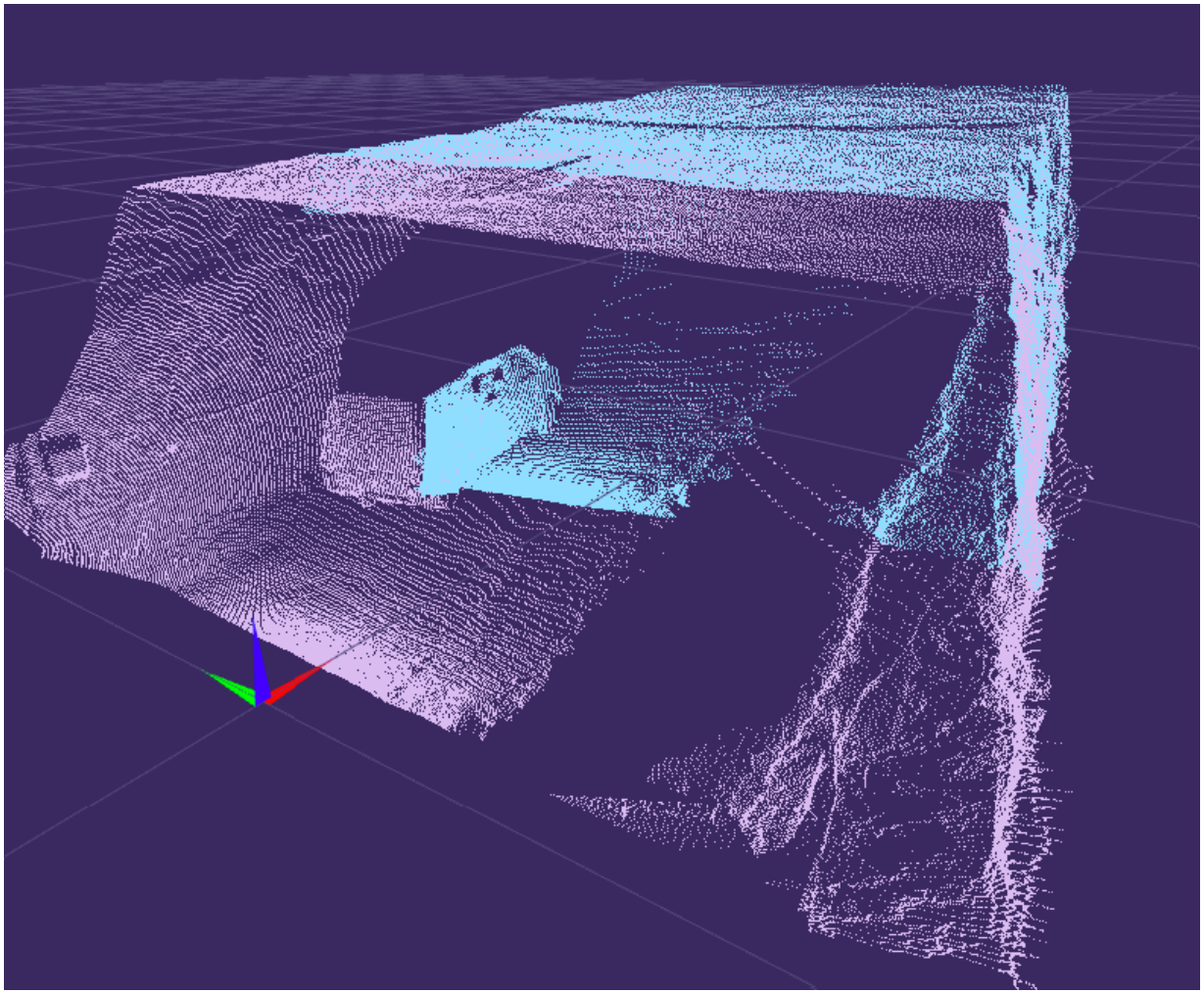
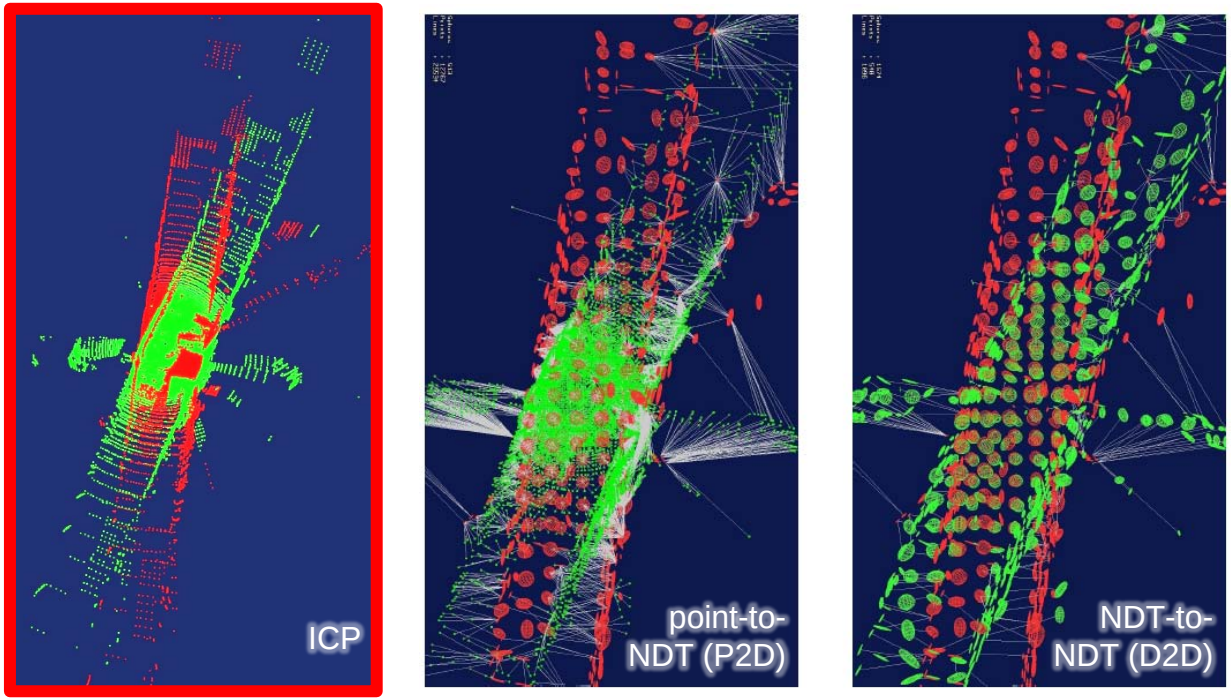
NDT-to-NDT Registration

- **NDT-2-NDT Registration [Stoyanov et al., 2012]**
  - registration



- **NDT-2-NDT Registration [Stoyanov et al., 2012]**
  - registration with ICP (iterative closest point)



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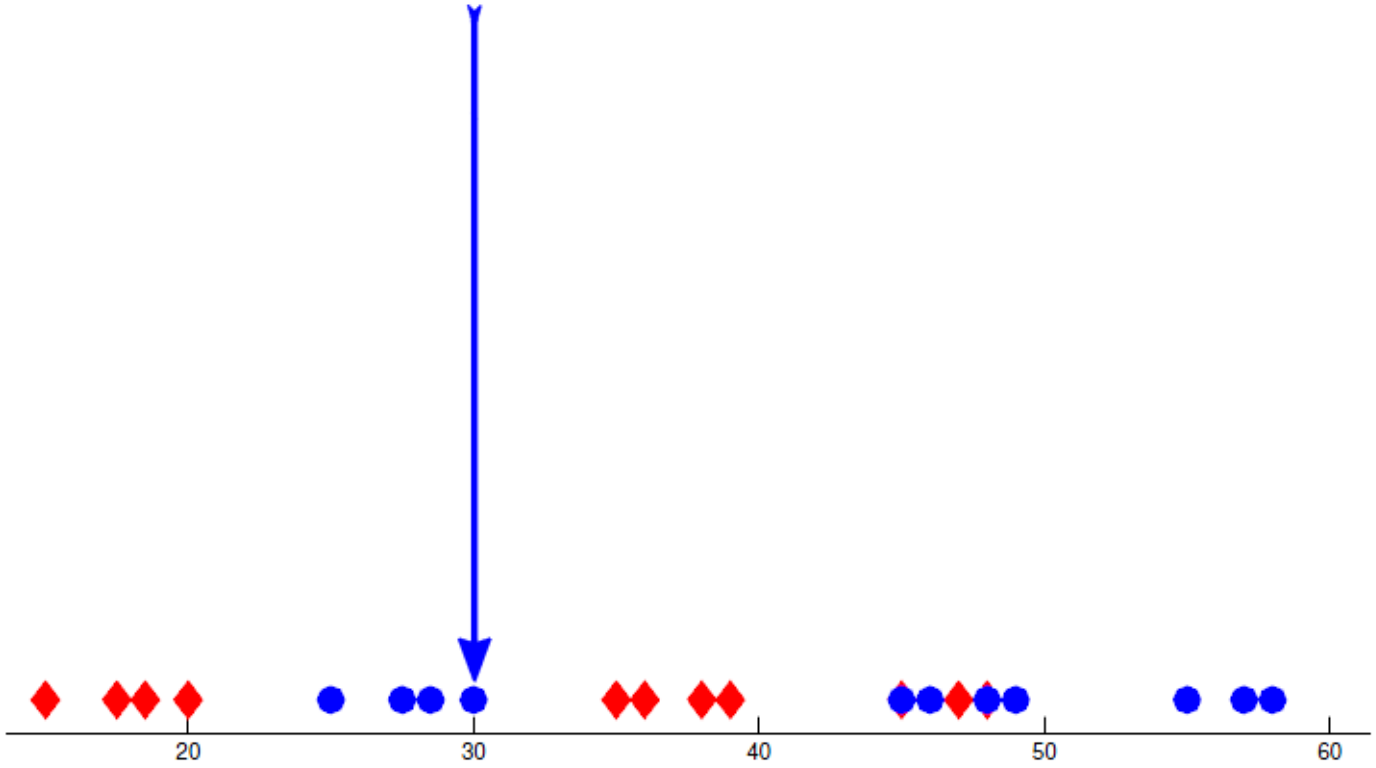

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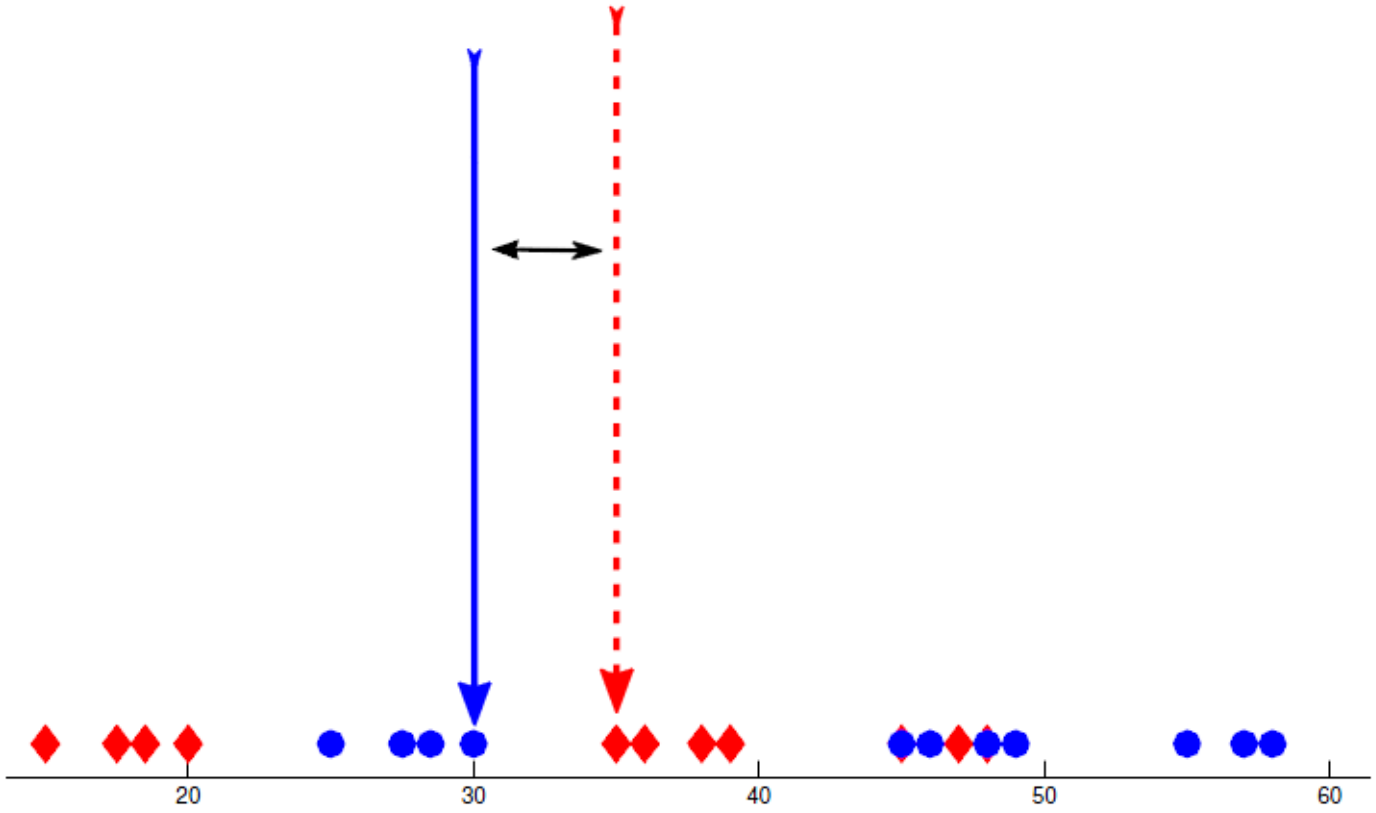

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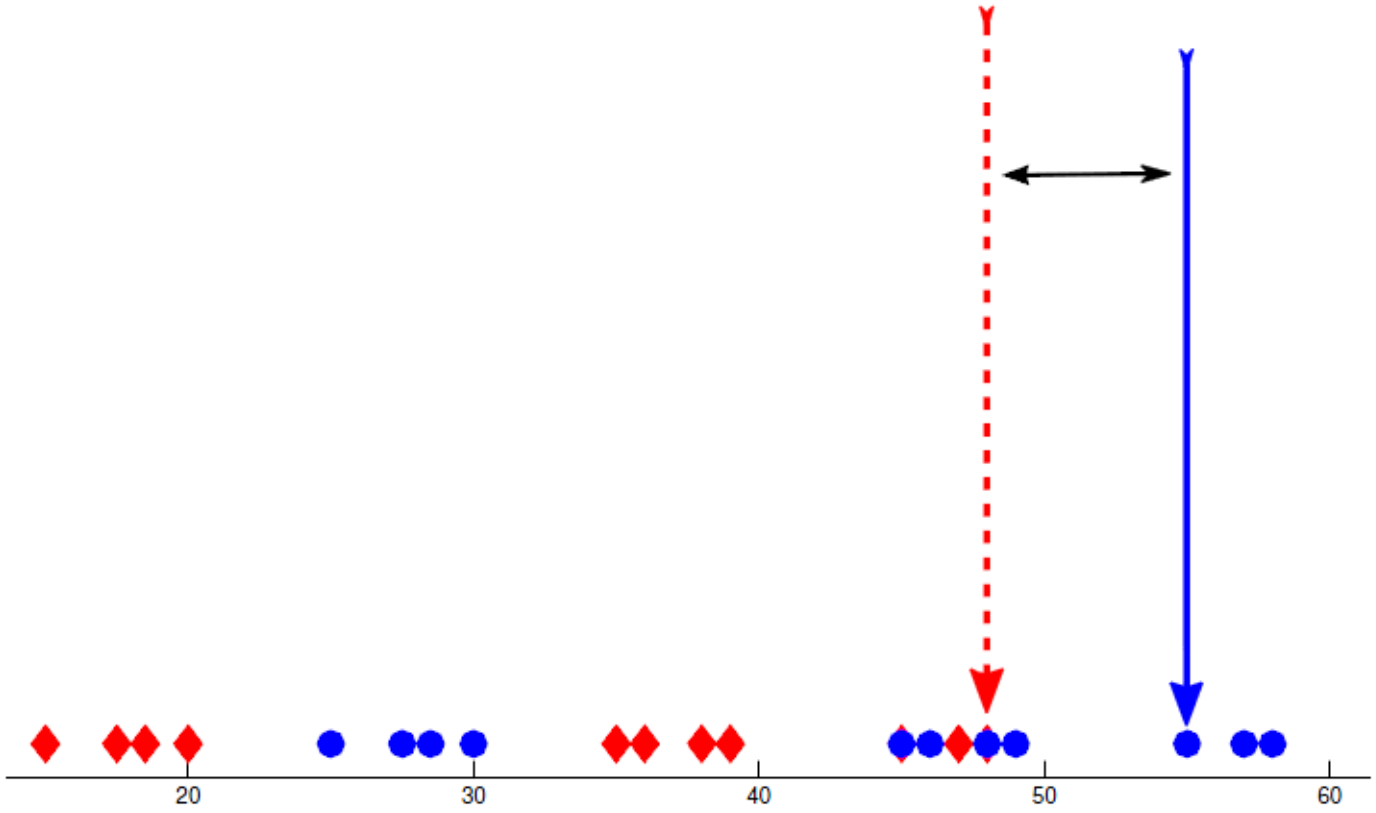

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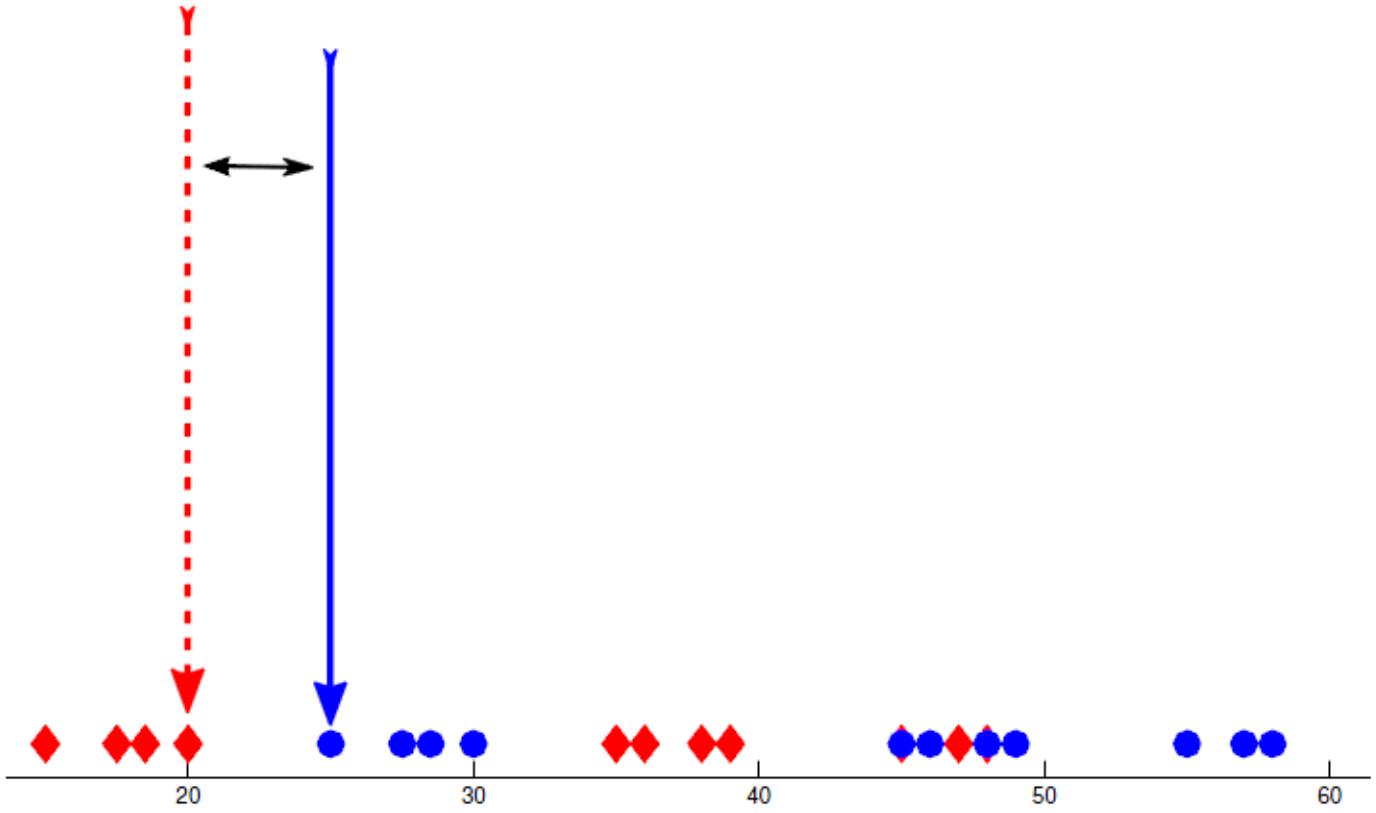

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- **NDT-2-NDT Registration [Stoyanov et al., 2012]**
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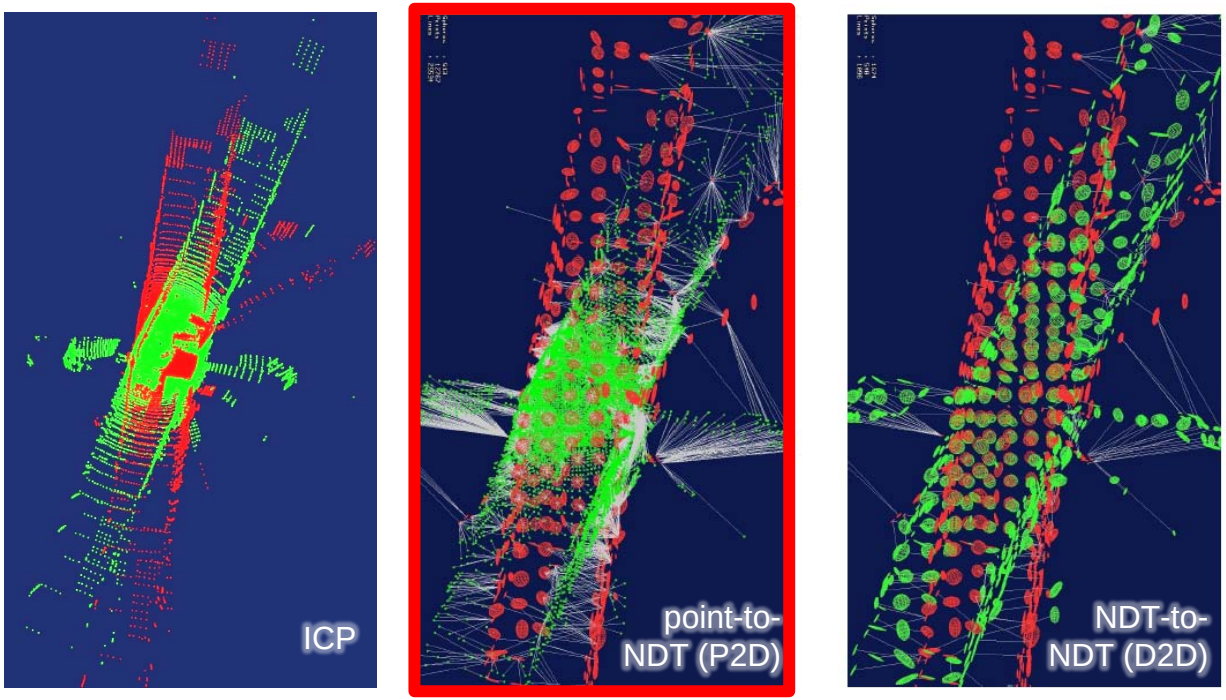
  - registration with 3D-NDT (Point-to-NDT)



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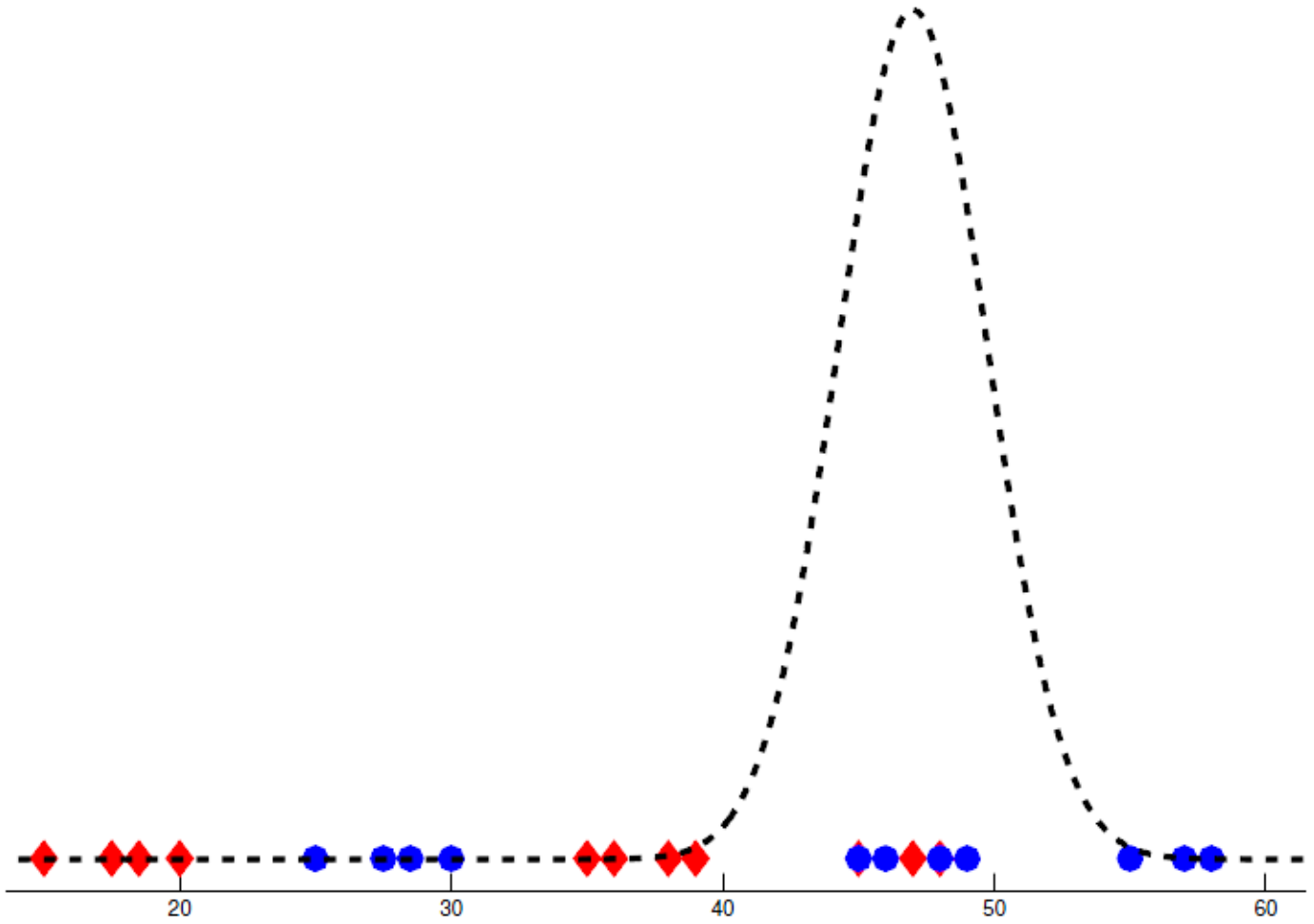

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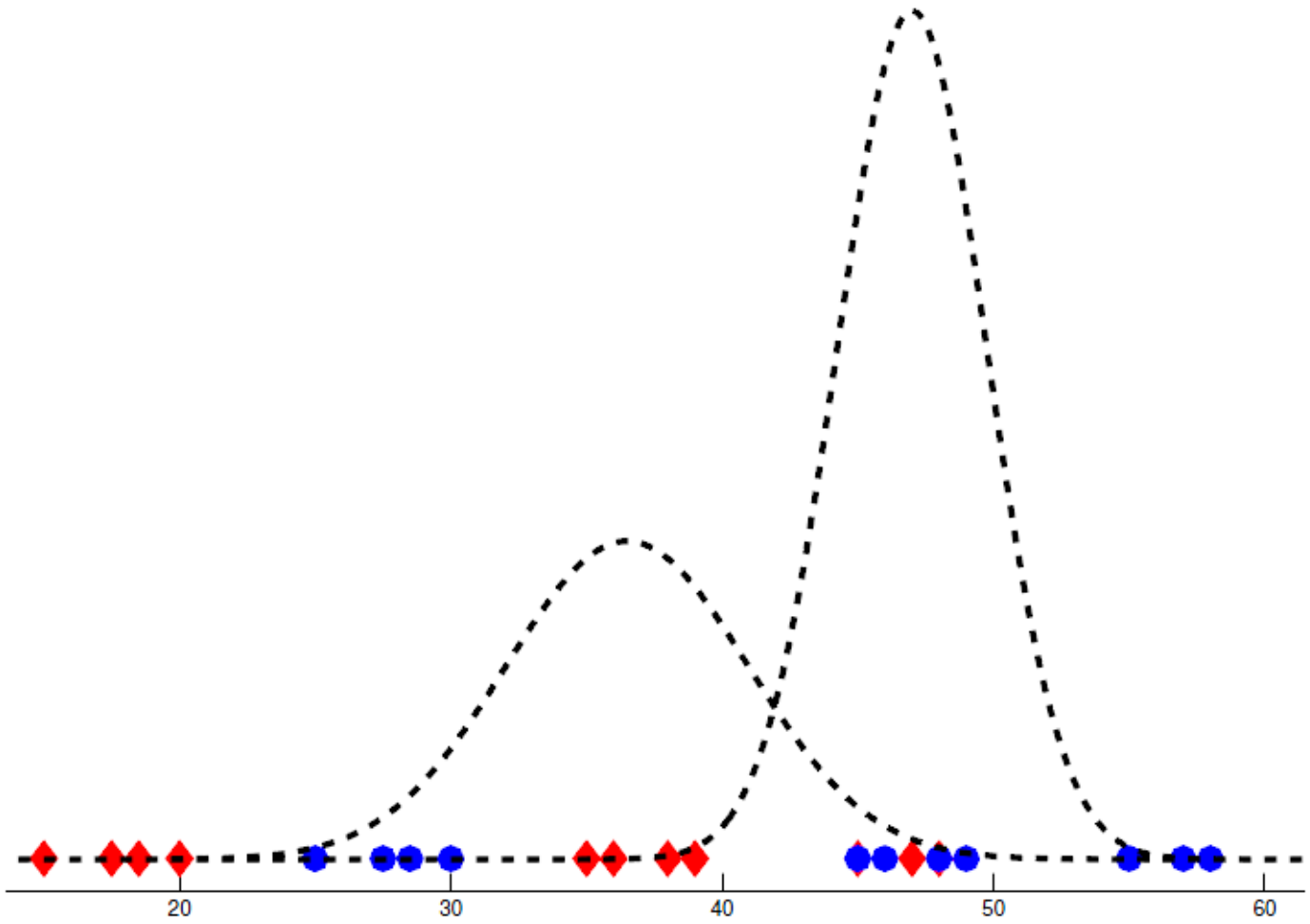

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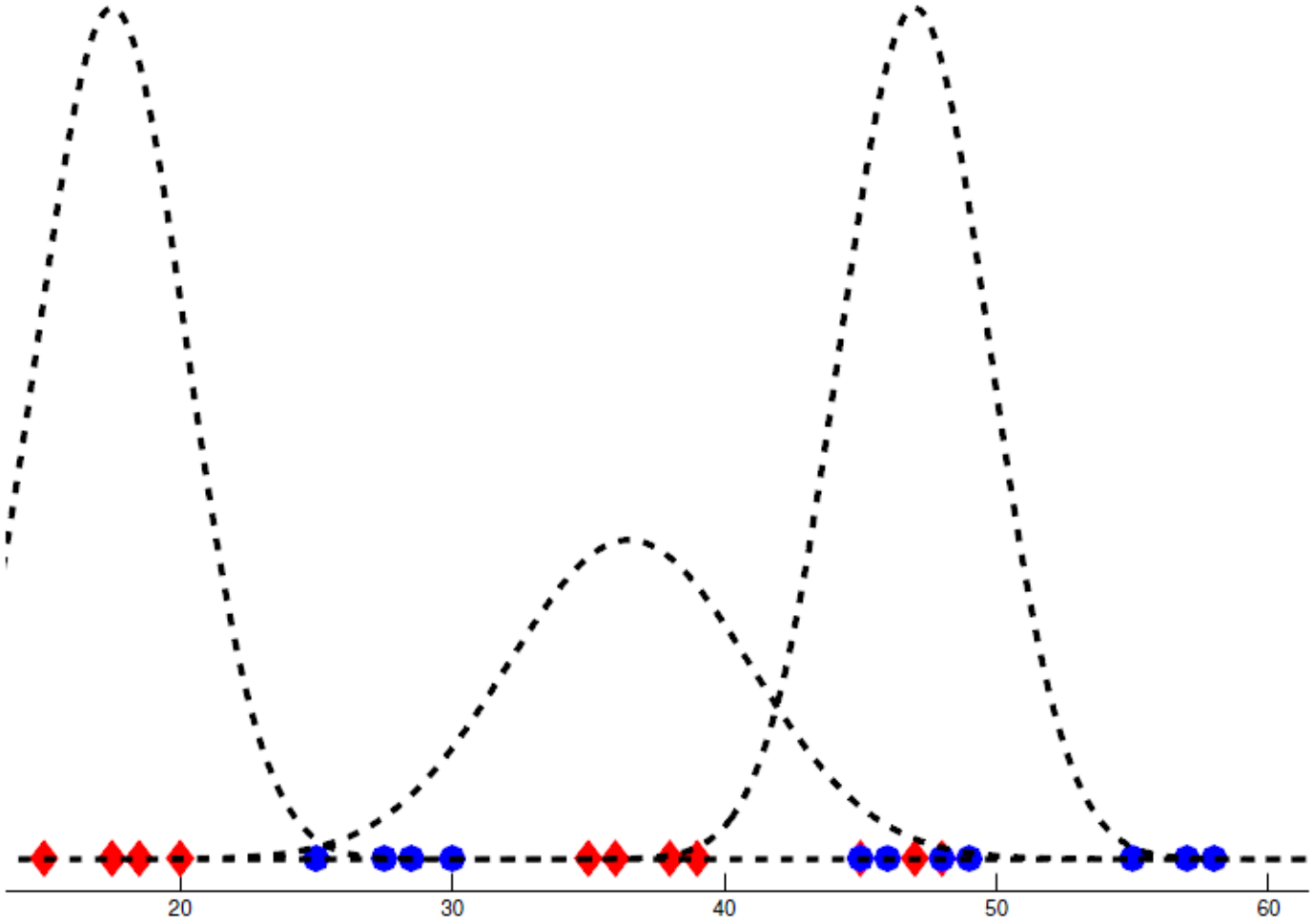

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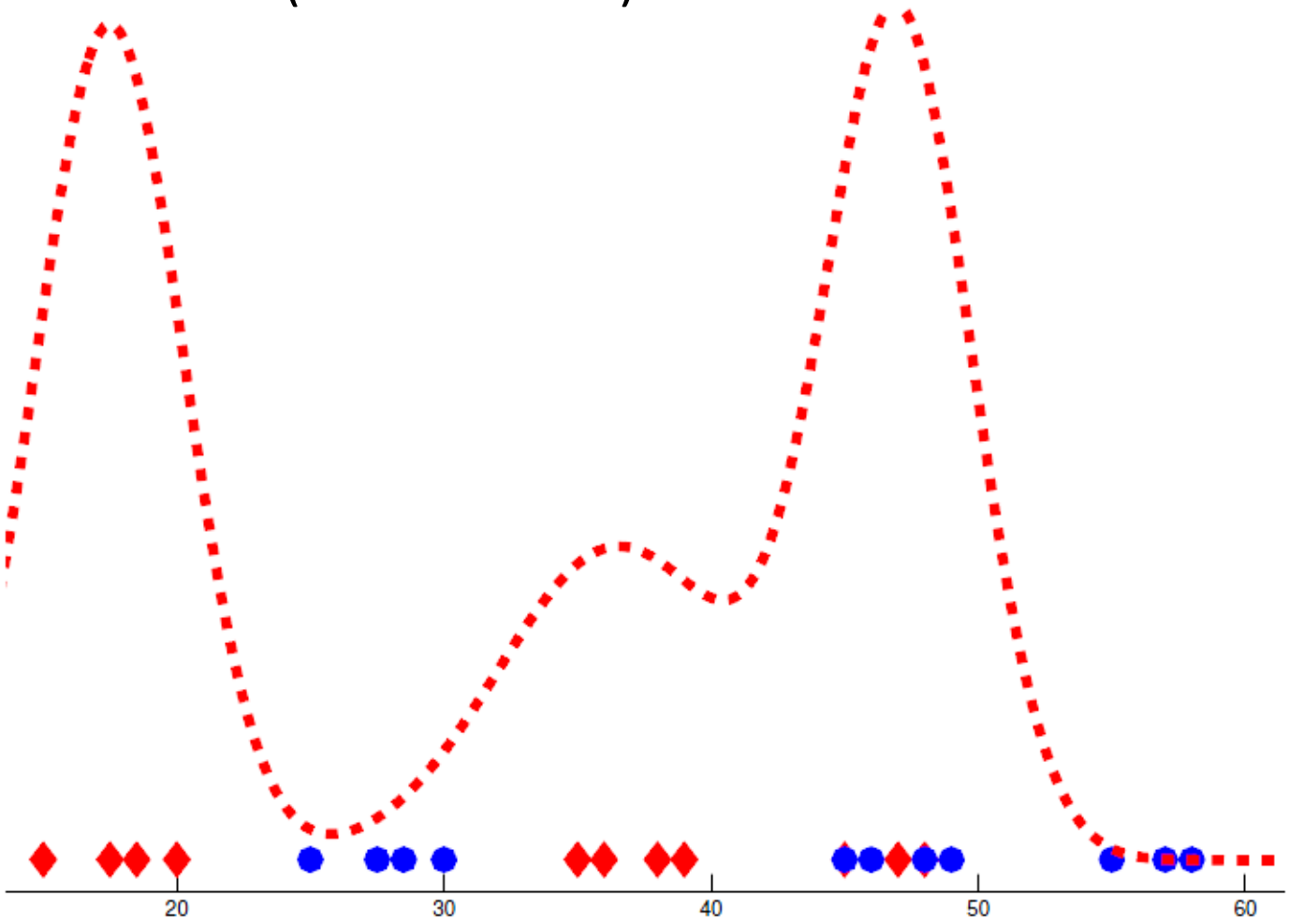

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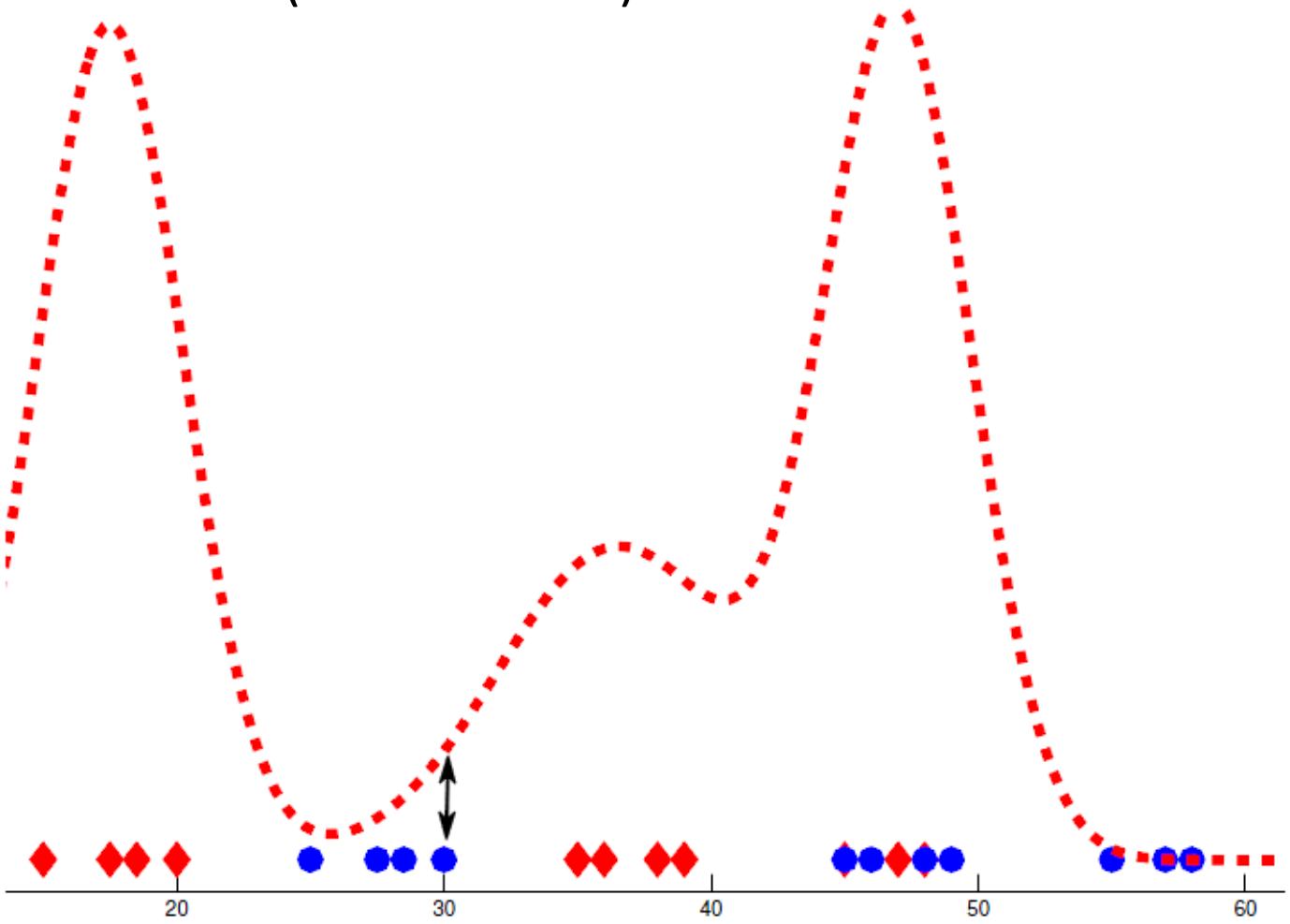

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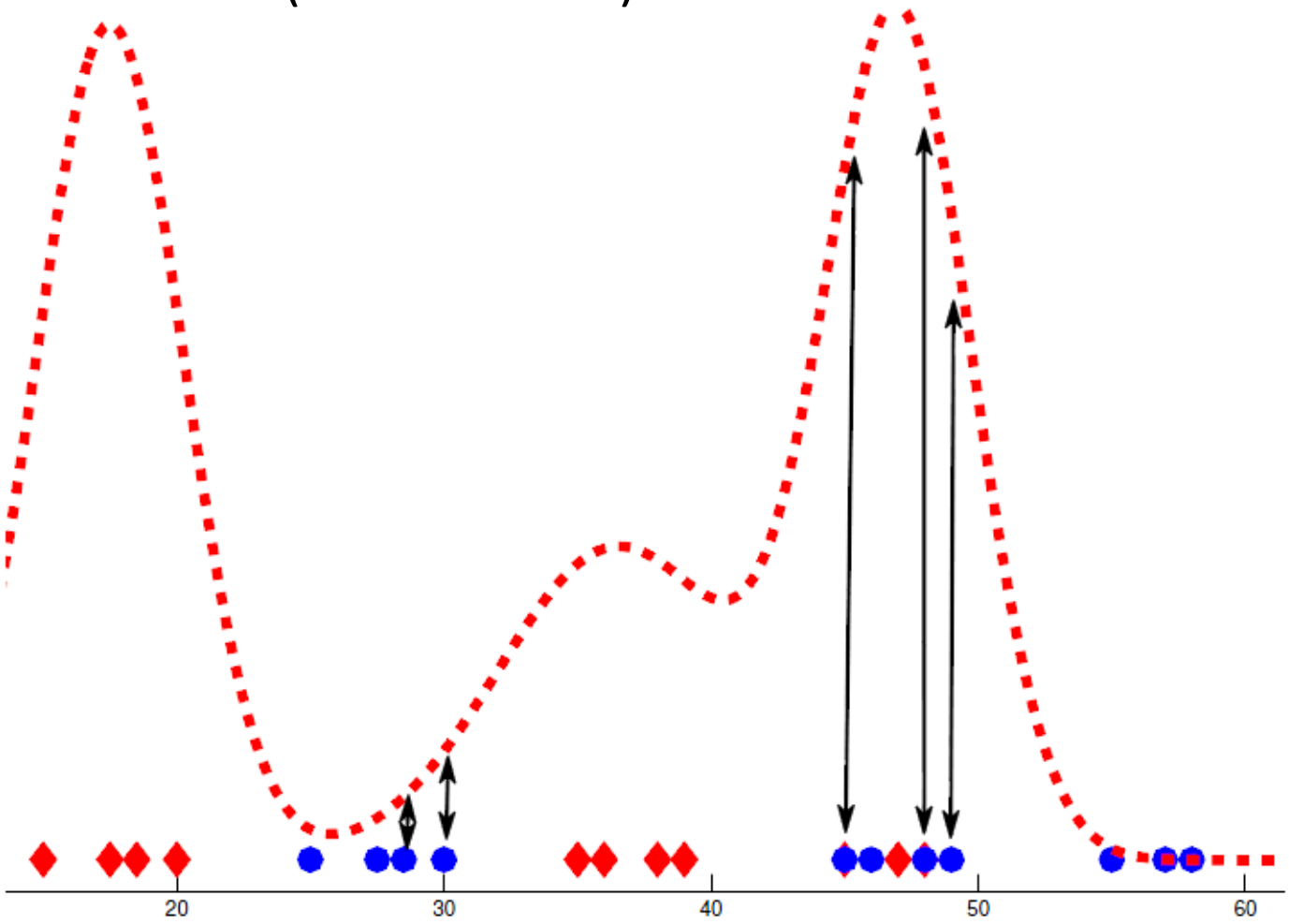

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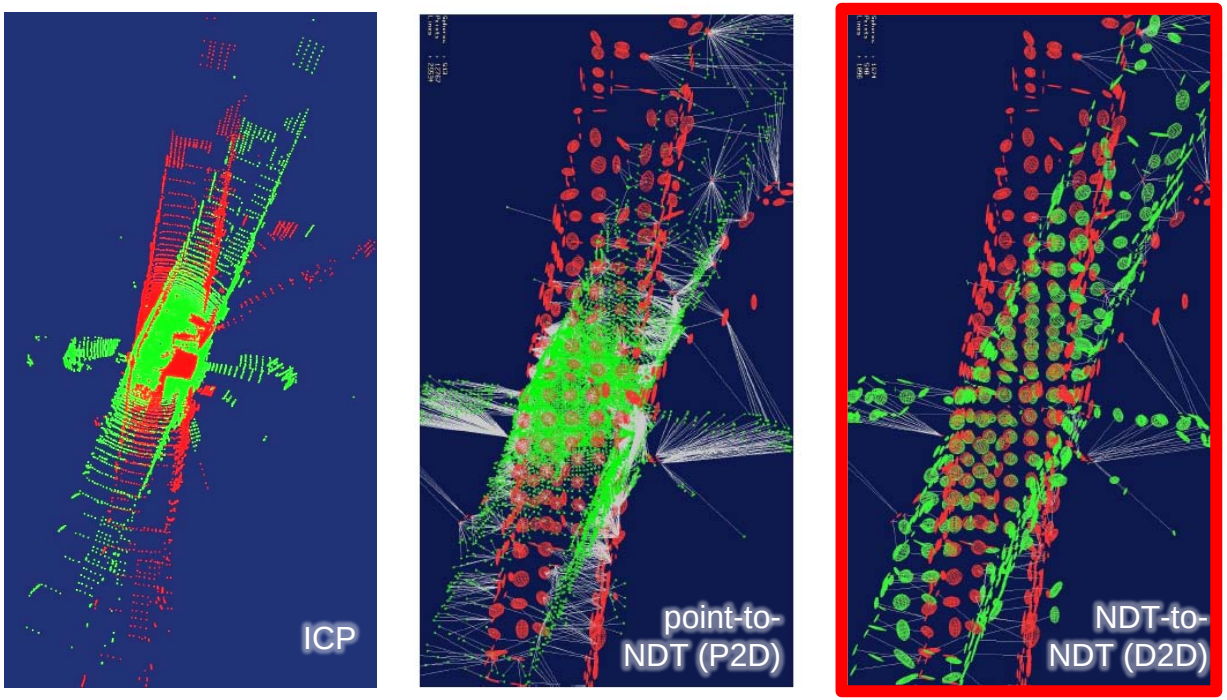

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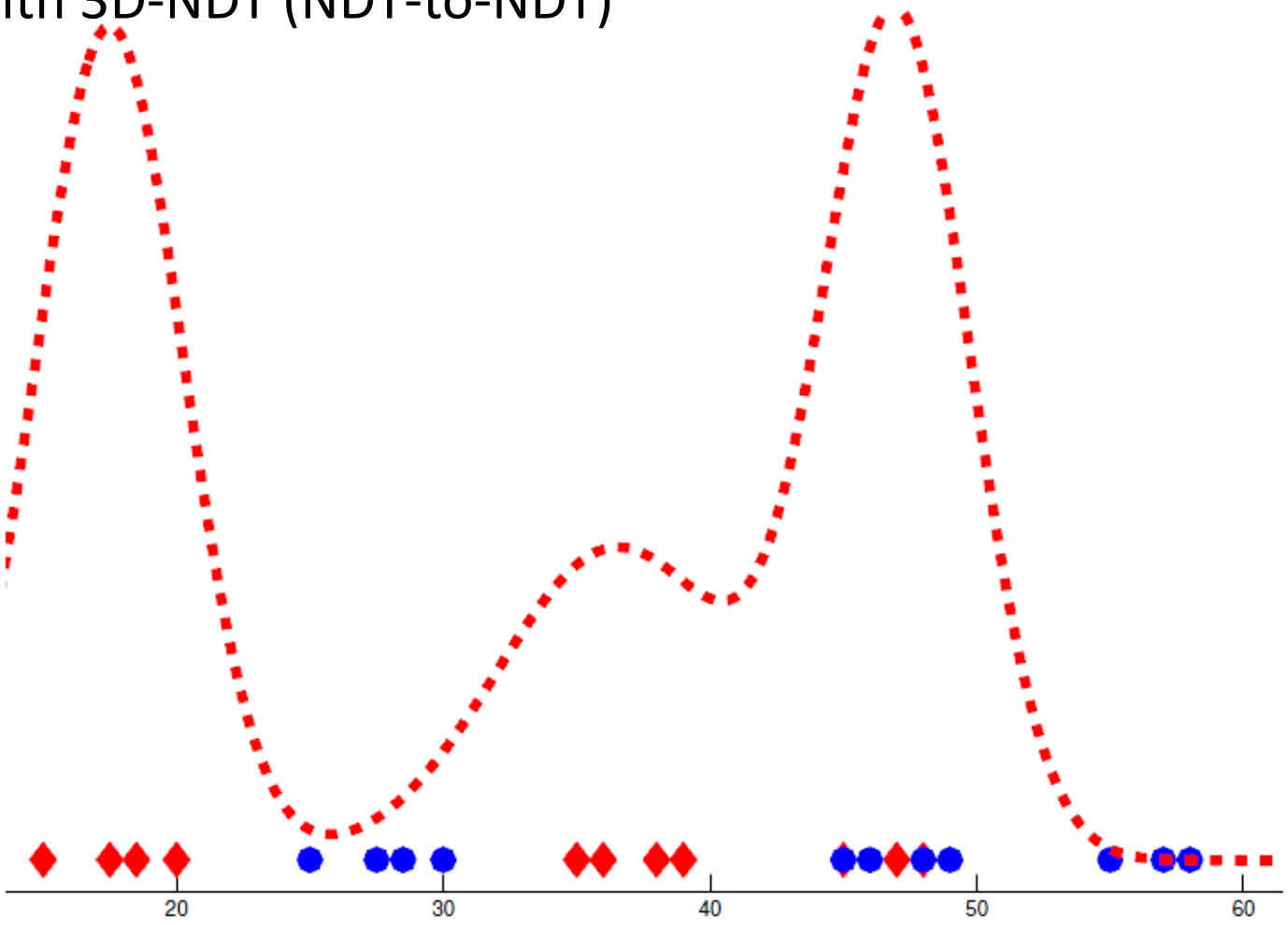

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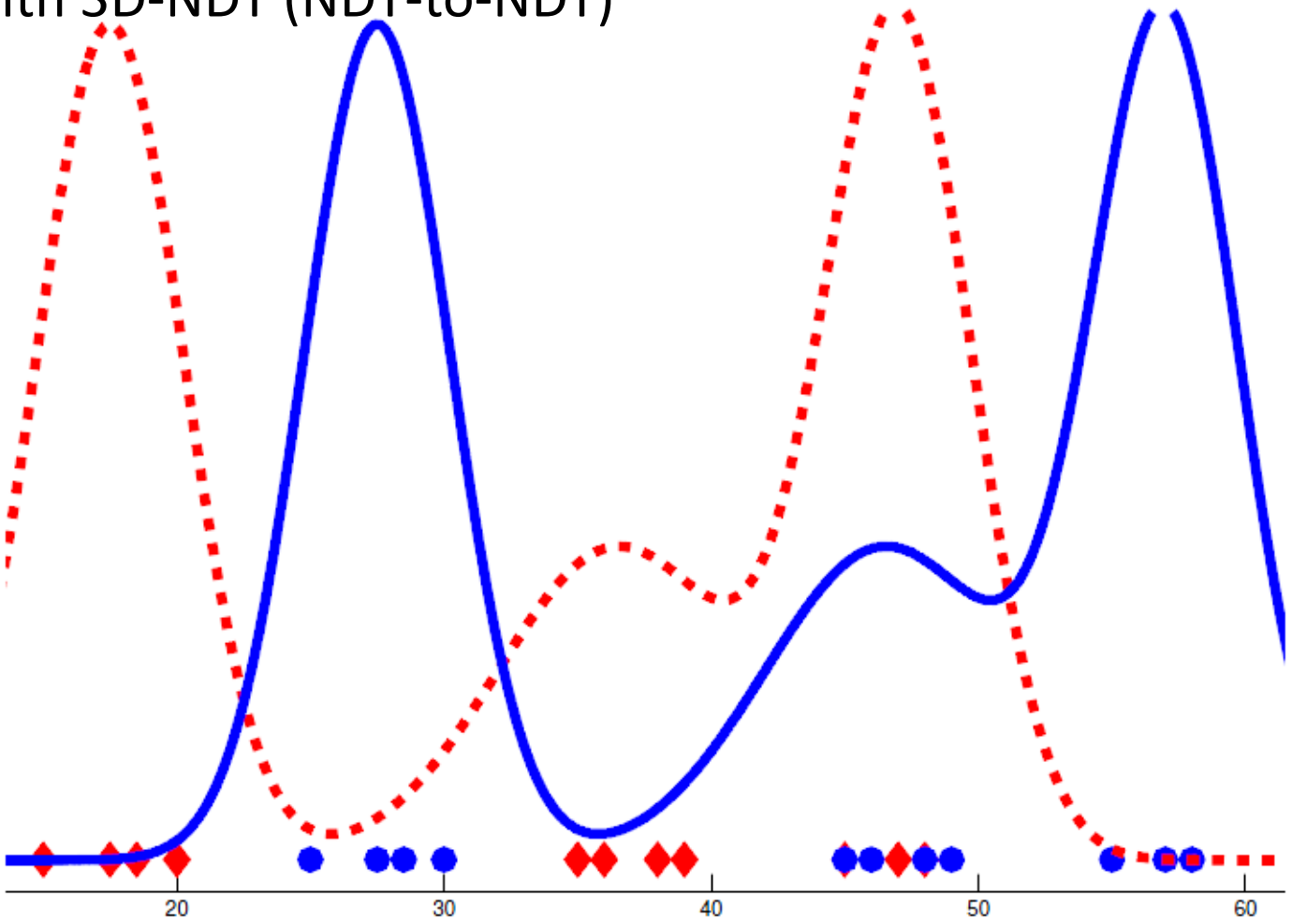

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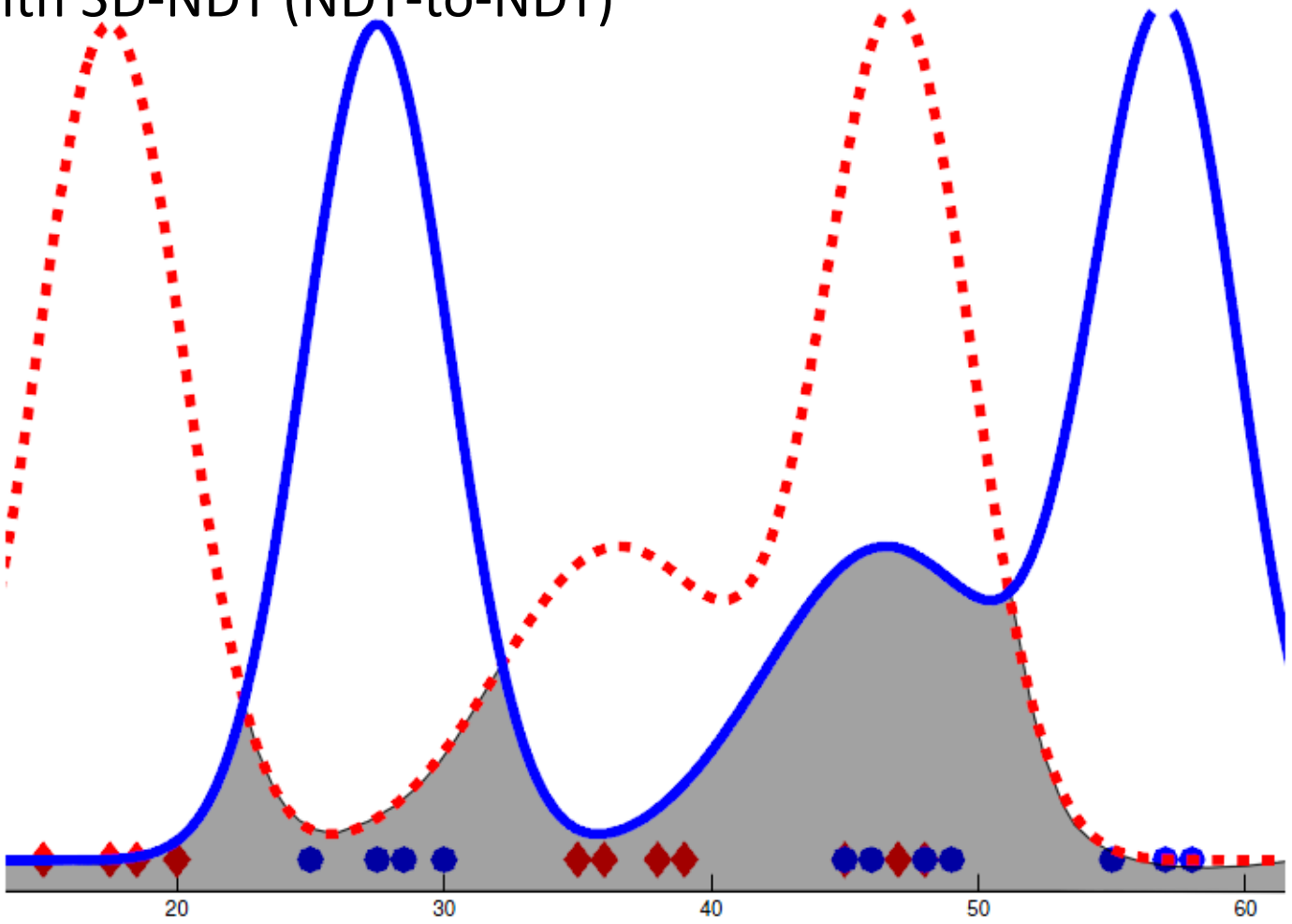

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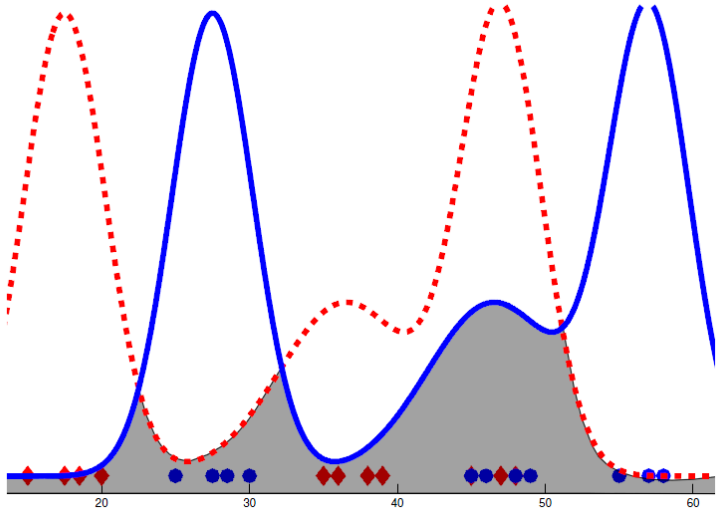

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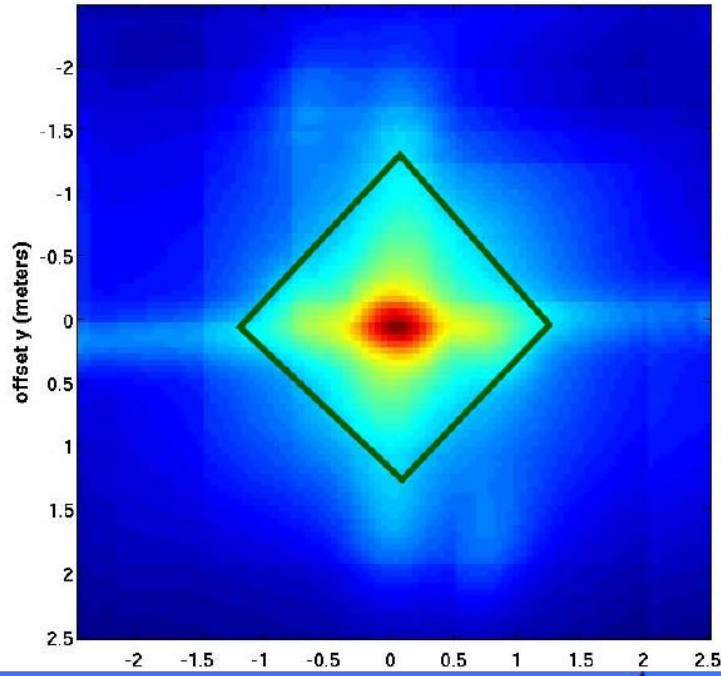

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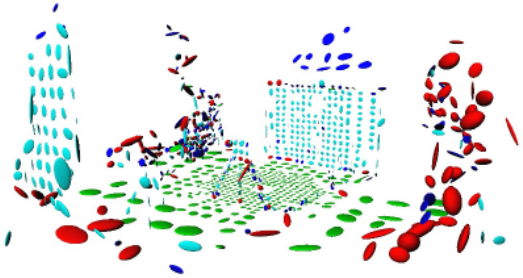
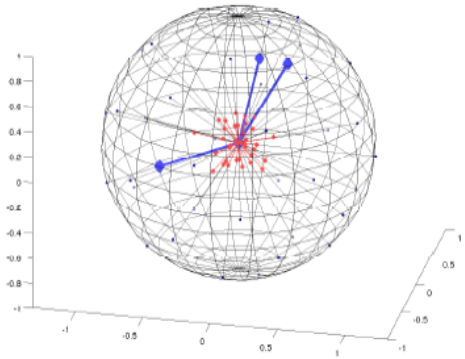
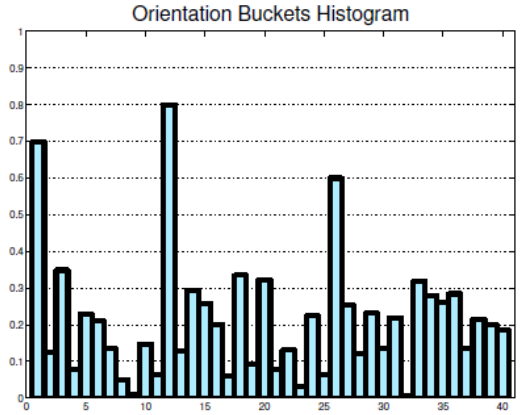
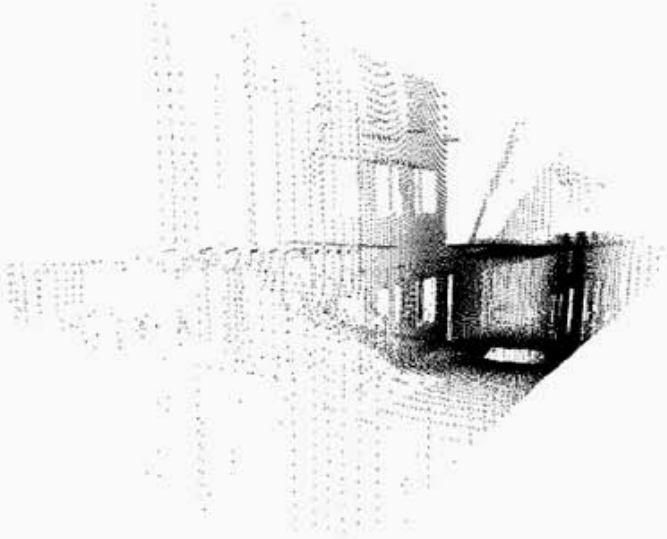
    - » find (local) maximum using Newton's method and analytical derivative expressions
    - » hot start
      - derive a simple initialization, based on the 3D-NDT Histogram
      - look for transformation resulting in best overlap between histograms.
      - select one or several of the best initial guesses







- **NDT-2-NDT Registration [Stoyanov et al., 2012]**
  - tested over two data sets — indoor and outdoor, 3D aLRF



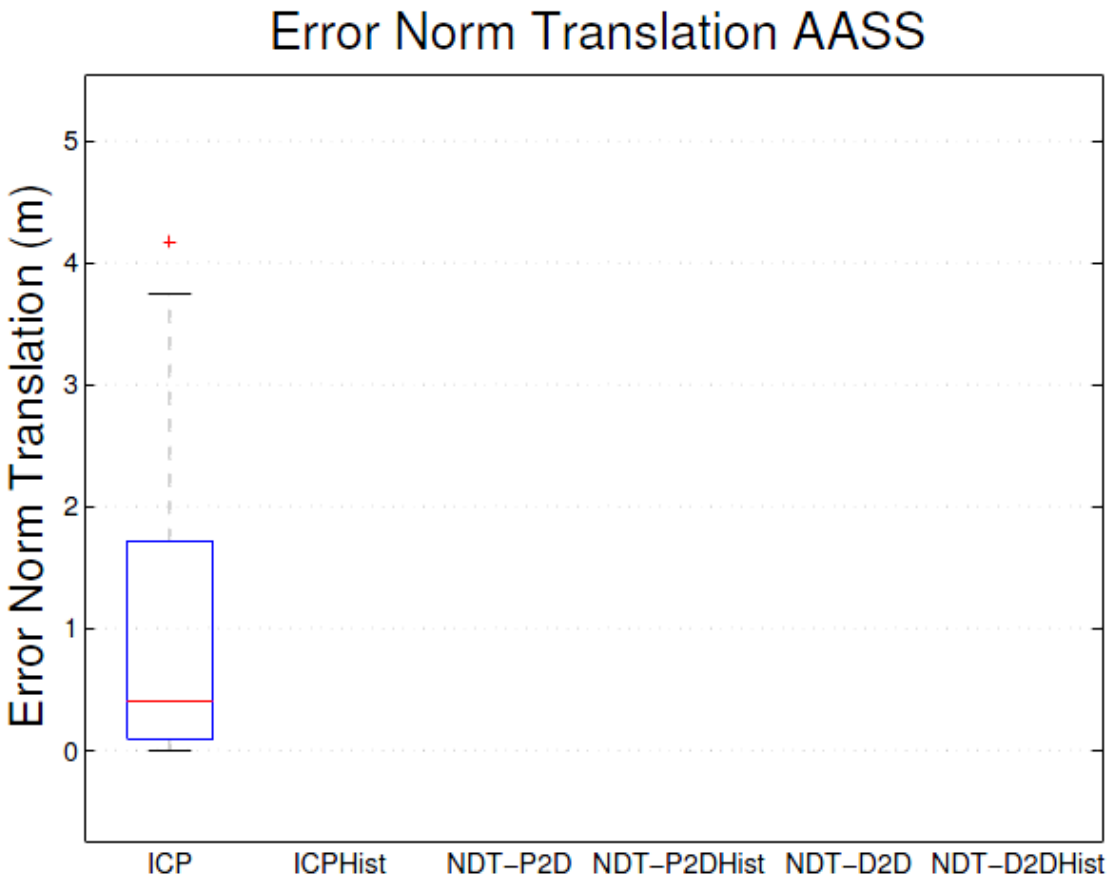
indoor: 60 point clouds

"AASS Loop"

outdoor: 469 point clouds

"AASS Loop"

- **NDT-2-NDT Registration [Stoyanov et al., 2012]**
  - results
    - » translation deviation from known ground truth transformations



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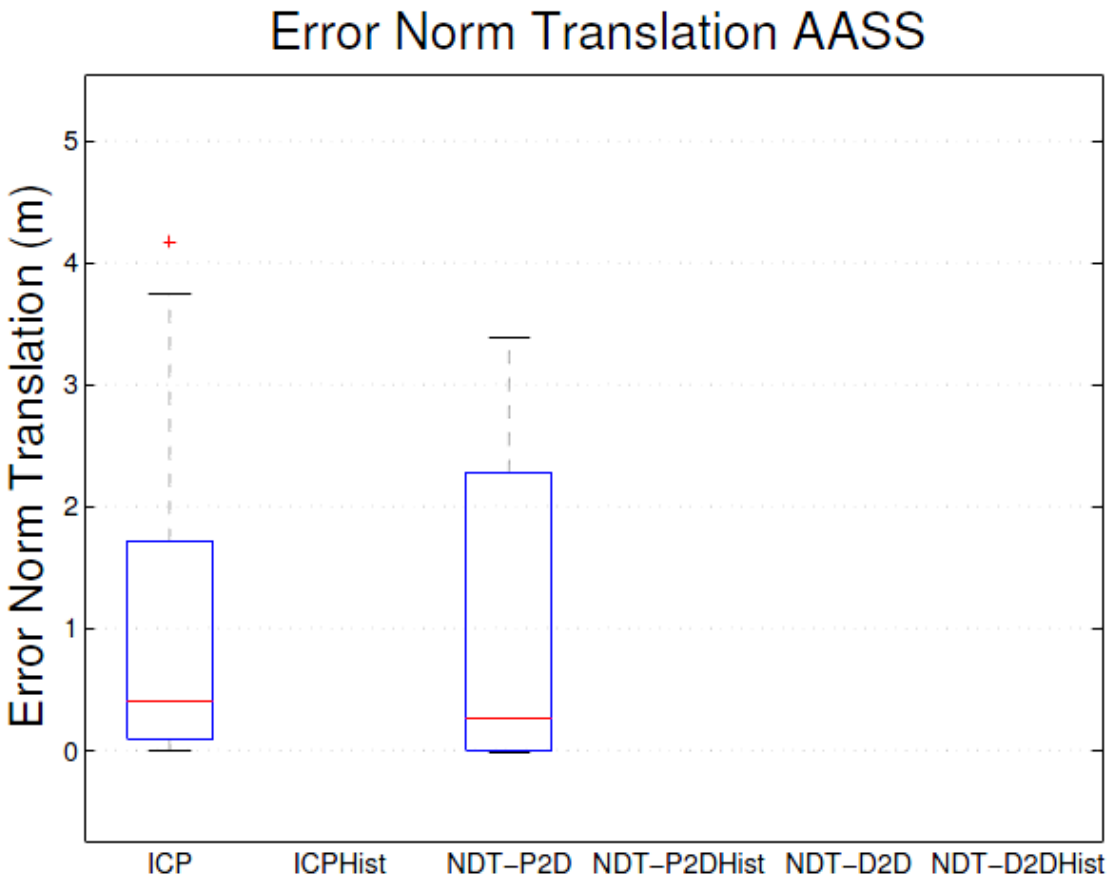

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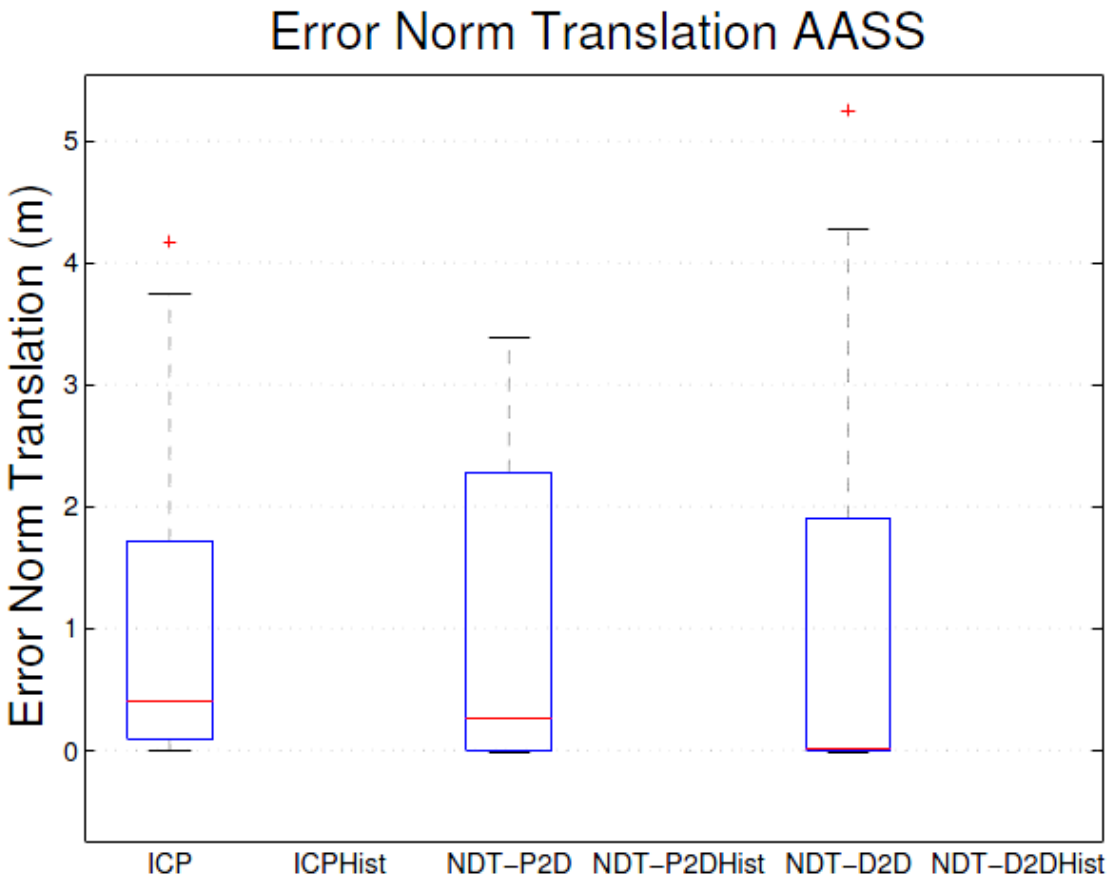

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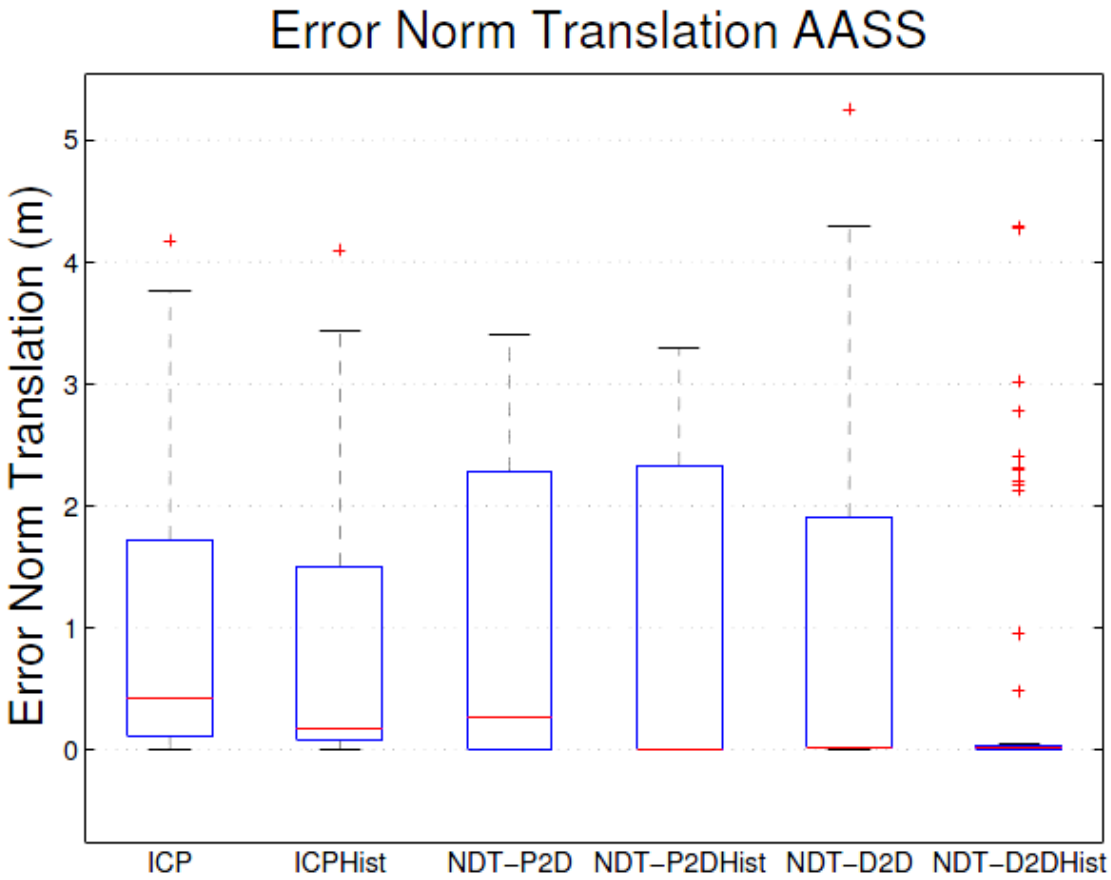

NDT-2-NDT Registration [Stoyanov et al., 2012]

- results
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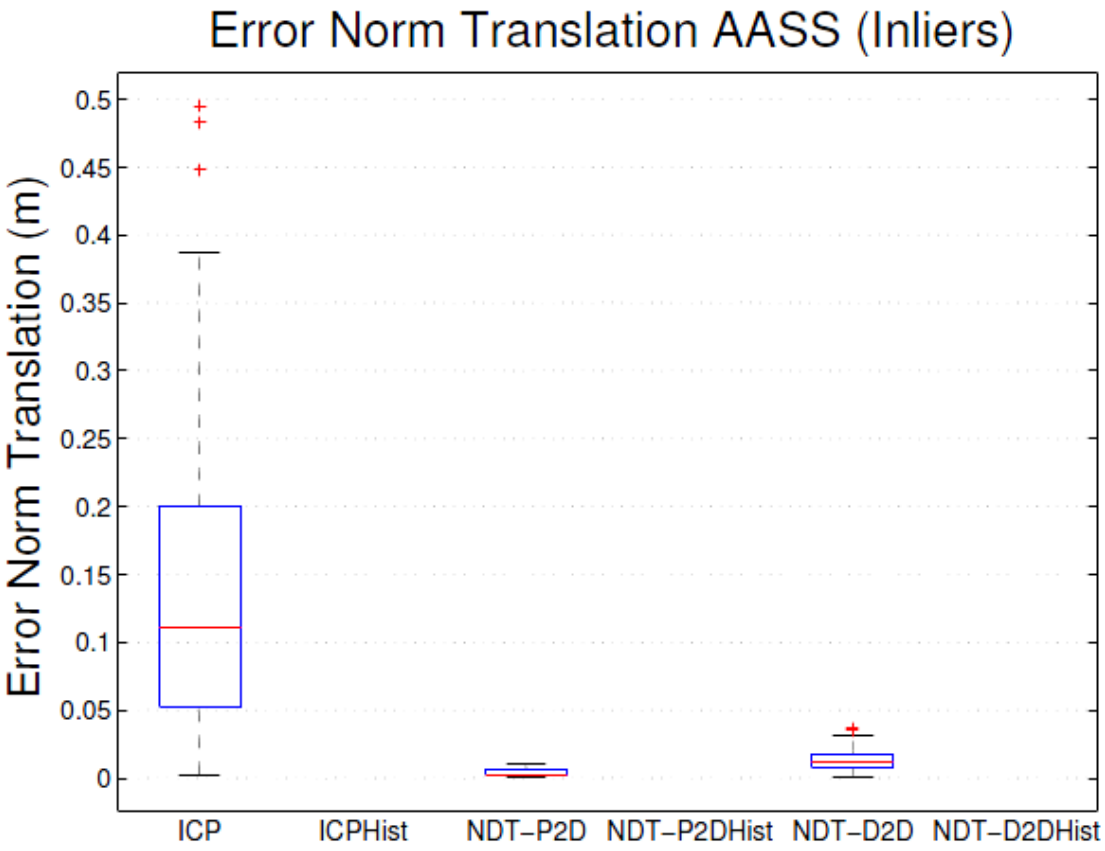
    - only successful registrations (inliers) → much better convergence of 3D-NDT



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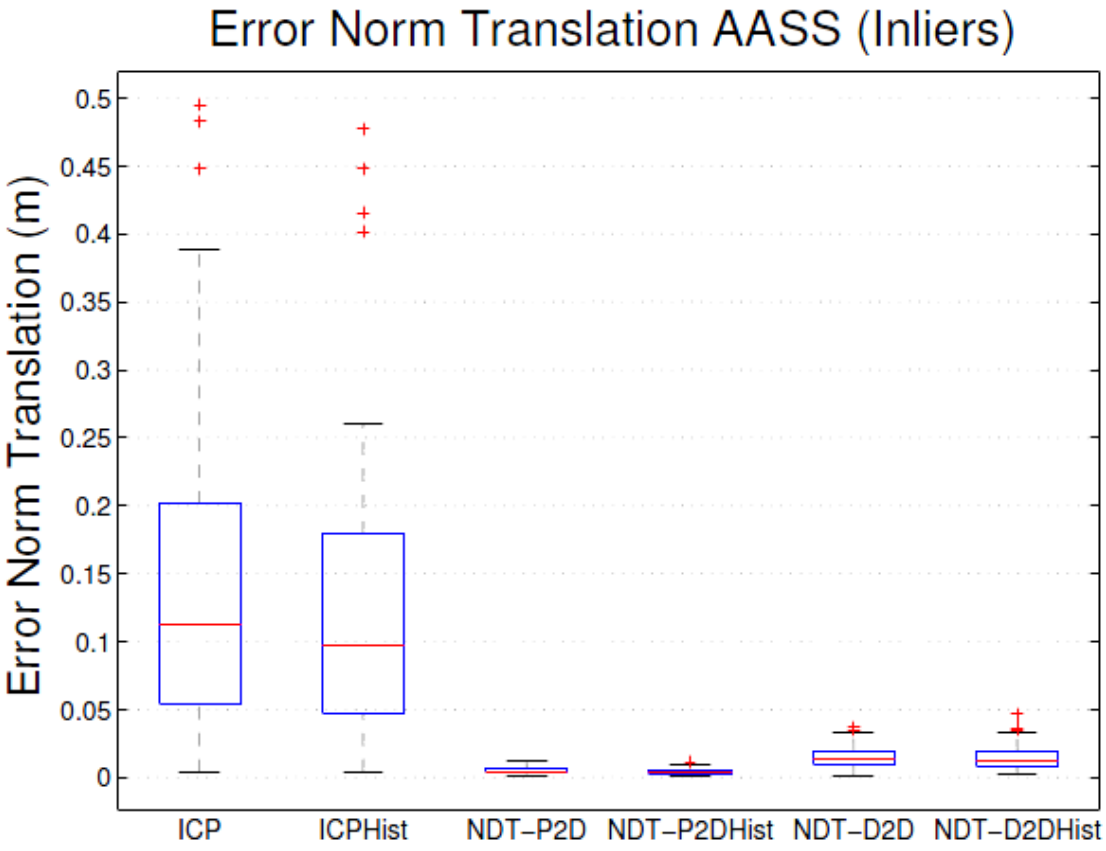

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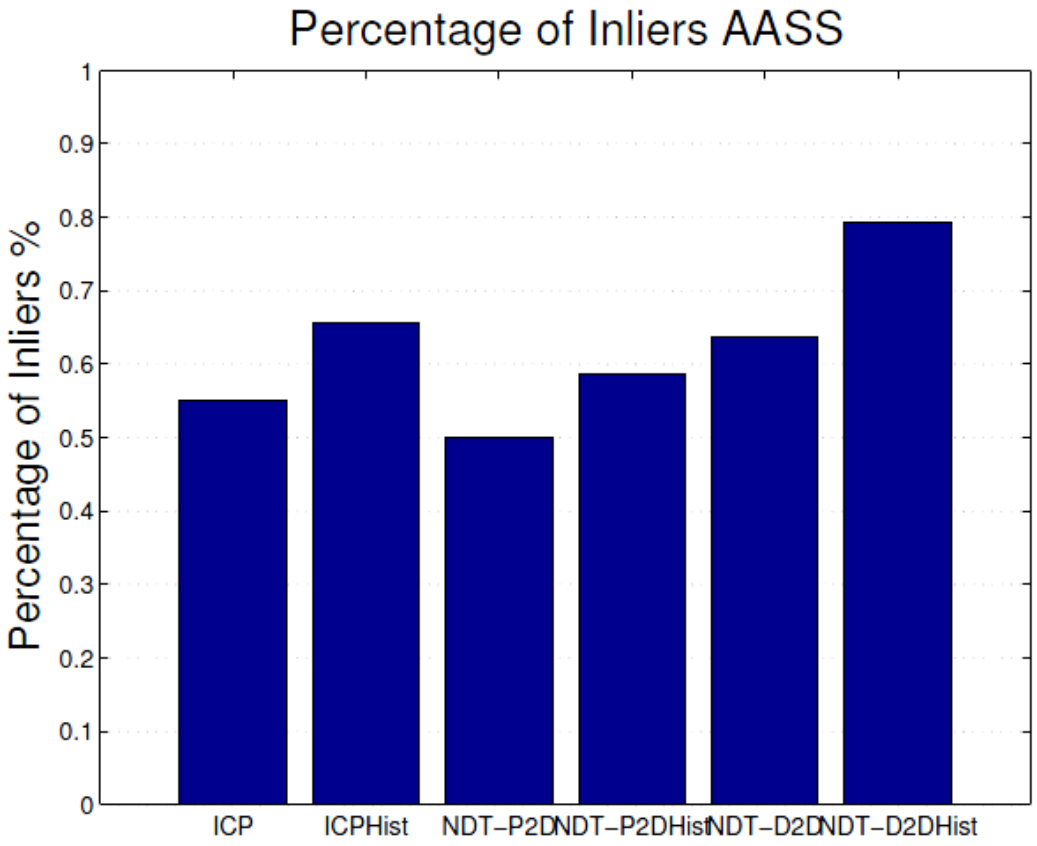

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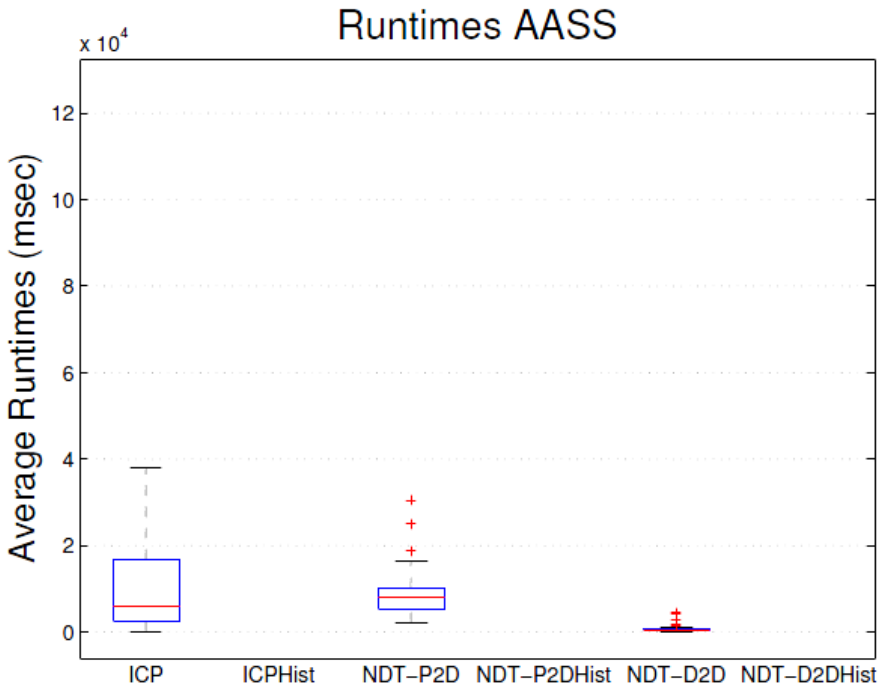

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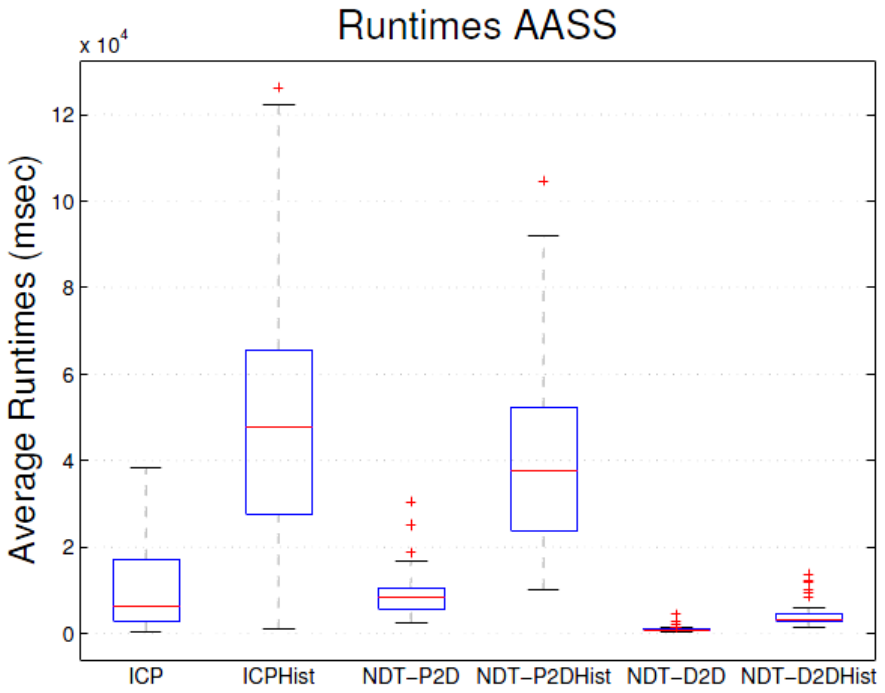
  - » average runtimes for NDT-to-NDT at around 500 milliseconds
    - runtime increases when using hotstart, but NDT-to-NDT with hotstart still faster than the other two implementations



Real Time Registration of RGB-D Data using Local Visual Features and 3D-NDT Registration

© A. J. Lilienthal et al. (Jul 26, 2012)

- **Sparse Rich 3D-NDT Registration** [Andreasson et al., 2012]
  - find local visual features (SURF) from (Kinect) image data
  - find closest matches and corresponding depth values (match candidates)
  - RANSAC on feature pairs
    → initial transformation estimate (hot start)
  - compute 3D-NDT components only for surrounding regions of match candidates
    - fixed support size

- **Sparse Rich 3D-NDT Registration** [Andreasson et al., 2012]
  - test data from [Sturm et al., 2011]
    - J. Sturm, S. Magnenat, N. Engelhard, F. Pomerleau, F. Colas, W. Burgard, D. Cremers, and R. Siegwart.
      "Towards a Benchmark for RGBD SLAM Evaluation".
      In Proc. of the RGB-D Workshop on Advanced Reasoning with Depth Cameras at Robotics: Science and Systems Conf. (RSS), Los Angeles, USA, June 2011.

- **Sparse Rich 3D-NDT Registration** [Andreasson et al., 2012]
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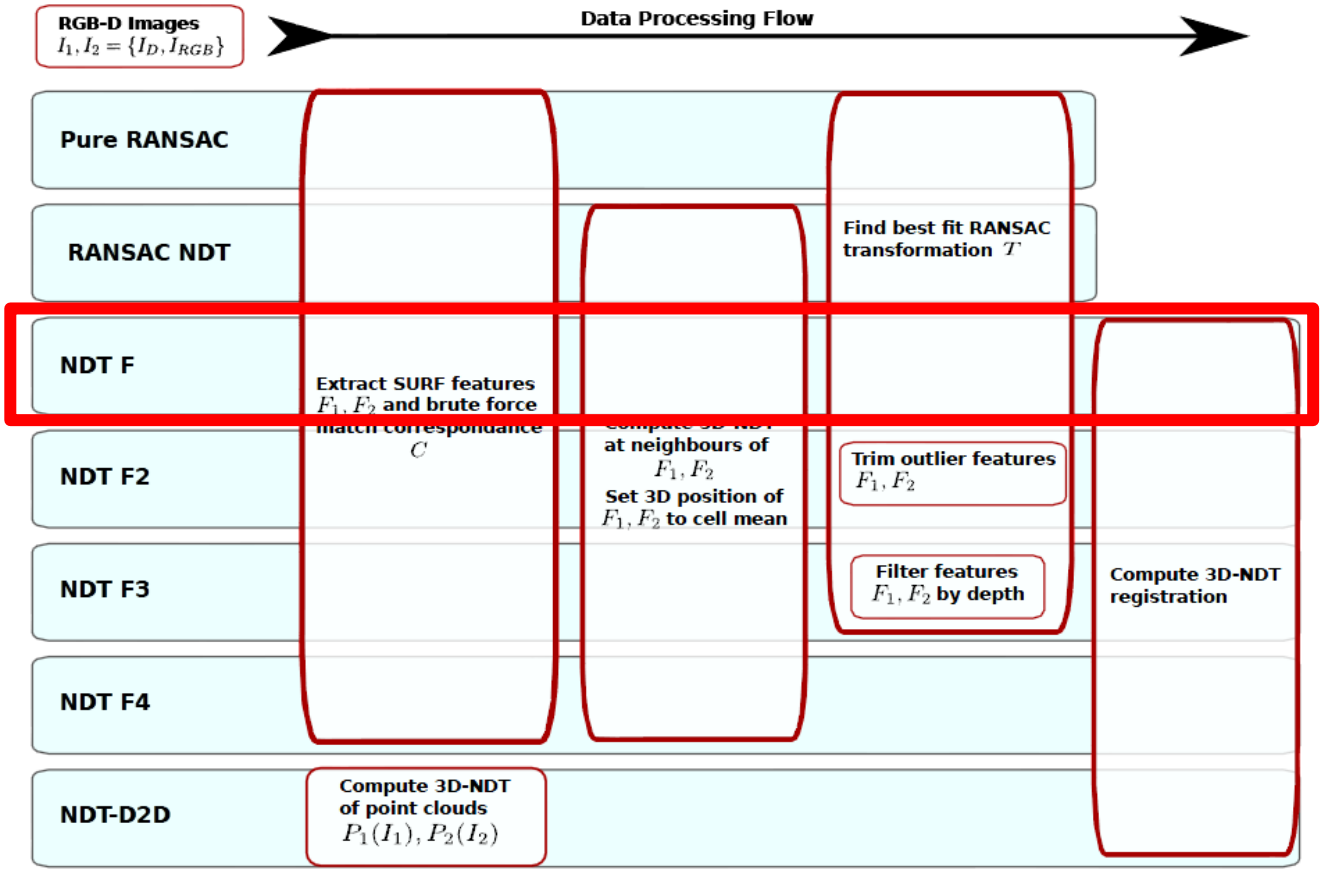
    - » RGB images downscaled by 1/4 (side length, for real-time performance)



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    - » RGB images downscaled by 1/4 (side length, for real-time performance)
    - » comparison of "NDT F" with [Steinbrucker et al., 2011]
      - F. Steinbrucker, J. Sturm, and D. Cremers.
        "Real-time Visual Odometry from Dense RGB-D Images".
        In Workshop on Live Dense Reconstruction with Moving Cameras at the Intl. Conf. on Computer Vision (ICCV), 2011.

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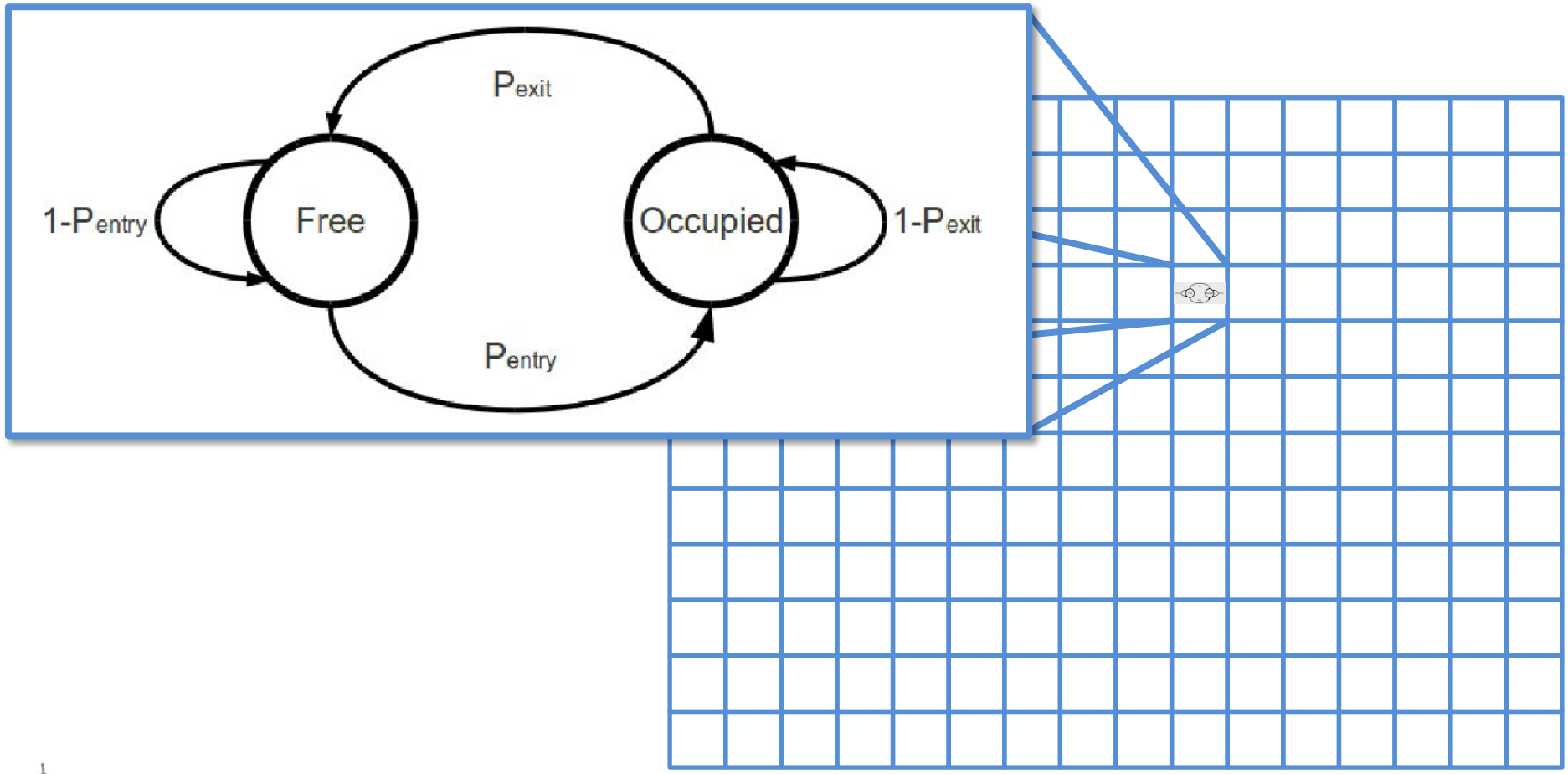
    - » comparison of "NDT F" with [Steinbrucker et al., 2011]

Dataset	$\bar{x}$ (m)	$\tilde{x}$ (m)	$\bar{\theta}$ (deg)	$\tilde{\theta}$ (deg)	$\bar{fps}$ (Hz)
1-360	0.014	0.010	0.592	0.483	17.5
1-desk2	0.016	0.012	1.009	0.820	15.3
1-floor	0.015	0.007	1.027	0.402	24.1
1-room	0.011	0.008	0.635	0.502	13.8
1-desk	0.0165	0.0122	1.1567	0.909	14.4
G-ICP [13]	0.0103	-	0.0154	-	0.13
Steinbrucker [4]	0.0053	-	0.0065	-	12.5
2-desk	0.0048	0.0039	0.3413	0.2961	19.7
G-ICP [13]	0.0062	-	0.0060	-	0.13
Steinbrucker [4]	0.0015	-	0.0027	-	12.5

iMAC Occupancy Grid Maps for Representation of Dynamic Environments

- **iMAC Occupancy Grid Maps** [Saarinen et al., 2012]
  - Jari Saarinen, Henrik Andreasson, and Achim J. Lilienthal. "Independent Markov Chain Occupancy Grid Maps for Representation of Dynamic Environments". IROS 2012, to appear.

- **iMAC Occupancy Grid Maps** [Saarinen et al., 2012]
  - model each cell as an independent Markov chain



- **iMAC Occupancy Grid Maps** [Saarinen et al., 2012]
  - model each cell as an independent Markov chain
  - learn Poisson rate parameters for exit and entry process

$$\hat{\lambda}_{exit} = \frac{\alpha_{exit}}{\beta_{exit}} = \frac{\#events:\ occupied\ to\ free + 1}{\#observations\ when\ occupied + 1}$$
$$\hat{\lambda}_{entry} = \frac{\alpha_{entry}}{\beta_{entry}} = \frac{\#events:\ free\ to\ occupied + 1}{\#observations\ when\ free + 1}$$

- **iMAC Occupancy Grid Maps** [Saarinen et al., 2012]
  - model each cell as an independent Markov chain
  - learn Poisson rate parameters for exit and entry process
  - identify different dynamics based on learned Poisson parameters

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Functional state	λ_{exit}	λ_{entry}
Static occupied	$\rightarrow 0$	High
Static free	High	$\rightarrow 0$
Semi-static	Low	Low
Dynamic	High	Low
Semi-static occupied (doors)	Low	High

- **iMAC Occupancy Grid Maps** [Saarinen et al., 2012]
  - model each cell as an independent Markov chain
  - learn Poisson rate parameters for exit and entry process
  - identify different dynamics based on learned Poisson parameters
  - use recency-weighted approach

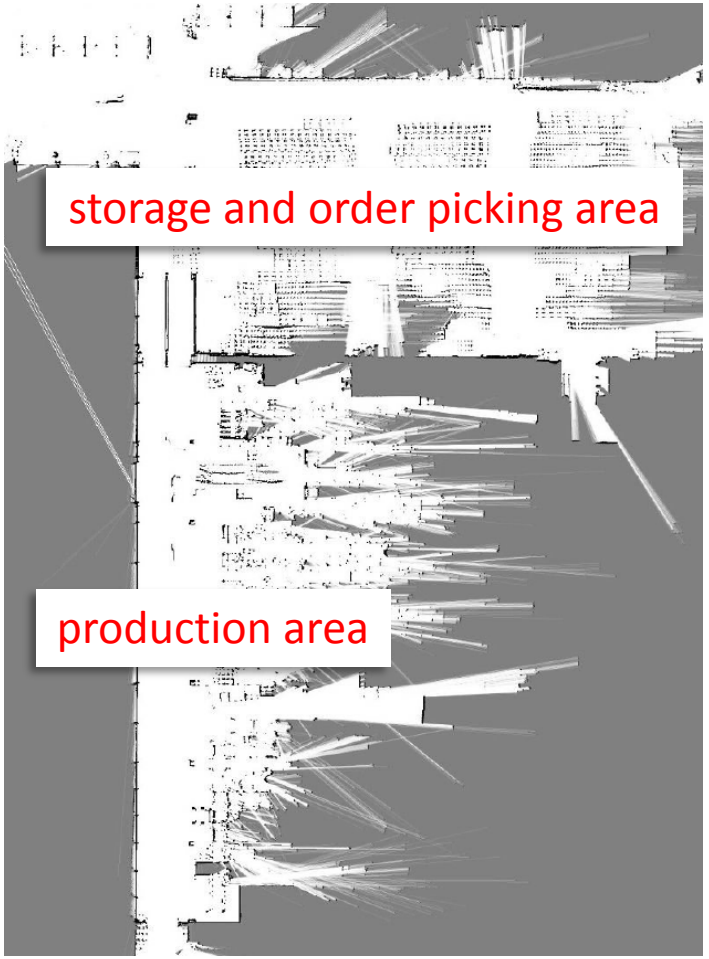
- **iMAC Occupancy Grid Maps** [Saarinen et al., 2012]
  - model each cell as an independent Markov chain
  - learn Poisson rate parameters for exit and entry process
  - use rate parameters as estimate of state change probability

$$\hat{\lambda}_{exit} \sim p(m = 0 | m = 1)$$
$$\hat{\lambda}_{entry} \sim p(m = 1 | m = 0)$$

Rich 3D Perception Work at AASS

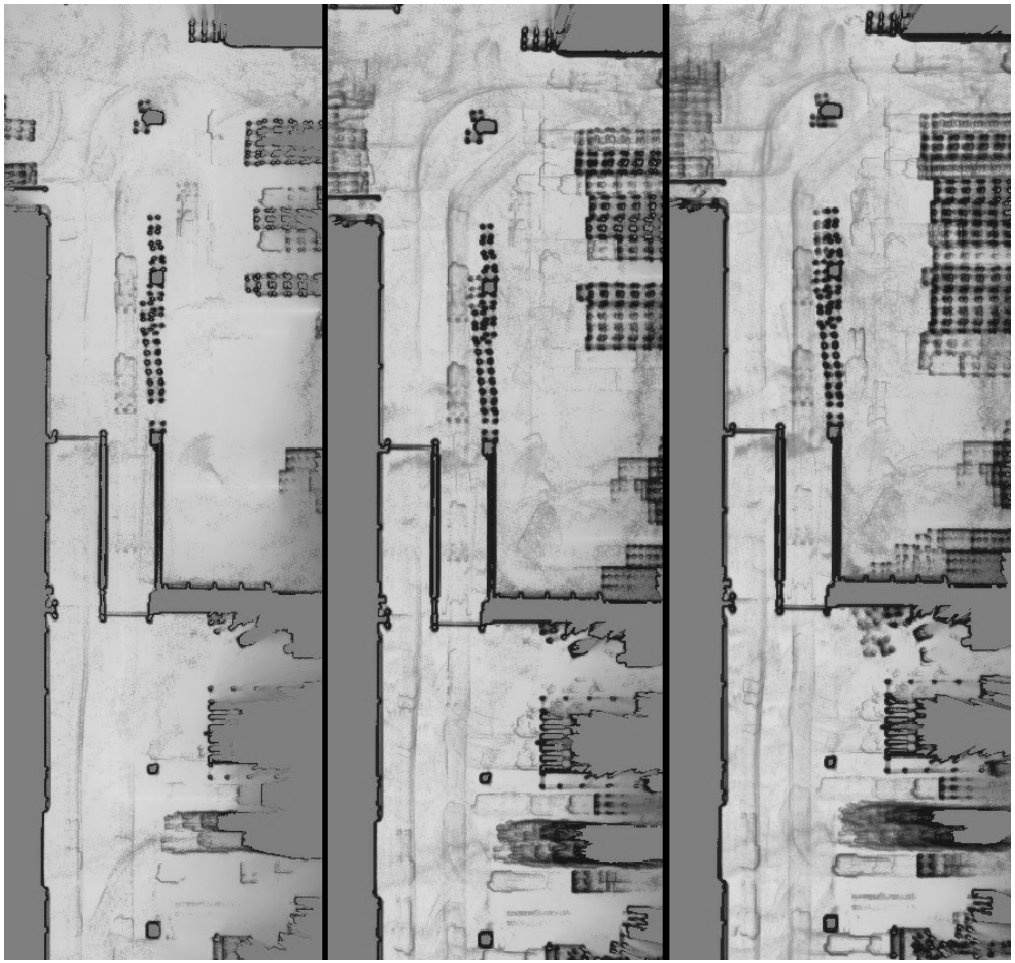
- **iMAC Occupancy Grid Maps** [Saarinen et al., 2012]
  - long-term data collection in industrial environment
    - » milk production plant
    - » Laser Guided Vehicle (LGV) in production use

- **iMAC Occupancy Grid Maps** [Saarinen et al., 2012]
  - long-term data collection in industrial environment
    - » milk production plant
    - » Laser Guided Vehicle (LGV) in production use
      - get orders from the production area and deliver them to the storage area



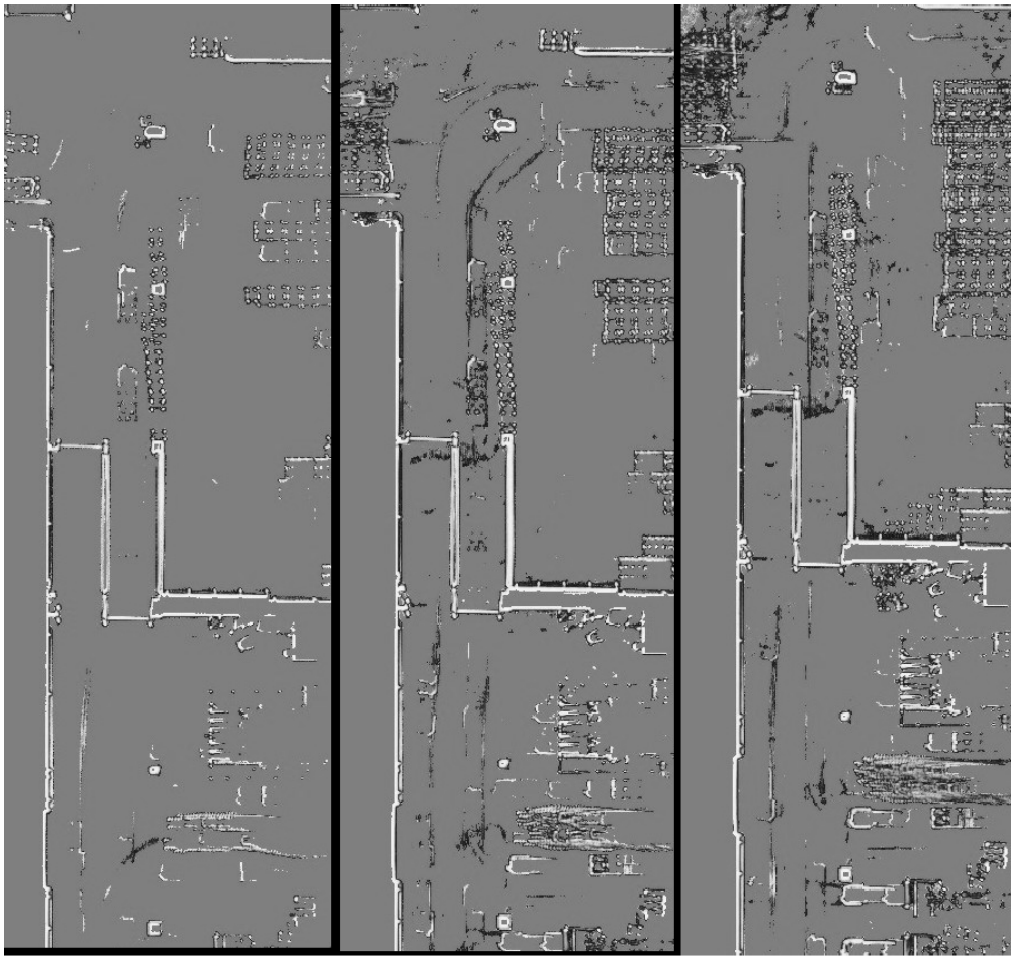
- **iMAC Occupancy Grid Maps** [Saarinen et al., 2012]
  - long-term data collection in industrial environment
    - » milk production plant
    - » Laser Guided Vehicle (LGV) in production use
    - » data from 2D Sick LRF
    - » pose data from positioning system
    - » 10h of operation (8.8km trajectory)
    - » dynamics in the environment
      - other LGVs (10)
      - manually operated forklifts
      - people
      - ever changing storage layout

- **iMAC Occupancy Grid Maps** [Saarinen et al., 2012]
  - long-term data collection in industrial environment
  - results (black ⇔ max.)
    - » λ_{entry} (logarithmic scale)



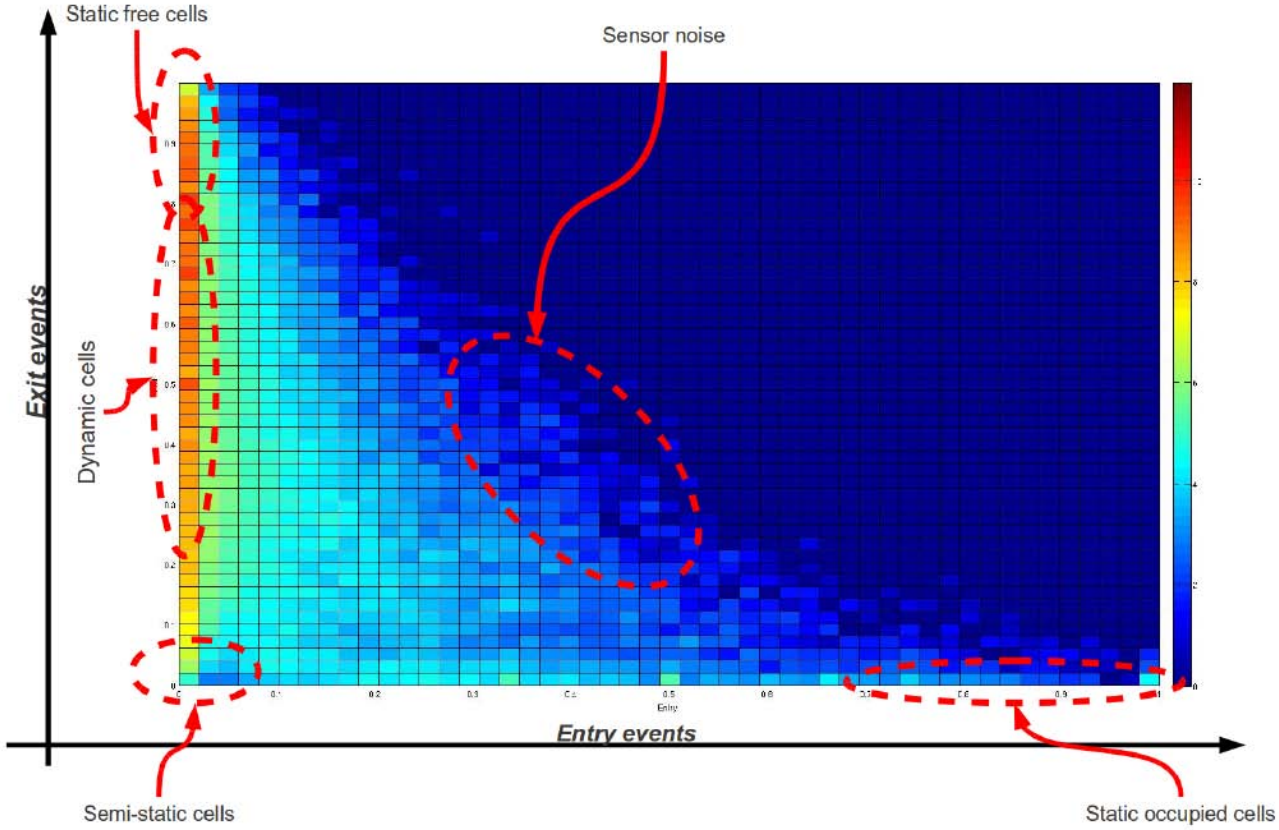
time

- **iMAC Occupancy Grid Maps** [Saarinen et al., 2012]
  - long-term data collection in industrial environment
  - results (black ⇔ max.)
    - » λ_{entry}
    - » λ_{exit}
      - busy corridors are more visible with time



time

- **iMAC Occupancy Grid Maps** [Saarinen et al., 2012]
  - long-term data collection in industrial environment
  - results (black ⇔ max.)
    - » λ_{entry}, λ_{exit} pairs



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    - » analyse timescales ⇔ analyse behaviour of Markov chains after N steps

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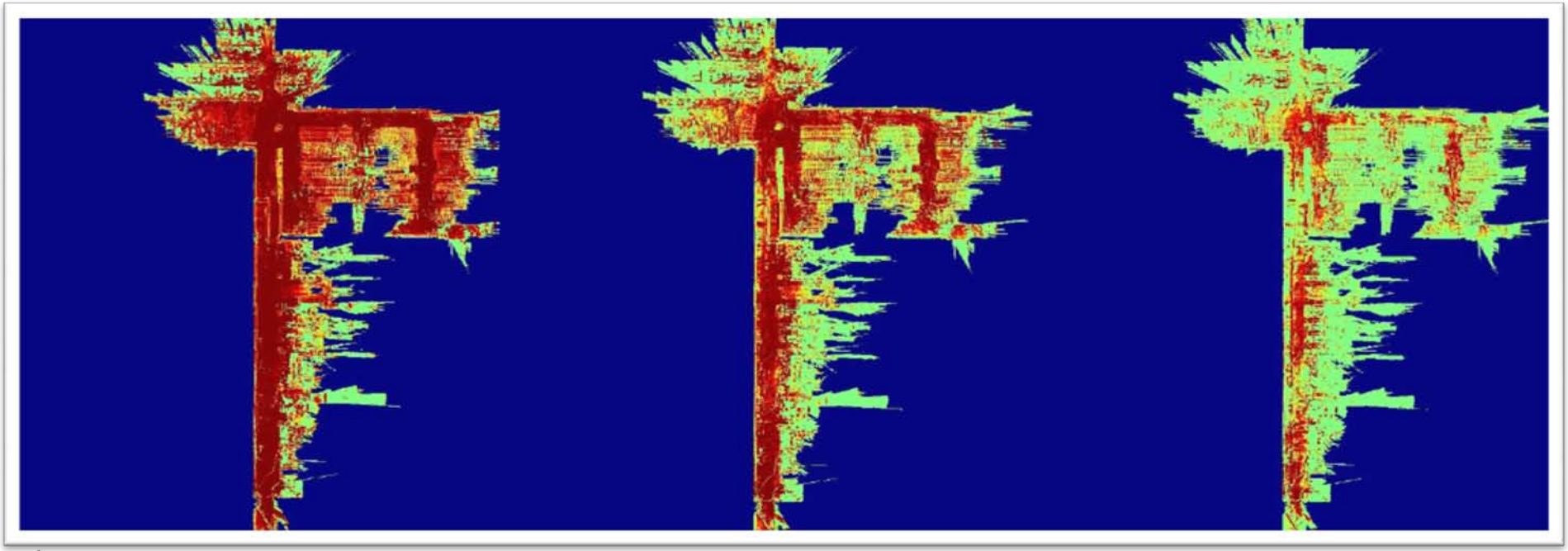
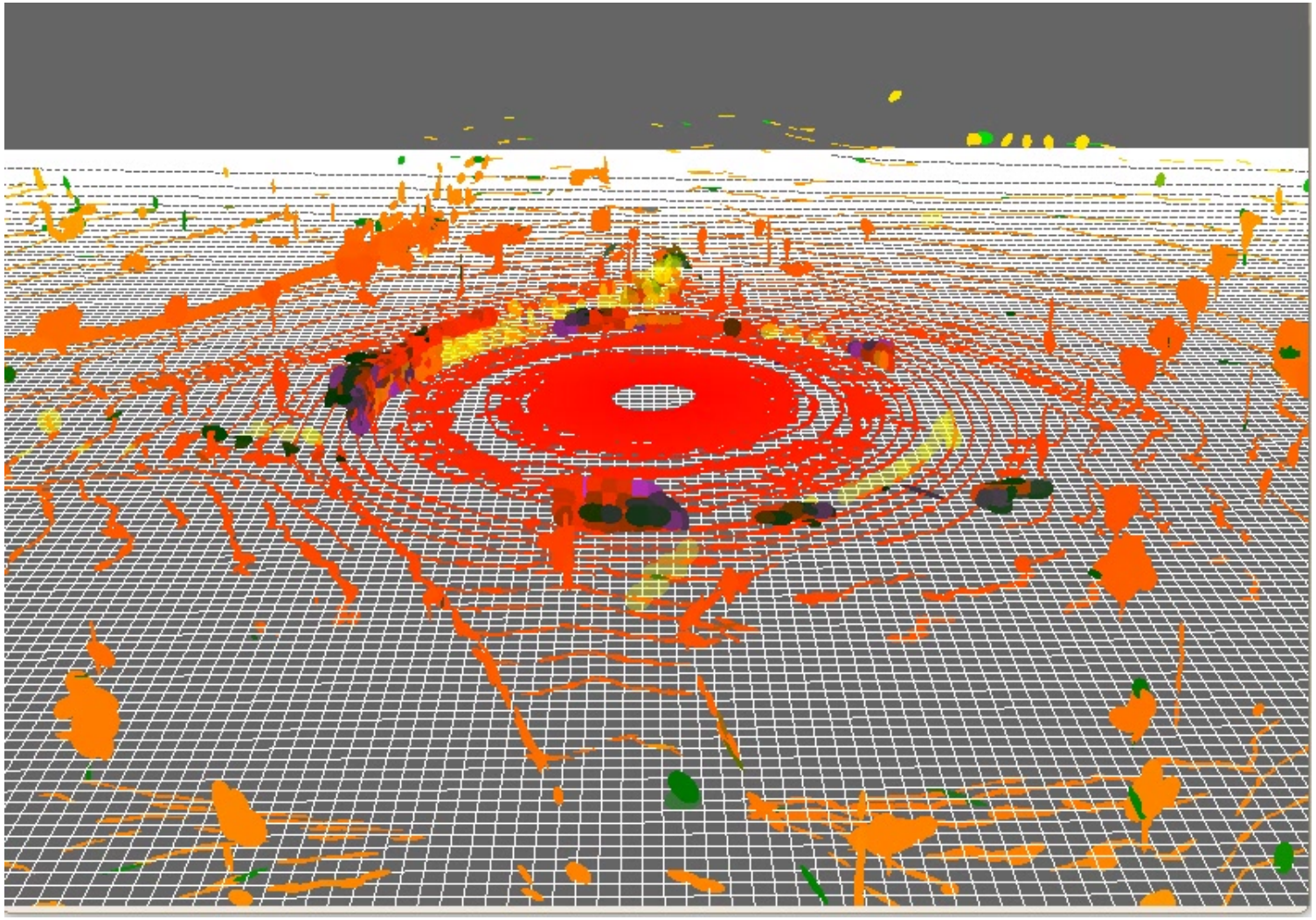
  - long-term data collection in industrial environment
  - analyse timescales ⇔ behaviour of Markov chains after N steps
    - activity shown for smaller N ⇔ shorter timescales
    - N=8 ⇔ motion and sensor noise
    - N=32 ⇔ starts to reveal semi-static parts

N=8 N=16 N=32

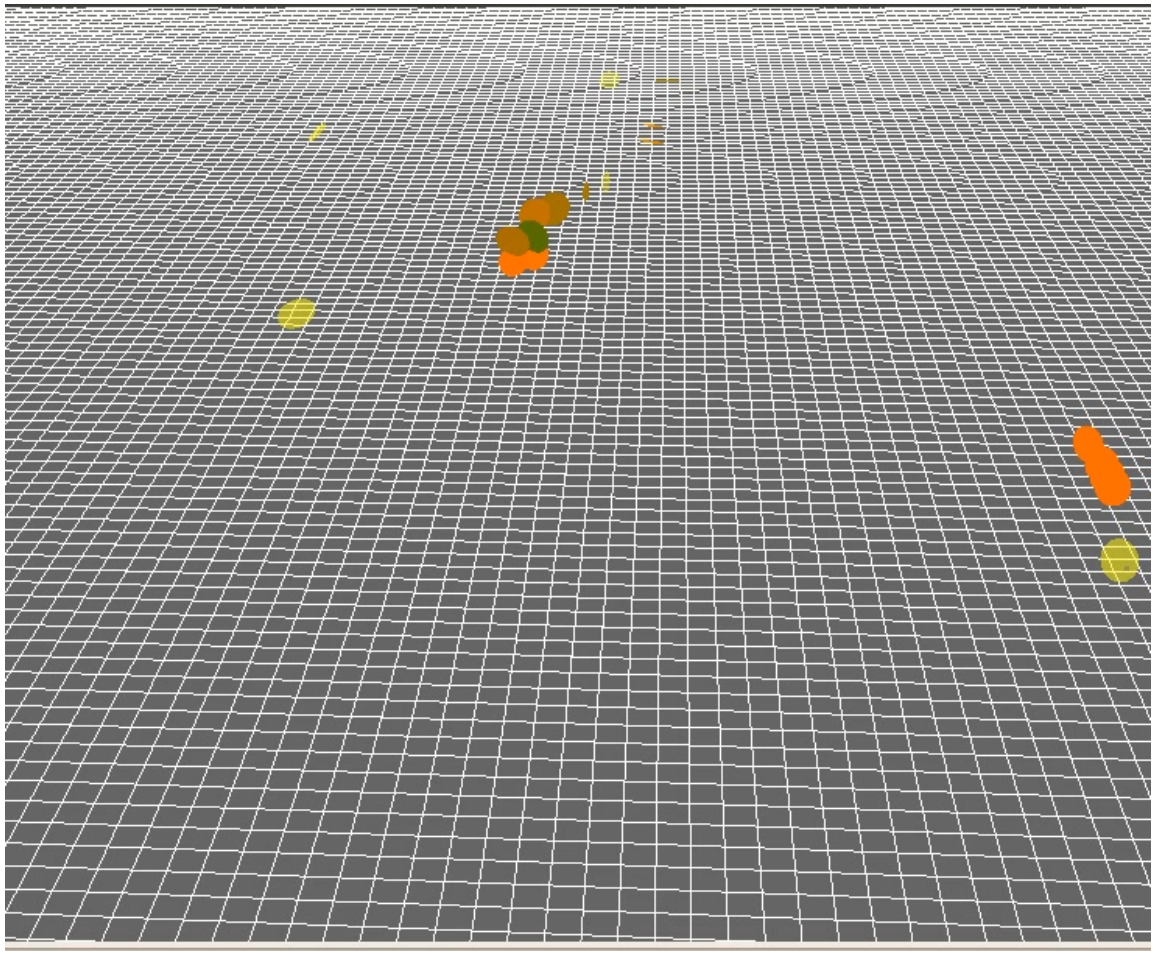


3D-NDT in Dynamic Environments (A First Glimpse)

- **3D-NDT Model Maintenance (Saarinen et al.)**
  - online updates



- **3D-NDT Model Maintenance (Saarinen et al.)**
  - online updates
  - create model at different timescales (diff → dyn. objects)



3D Perception for Transport and Inspection Robots

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