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)
AASS MR&O Lab – Profile
Örebro and its University

- 59°16' north, population ~130k
1. Örebro and its University

- 59°16' north, population ~130k
- ~17k students, ~1200 employees,
- 7 schools, 15 research centers
1. Örebro and its University
   - 59°16' north, population ∼130k
   - ∼17k students, ∼1200 employees,
   - 7 schools, 15 research centers

2. 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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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
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<tr>
<th>Name</th>
<th>Position</th>
<th>Since</th>
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<tr>
<td>Håkan Almqvist</td>
<td>Ph.D. Student</td>
<td>Sep 2009</td>
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<td>Achim J. Lilienthal</td>
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<td>Jul 2005</td>
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<td>Anani Ananiev</td>
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<td>Krzysztof Charusta</td>
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<td>Marcello Cirillo</td>
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<td>Feb 2011</td>
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<td>Houssam Albitar</td>
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<td>Daniel Canelhas</td>
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<td>Ivan Kalaykov</td>
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1. **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
Forklift Trucks (Danaher Motion, Linde MH, Stora Enso)

Picking up paper reels at unknown positions
Demonstration held at Vänerhamn, Karlstad 2009-04-03

speed x 2
- Forklift Trucks (Danaher Motion, Linde MH, Stora Enso)
  - environment with a dynamic "background"
- **Forklift Trucks** (Danaher Motion, Linde MH, Stora Enso)
  - environment with a dynamic "background"
  - requires 3D sensing

1 meter “drop” to the railway tracks
1. **Forklift Trucks** *(Danaher Motion, Linde MH, Stora Enso)*

(speed x 1)
MR&O Lab Profile – Two Major Research Directions

- **Forklift Trucks** (Danaher Motion, Linde MH, Stora Enso)
- **Wheel Loaders** (VolvoCE, VolvoTech, NCC)
MR&O Lab Profile – Two Major Research Directions

- **Forklift Trucks** (Danaher Motion, Linde MH, Stora Enso)
- **Wheel Loaders** (VolvoCE, VolvoTech, NCC)
- **Mining Vehicles** (Atlas Copco, Fotonic)
1. MR&O Lab Profile – Two Major Research Directions

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- **Hospital Transport Vehicles** (RobCab)
MR&O Lab Profile – Two Major Research Directions

- Forklift Trucks (Danaher Motion, Linde MH, Stora Enso)
- Wheel Loaders (VolvoCE, VolvoTech, NCC)
- Mining Vehicles (Atlas Copco, Fotonic)
- Hospital Transport Vehicles (RoboCab)
- 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
- develop "electronic nose" towards a "mobile nose"
- examples: gas sensor networks (air pollution monitoring), inspection robots (landfill site surveillance, gas leak localization)
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, Linde MH, Stora Enso)
- Wheel Loaders (VolvoCE, VolvoTech, NCC)
- Mining Vehicles (Atlas Copco, Fotonic)
- Hospital Transport Vehicles (RobCab)
- Garbage Bin Collection and Cleaning (RoboTech)
  - ... and pollution monitoring
- Forklift Trucks (Danaher Motion, Linde MH, Stora Enso)
- Wheel Loaders (VolvoCE, VolvoTech, NCC)
- Mining Vehicles (Atlas Copco, Fotonic)
- Hospital Transport Vehicles
- Garbage Bin Collection and Cleaning (RoboTech)
- Landfill Site Inspection (Atleverket)
Field Robotics and
3D Perception Projects at AASS
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)
2. History of "Field Robotics" Projects

- NSAL (2005–2012)

  » Multiple autonomous forklifts for loading and transportation applications
  » main contribution
    - navigation without reflectors
    - autonomous paper reel handling
2. History of "Field Robotics" Projects

- NSAL (2005–2012)
  - 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"
2. History of "Field Robotics" Projects

- NSAL (2005–2012)
  » Multiple autonomous forklifts for loading and transportation applications
  » Safe autonomous industrial vehicles for industrial environments
  » Topics
    - Localization with minimum infrastructure (single fish-eye camera, 2D LRF)
    - Detection and distance prediction of humans with reflective vest
### History of "Field Robotics" Projects

- **NSAL (2005–2012)**
  - 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"
    - trajectory prediction / path planning, with traffic rules (➔ flexibility + predictability)
History of "Field Robotics" Projects

- NSAL (2005–2012)
  » logistics + safe autonomous vehicle navigation in dynamic environments
History of "Field Robotics" Projects

- NSAL (2005–2012)

  » 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
History of "Field Robotics" Projects

- NSAL (2005–2012)

» logistics + safe autonomous vehicle navigation in dynamic environments
  - Objective 2 – Rich 3D Perception
  - Objective 1 – Safe Motion
    - collision avoidance, trajectory modification, tracking of vehicles/humans, real-time response
2. History of "Field Robotics" Projects

- **NSAL (2005–2012)**
  - Logistics + safe autonomous vehicle navigation in dynamic environments
    - 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
2. History of "Field Robotics" Projects
   - NSAL (2005–2012)

   » logistics + safe autonomous vehicle navigation in dynamic environments
   - requirements elicited from industrial partners
   - → solutions integrated into a "SAUNA System"
2. History of "Field Robotics" Projects

- **NSAL (2005–2012)**
  - 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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- **NSAL (2005–2012)**
  - Logistics + safe autonomous vehicle navigation in dynamic environments
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History of "Field Robotics" Projects

- NSAL (2005–2012)
- SAUNA (2011–2014)
- All-4-eHAM (2009–2012) \(^{\text{AASS, Volvo CE, NCC Roads}}\)
  - Autonomous wheel loaders for efficient handling of heterogeneous materials
History of "Field Robotics" Projects

- NSAL (2005–2012)
- SAUNA (2011–2014)
- All-4-eHAM (2009–2012) AASS, Volvo CE, NCC Roads

» 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
History of "Field Robotics" Projects

- NSAL (2005–2012)
- SAUNA (2011–2014)

  » 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)
History of "Field Robotics" Projects

- NSAL (2005–2012)
- SAUNA (2011–2014)
- RobLog (2011–2015) AASS, Vollers, Qubica, BIBA, Jacobs, Pisa, HSRT
  » Unloading Containers (Cognitive Robot for Automation of Logistic Processes)
2. History of "Field Robotics" Projects

- NSAL (2005–2012)
- SAUNA (2011–2014)
- RobLog (2011–2015) AASS, Vollers, Qubica, BIBA

» Unloading Containers
  - industrial scenario (coffee sacks)
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  - industrial scenario (coffee sacks)
  - advanced scenario
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### History of "Field Robotics" Projects

- **NSAL** (2005–2012)
- **SAUNA** (2011–2014)
- **All-4-eHAM** (2009–2012) → **ALLO** (2012–2015)
- **RobLog** (2011–2015) AASS, Vollers, Qubica, BIBA, Jacobs, Pisa, HSRT

  - Unloading Containers
    - industrial scenario (coffee sacks)
    - advanced scenario
History of "Field Robotics" Projects

- NSAL (2005–2012)
- SAUNA (2011–2014)
- SPENCER (2013–2016) AASS, TUM, Twente, CNRS, RWTH, BlueBotics, KLM, Freiburg
  » group-friendly navigation
2. History of "Field Robotics" Projects

- NSAL (2005–2012)
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  - group-friendly navigation
  - identification of likely spokespersons
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- NSAL (2005–2012)
- SAUNA (2011–2014)
- SPENCER (2013–2016) AASS, TUM, Twente, CNRS, RWTH, BlueBotics, KLM, Freiburg
  - group-friendly navigation
  - identification of likely spokespersons
  - Schengen fast track scenario
History of "Field Robotics" Projects

- NSAL (2005–2012)
- SAUNA (2011–2014)
- **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
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

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  - 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 $\iff$ 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
3. 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, ...
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, ...
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
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
### 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

Less Dynamic
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
3D Perception Requirements

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

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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

- 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 \(\rightarrow\) 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 \(\rightarrow\) 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
3. **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**

**Rich 3D?**

- Better extrapolation on sparse measurements
- Additional information → key points
- Rich 3D models may often be layered maps
- Also required for rich 3D
- 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]
3D Normal Distributions Transform (3D-NDT)

- extension to 3D scan registration [Magnusson et al., 2007]

- 3D-NDT is
  - sparse
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    - Point-to-NDT
      [Magnusson et al., 2007]
    - NDT-to-NDT
      [Stoyanov et al., 2012]
4. **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
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
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)
5. **NDT-2-NDT Registration** [Stoyanov et al., 2012]
   - registration with ICP (iterative closest point)
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Rich 3D Perception Work at AASS

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5. Rich 3D Perception Work at AASS

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  - compute likelihood of \( M_{\text{NDT}}(\mathcal{P}_2) \) given \( M_{\text{NDT}}(\mathcal{P}_1) \)
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Rich 3D Perception Work at AASS
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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"
5. NDT-2-NDT Registration [Stoyanov et al., 2012]

- results
  - translation deviation from known ground truth transformations

![Error Norm Translation AASS](chart.png)
5. **NDT-2-NDT Registration [Stoyanov et al., 2012]**
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    - only successful registrations (inliers) → much better convergence of 3D-NDT
    - percentage of inliers highest for NDT-to-NDT and increases when using hotstart

![Bar chart showing percentage of inliers for different methods]

Percentage of Inliers AASS

- ICP
- ICPHist
- NDT-P2
- NDT-P2Hist
- NDT-D2
- NDT-D2Hist
NDT-2-NDT Registration [Stoyanov et al., 2012]

- results
  - translation deviation from known ground truth transformations
    - only successful registrations (inliers) → much better convergence of 3D-NDT
    - percentage of inliers highest for NDT-to-NDT and increases when using hotstart
  - average runtimes for NDT-to-NDT at around 500 milliseconds
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    - percentage of inliers highest for NDT-to-NDT and increases when using hotstart
  - 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
5. **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
5.

**Sparse Rich 3D-NDT Registration** [Andreasson et al., 2012]

- test data from [Sturm et al., 2011]
  - "Towards a Benchmark for RGBD SLAM Evaluation".
5. **Sparse Rich 3D-NDT Registration** [Andreasson et al., 2012]

- test data from [Sturm et al., 2011]
- test of different registration variations
  - RGB images downscaled by 1/4 (side length, for real-time performance)
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  - comparison of "NDT F" with [Steinbrucker et al., 2011]
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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]

<table>
<thead>
<tr>
<th>Dataset</th>
<th>$\bar{x}$ (m)</th>
<th>$\tilde{x}$ (m)</th>
<th>$\bar{\theta}$ (deg)</th>
<th>$\tilde{\theta}$ (deg)</th>
<th>$f_{ps}$ (Hz)</th>
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<tbody>
<tr>
<td>1-360</td>
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<td>1-floor</td>
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<td>0.007</td>
<td>1.027</td>
<td>0.402</td>
<td>24.1</td>
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<td>1-room</td>
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<td>0.008</td>
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<tr>
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<td>0.0122</td>
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<td>G-ICP [13]</td>
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<td>0.0060</td>
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<td>0.0015</td>
<td>-</td>
<td>0.0027</td>
<td>-</td>
<td>12.5</td>
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</tbody>
</table>
iMAC Occupancy Grid Maps for Representation of Dynamic Environments
5. **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".
5. **iMAC Occupancy Grid Maps** [Saarinen et al., 2012]
   - model each cell as an independent Markov chain
5. **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

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

\[
\hat{\lambda}_{\text{entry}} = \frac{\alpha_{\text{entry}}}{\beta_{\text{entry}}} = \frac{\text{#events: free to occupied} + 1}{\text{#observations when free} + 1}
\]
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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\hat{\lambda}_{\text{entry}} = \frac{\alpha_{\text{entry}}}{\beta_{\text{entry}}} = \frac{\#\text{events: free to occupied} + 1}{\#\text{observations when free} + 1}
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<table>
<thead>
<tr>
<th>Functional state</th>
<th>(\hat{\lambda}_{\text{exit}})</th>
<th>(\hat{\lambda}_{\text{entry}})</th>
</tr>
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<tbody>
<tr>
<td>Static occupied</td>
<td>(\rightarrow 0)</td>
<td>High</td>
</tr>
<tr>
<td>Static free</td>
<td>High</td>
<td>(\rightarrow 0)</td>
</tr>
<tr>
<td>Semi-static</td>
<td>Low</td>
<td>Low</td>
</tr>
<tr>
<td>Dynamic</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Semi-static occupied (doors)</td>
<td>Low</td>
<td>High</td>
</tr>
</tbody>
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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
5. \textbf{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

\[
\hat{\lambda}_{exit} \sim p(m = 0 | m = 1) \\
\hat{\lambda}_{entry} \sim p(m = 1 | m = 0)
\]
5. **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
5. **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
5. 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
5. **iMAC Occupancy Grid Maps** [Saarinen et al., 2012]
   - long-term data collection in industrial environment
   - results (black ↔ max.)
     - $\lambda_{\text{entry}}$ (logarithmic scale)
5. **iMAC Occupancy Grid Maps** [Saarinen et al., 2012]

- long-term data collection in industrial environment
- results (black $\Leftrightarrow$ max.)
  - $\lambda_{\text{entry}}$
  - $\lambda_{\text{exit}}$
    - busy corridors are more visible with time
5. iMAC Occupancy Grid Maps [Saarinen et al., 2012]
   - long-term data collection in industrial environment
   - results (black ⇔ max.)
     - $\lambda_{\text{entry}}, \lambda_{\text{exit}}$ pairs
iMAC Occupancy Grid Maps [Saarinen et al., 2012]

- long-term data collection in industrial environment
- results (black ⇔ max.)
  » analyse timescales ⇔ analyse behaviour of Markov chains after N steps
- **iMAC Occupancy Grid Maps** [Saarinen et al., 2012]
  - 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

![Rich 3D Perception Work at AASS](image)
3D-NDT in Dynamic Environments
(A First Glimpse)
5. Rich 3D Perception Work at AASS

- 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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