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Distributed Motion Planning for Industrial Random Bin Picking

by

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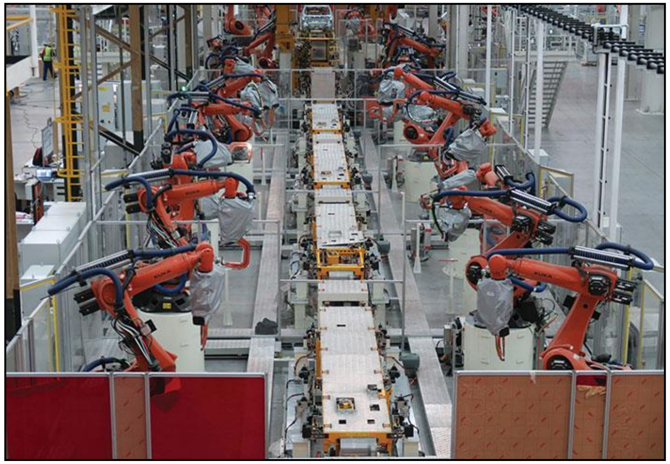
Outline

1. Introduction and Motivation
2. The Bin Picking Problem
3. Robot Path Planning Methods
4. Distributed System Architecture
5. Experimental Setup
6. Results and Discussion

Introduction and Motivation

- Manufacturing Evolution from Line to Matrix
  - Lot Size 1 Production in Robotic Cells
  - Loading of Machine Tools or Mobile Robots
  - Handling of Parts in changing Environment



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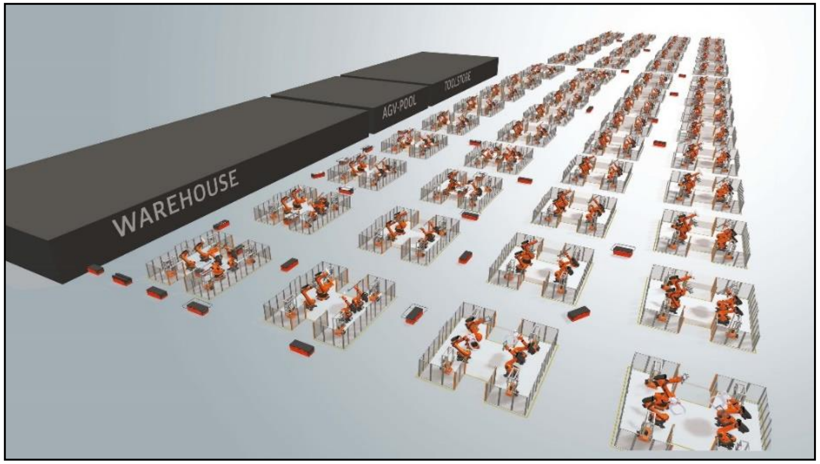

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Introduction and Motivation

- Human Robot Collaboration Trend
  - Manipulating material and products either by humans or by robots results in unknown position, orientation, configuration and other properties of the parts, even if put to a predefined zone, like swap areas or bins.
  - Placing and picking parts to and from bins while considering changing environment will be a regular task for industrial robots in the near future.
- Industrial Bin Picking demands for fast online Motion Planning

The Bin Picking Problem

- A bin contains known objects, that need to be removed from that bin.
- Tasks and Methods
  - Find object (Computer Vision) [1,2]
  - Move to pick point (Motion Planning) [4]
  - Grasp object (Gripper Design) [3]
  - Move object to place point (Motion Planning) [4]
- Motion Planning Task needs to generate a collision-free trajectory for robot and object in a minimum of time.

Robot Path Planning Methods

- Probabilistic Roadmaps (PRM) [5]
  - Sampling of 6-DOF configuration space
  - Store samples that are collision-free in workspace
  - Connect samples with k-nearest neighbor to roadmap
  - Find shortest path in roadmap to generate trajectory

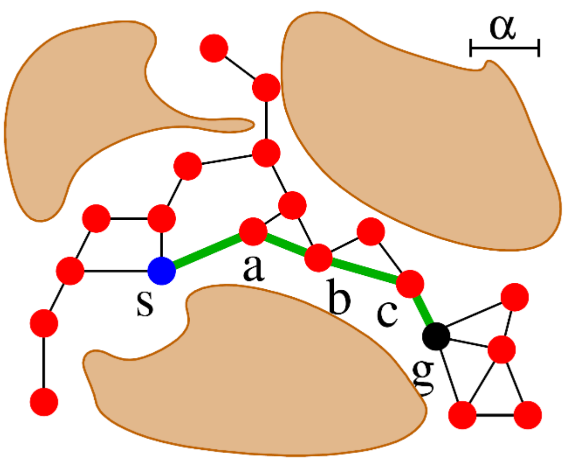


Fig 3: Schematic Robot Configuration Space with Obstacles and PRM

Robot Path Planning Methods

- Rapidly exploring Random Trees (RRT) [6]
  - Generate random sample in configuration space
  - Find nearest node in (initial) tree and expand it
    - Generate n samples around node configuration
    - Keep collision-free samples
    - Add nearest one to random sample to tree
  - Terminate on approaching goal configuration

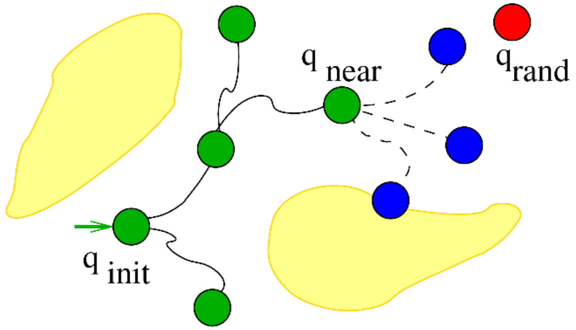
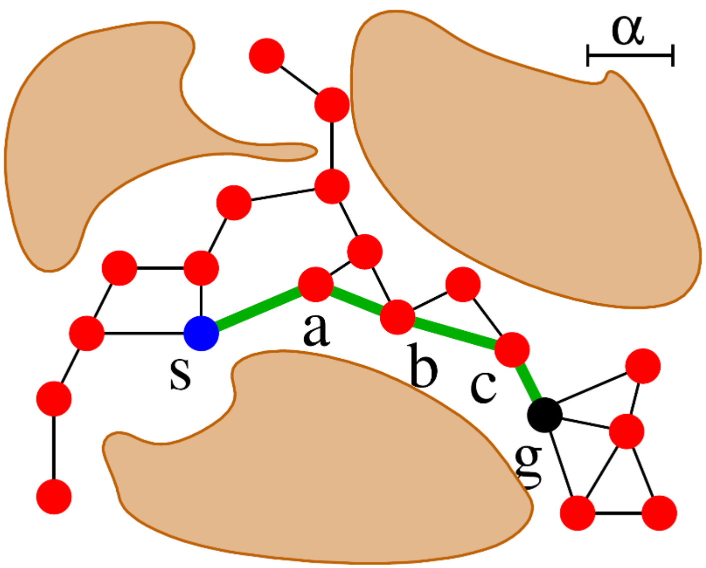


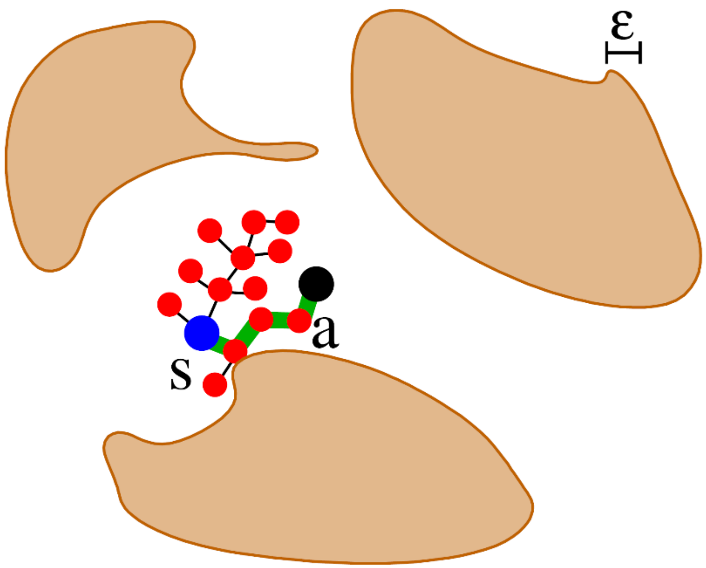
Fig 4: Schematic Robot Configuration Space with Obstacles and RRT

Robot Path Planning Methods

- Two Stage Planning Approach



1. PRM



2. RRT

Distributed System Architecture

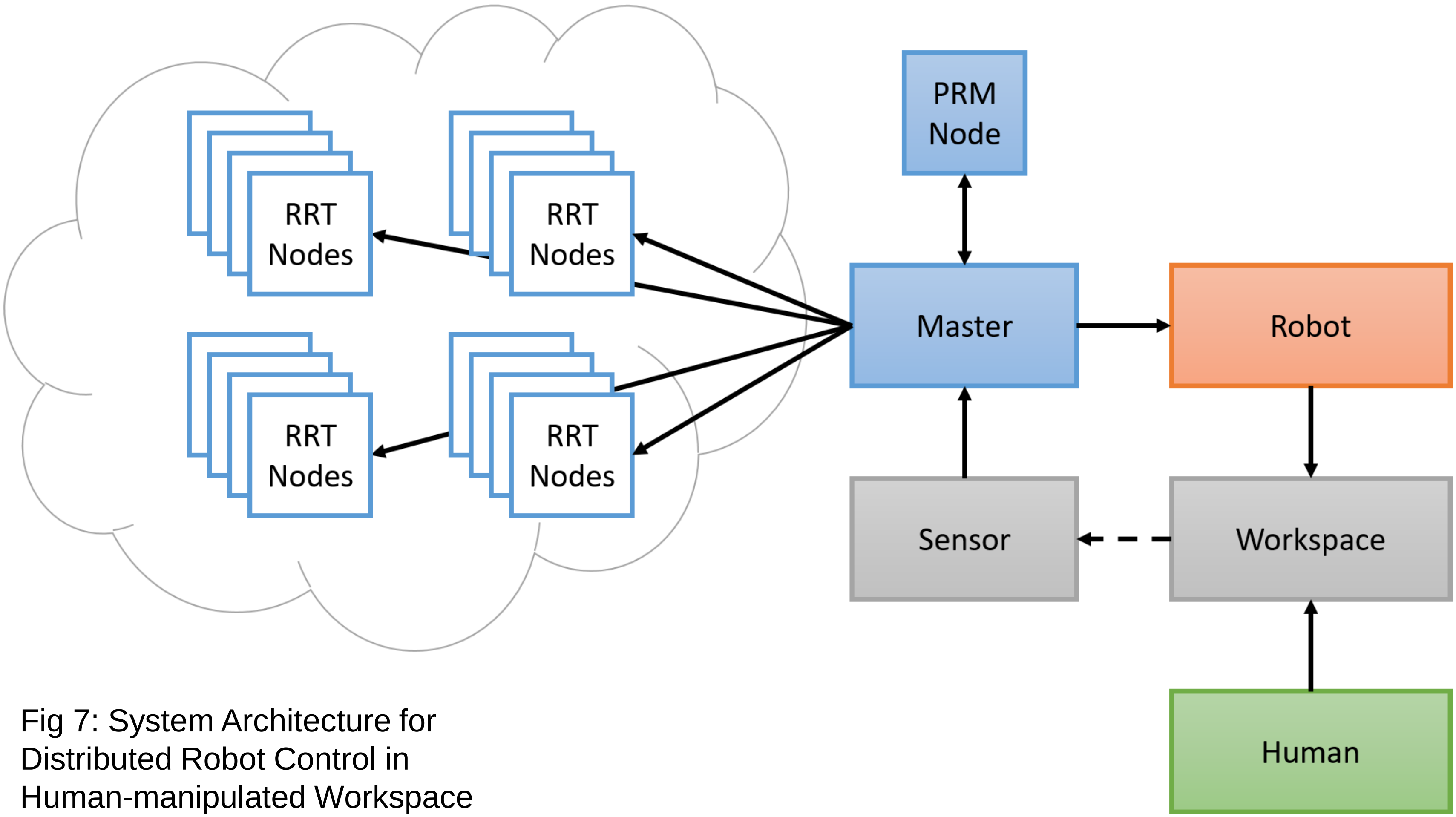


Fig 7: System Architecture for Distributed Robot Control in Human-manipulated Workspace

Distributed System Architecture

- Split path to coarse waypoints with PRM.
- Find collision-free fine paths between waypoints with RRT in parallel.
- Master node distributes tasks to PRM and RRT services and joins the final fine trajectories.
- If RRT services are more than waypoints then
  - Fine RRT paths are requested multiple times and the first planner terminating wins. (OR strategy)
  - New PRM waypoints are inserted in the longest edge.

Computation and Communication Infrastructure

Laptop
(4 threads)

Server / Private Cloud
(40 threads)

Public Cloud
(> 1000 threads)

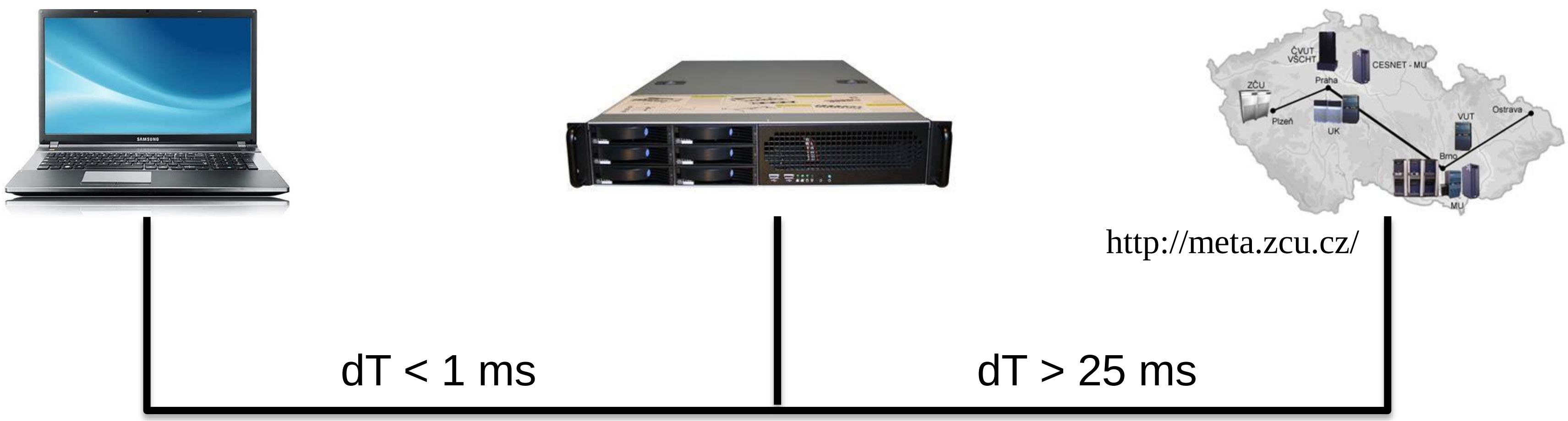


Fig 8: Computing Power vs. Latency

Computation and Communication Infrastructure

- Hypothesis
  - Computation of all services on one device (Laptop) has lowest Latency but lowest Performance
  - Distributing RRT services to Private Cloud has low Latency and high Performance
  - Distributing RRT services to Public Cloud has high Latency and medium Performance
- Infrastructure Choice depends on Availability and Scalability

Experimental Setup

- Motion Planning between Start/Goal Positions

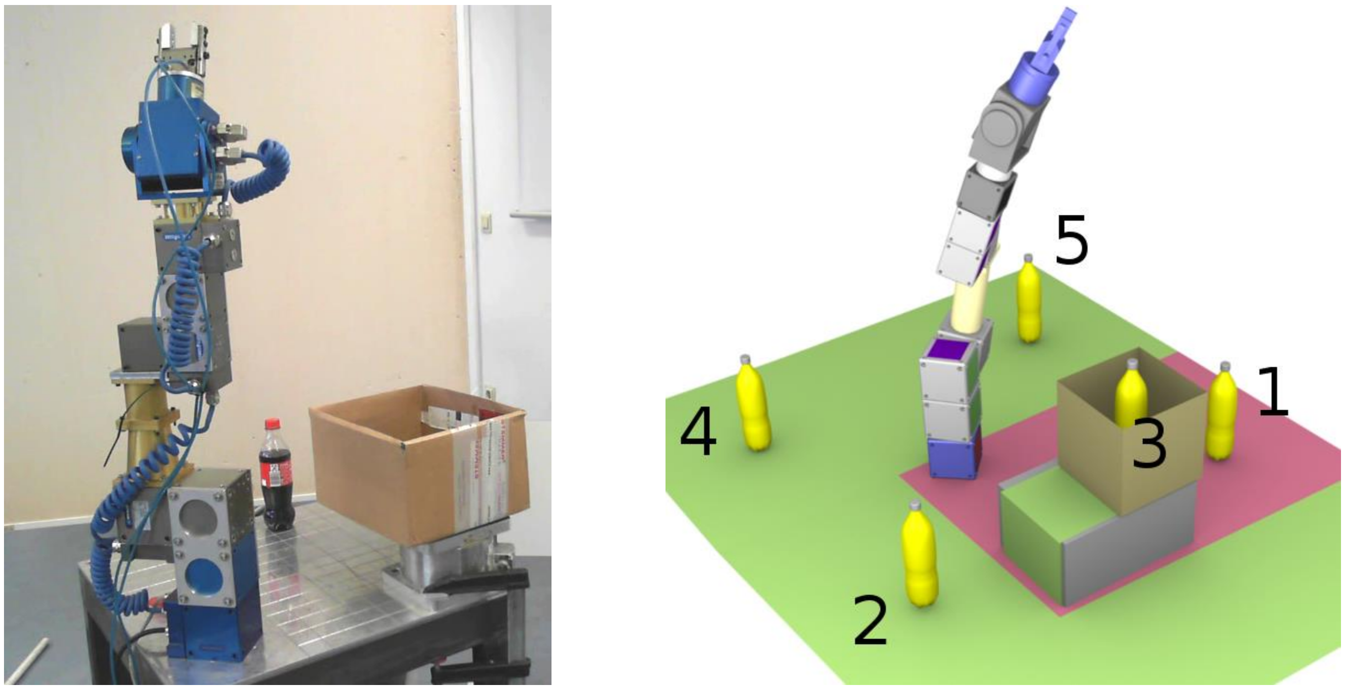


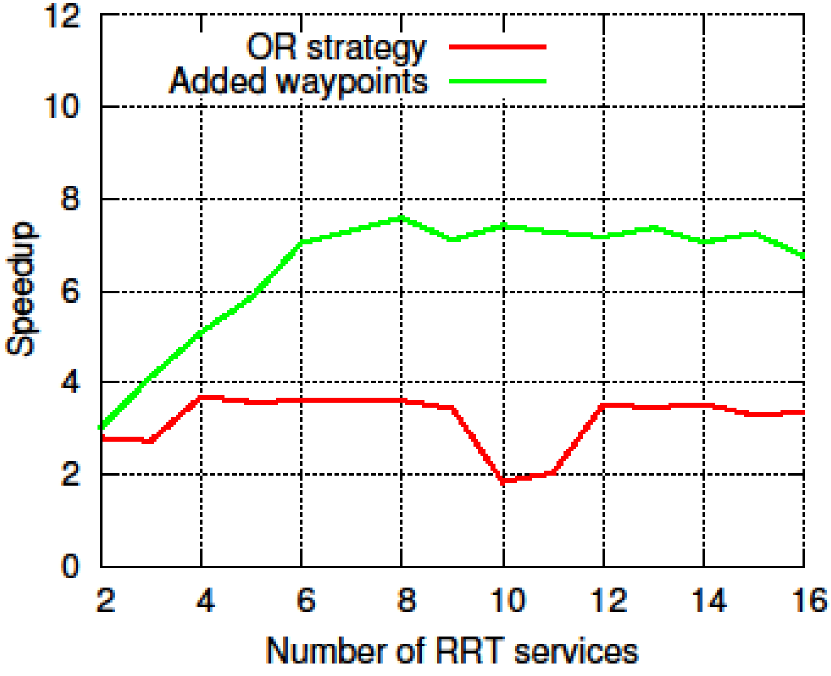
Fig 9: Modular Robot AMTEC in Laboratory and Blender Model

Experimental Setup

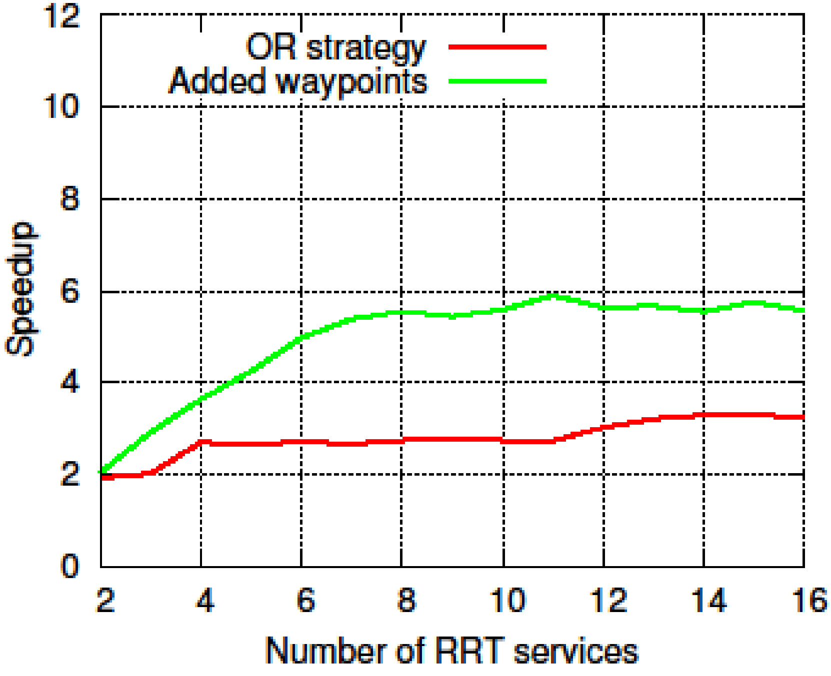
- Verification with 6-DOF Amtec robot
- 5 start/goal configurations
- Lazy-PRM [22] with resolution α = 1cm
- Task-space RRT [24] with resolution ε = 0.1cm
- Computation on virtual machines (VM)
  - 1 VM with 16 cores (centralized)
  - 16 VMs with 1 core (distributed)
- Latency between Master and RRT nodes
  - 28 ms (std 0.12ms)

Results and Discussion

- G1 → G2, Speedup gain to local computation

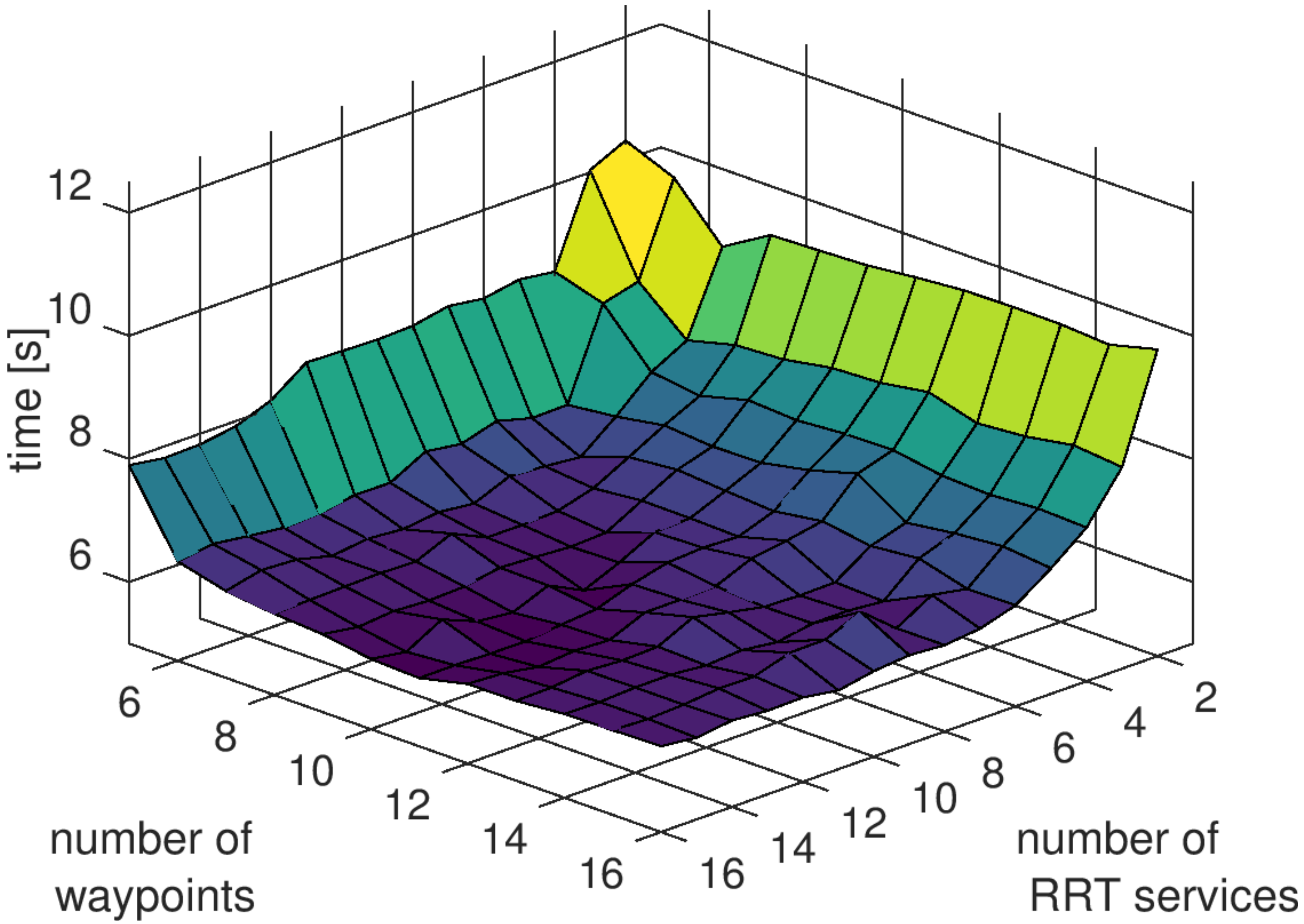


1 VM, 16 cores



16 VMs, 1 core

Results and Discussion



Results and Discussion

- High complexity tasks benefit from parallelization
  - The configuration space of the robot, that is handling a non-trivial object through a variable environment, is highly restricted when navigating in the workspace.
  - The presented approach is able to react to the challenging and additionally changing conditions in a 2-6 times faster way than classical methods.
  - The use of a distributed computing infrastructure, like virtual machines in the cloud, is feasible even with moderate latency connections.

Future Work

- Edge Cloud Control with Low Latency Networks
  - Factory Logistics (AGV) Use Case
  - Private/Edge Cloud Infrastructure
  - 4G/5G Mobile Communication
  - Centralized Path Planning Services
- Real-time Closed Loop Feedback Control in Distributed Control Systems
  - Using Model-predictive Control to handle variable Latency for Linear Systems

Future Work

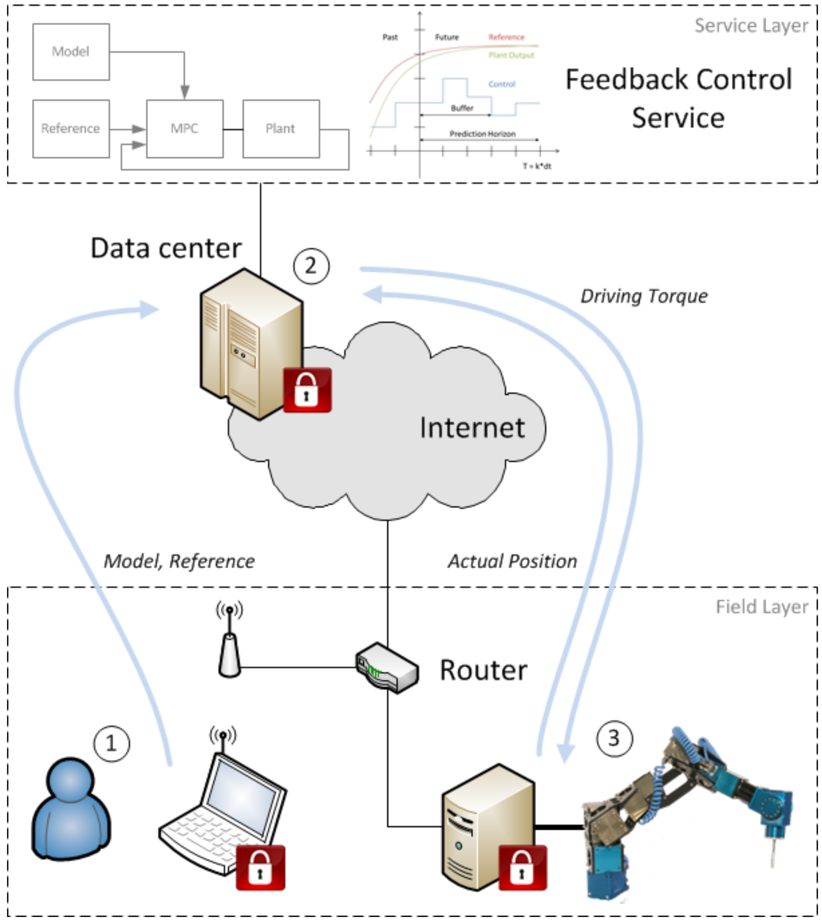


Fig 12: Scheme of cloud-based feedback control for industrial robots

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Thank You.