TECHNISCHE UNIVERSITÄT DRESDEN

Fakultät Informatik | Institut für Software- und Multimediatechnik | Lehrstuhl für Softwaretechnologie

Model-driven Multi-Quality Auto-Tuning of Robotic Applications

MORSE 2015

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HAEC

DRESDEN concept
Exzellenz aus Wissenschaft und Kultur

Outline

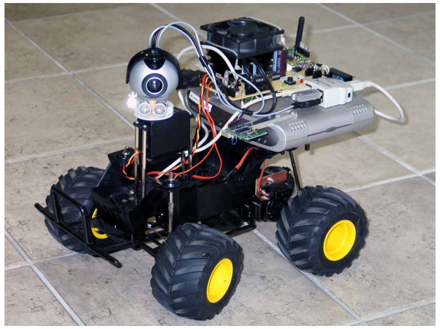
1. Motivation and Background
2. MQuAT for Simultanous Localization and Mapping (SLAM)
3. Evaluation of SLAM as a Service
4. Summary and Future Work

Model-driven Multi-Quality Auto-Tuning of Robotic Applications

MOTIVATION AND BACKGROUND

Simultaneous Localization and Mapping (SLAM)

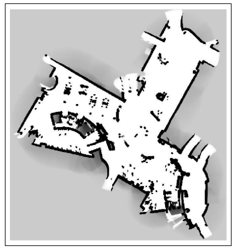

2D Laser Scanner


RGB Camera


Stereo Camera + Ultra-Sonic Sensor

Many mobile Robots must operate in varying or unkown environments.

- **No static map feasible** (changing layouts or unkown enviroments)
- **Dynamic creation of a map**
- **Dynamic localization within the dynamically created map**



SLAM algorithms create a map by interpreting sensor data and localize the position of the corresponding entity simultanously.

SLAM Variability

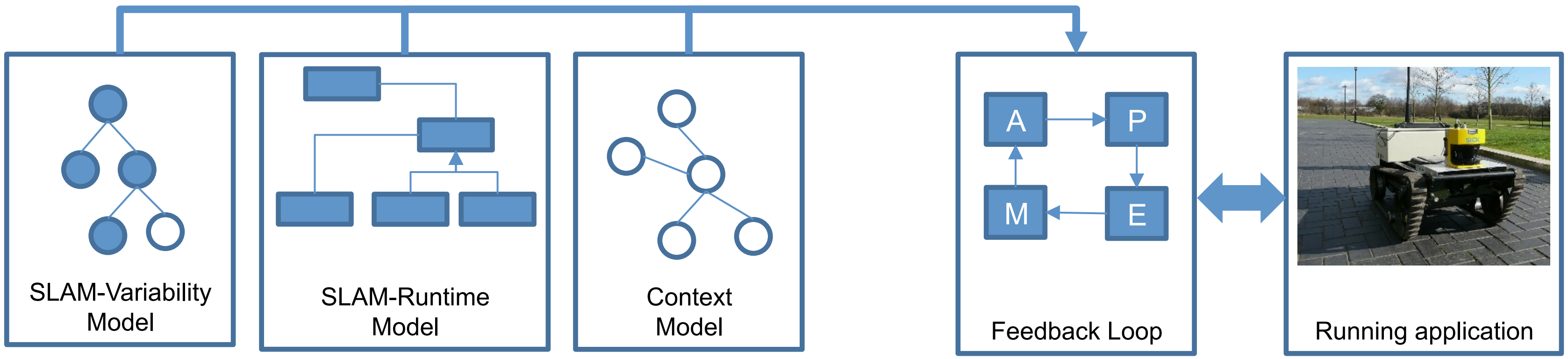
- **60+ different implementations** found in a online search
- **Different requirements w.r.t.**
  - Resource consumption (e.g., cpu, main memory)
  - Performance
  - Precision of the algorithm
  - Context dependencies (e.g., outdoor, indoor, available hardware etc.)
  - Software platform (e.g., programming language, robotic framework etc.)
- **Very poor reuse**
  - No standardization of the used data types (e.g., grid maps, feature maps, laser scanner data etc.)
  - No modularization
  - Complete re-implementation on changed requirements
- **Requirements may change during runtime**
  - Runtime adaptivity needed

Strategic Goal 1: Modularization of SLAM to increase reuse

Strategic Goal 2: Self-Adaptive SLAM for enhancing robotic applications

What we need

- PIM for SLAM process
- PIM for data-representations
- PSM for SLAM modules (with requirements and NFPs)
- Models for variability



Framework GeneralRobot

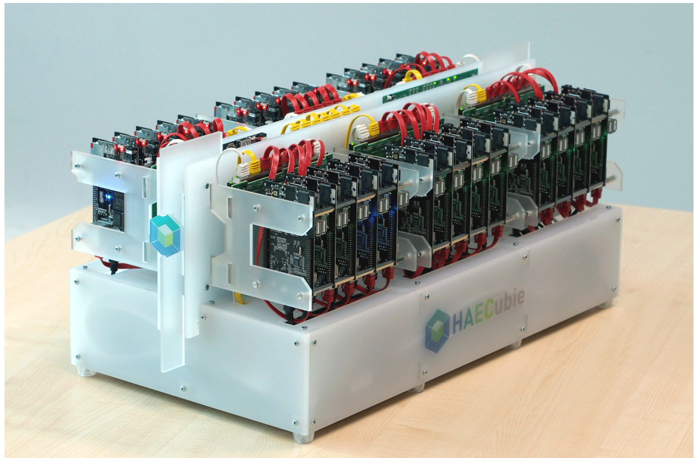
- Component-based Middleware for Robotic Applications
- Modules for map creation, localization, navigation etc.
- Static variability for SLAM (configuration file)
- High-level modules (i.e., non-hierarchical components)
  - Variabilty managed manually within Java-Code
  - Scattering and Tangling of variability management code
  - No focus on maintainability and reusability

Stable running robotic applications

- „August der Smarte“ – Tour Guide Robot in the museum „Technische Sammlungen Dresden“
- AAL Robot in a elderly care institution in Dresden

CRC 912 - Highly Adaptive Energy-Efficient Computing

- New hardware- and software-architectures for **energy proportional solutions**
- Domain: Server Applications
- HAEC Box as prototypical hardware platform
  - Cluster of *Cubieboards* as single-board computers
  - Boards can be switched-off on demand to reduce energy consumption



Multi-Quality Auto-Tuning (MQuAT) for the runtime optimization of software architectures

Collaboration

Software Technology Group

- MDSD Experts
- Abstract SLAM process
- SLAM variability models

HAEC

- Model-Driven Optimization
- Benchmarking Framework
- Framework for Feedback Loops

Hochschule für Technik und Wirtschaft Dresden
University of Applied Sciences

- Robotic Experts
- SLAM implementation artifacts
- Simulation environment

Model-driven Multi-Quality Auto-Tuning of Robotic Applications

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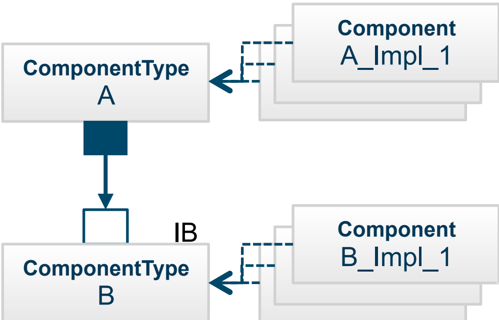
Model-driven Multi-Quality Auto-Tuning of Robotic Applications

MQUAT FOR SIMULTANOUS LOCALIZATION AND MAPPING (MQUAT-SLAM)

Multi-Quality Auto-Tuning (MQuAT)

- **Structural Model:** SW/HW Description Language for architectures
  - Each component type can have **multiple implementations** (SW variation points)
- **Variant Model:** State of HW/SW components (e.g., current SW architecture, CPU load etc.)
- **Non-functional properties** of provided/required ports described with contracts (QCL)
- Component-stub code + ILP generation
- Benchmarking framework + THEATRE runtime environment (implementation of feedback loop)




```
contract B for port type IB {
    requires resource CPU {
      min frequency: 2 GHz
    }
    requires resource Net {
      min bandwidth: 10 MBit/s
    }

    provides min resolution: 1 ppmm
    provides min responseTime: 2ms
}
```

Current State of SLAM algorithms

- Almost no reuse of SLAM code (Re-Implementation for varying requirements)
- Almost no reuse in adaptivity-handling code (Re-Implementation for each solution)
- Variability handling within business logic

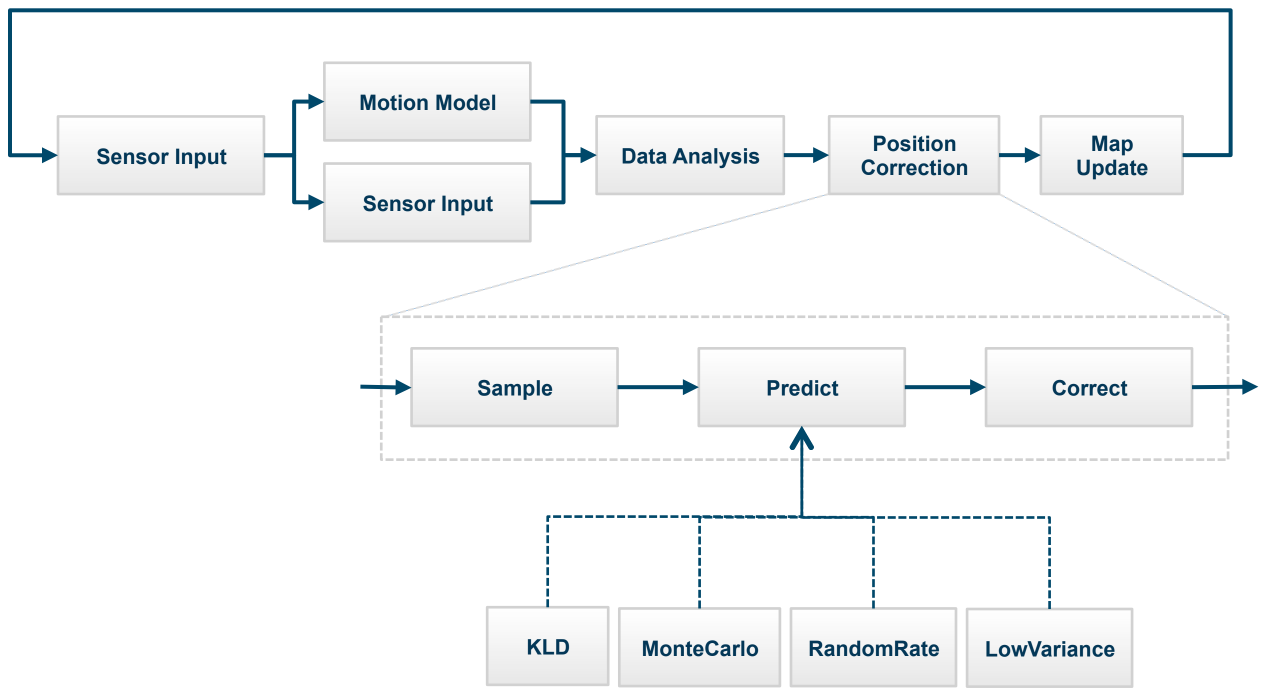
Desired State

- SLAM-Framework with all alternative implementation variants
- Automatic generation of adaptivity-handling code
- External feedback loop to resolve scattering and tangling
- Change of objective function changes energy consumption, performance, and precision

Contribution

- MQuAT for SLAM process (SLAM modularization, Code generation, ILP generation, Feedback Loop)
- Optimizer follows changes of objective function
- Case study to show feasability

SLAM Process Model

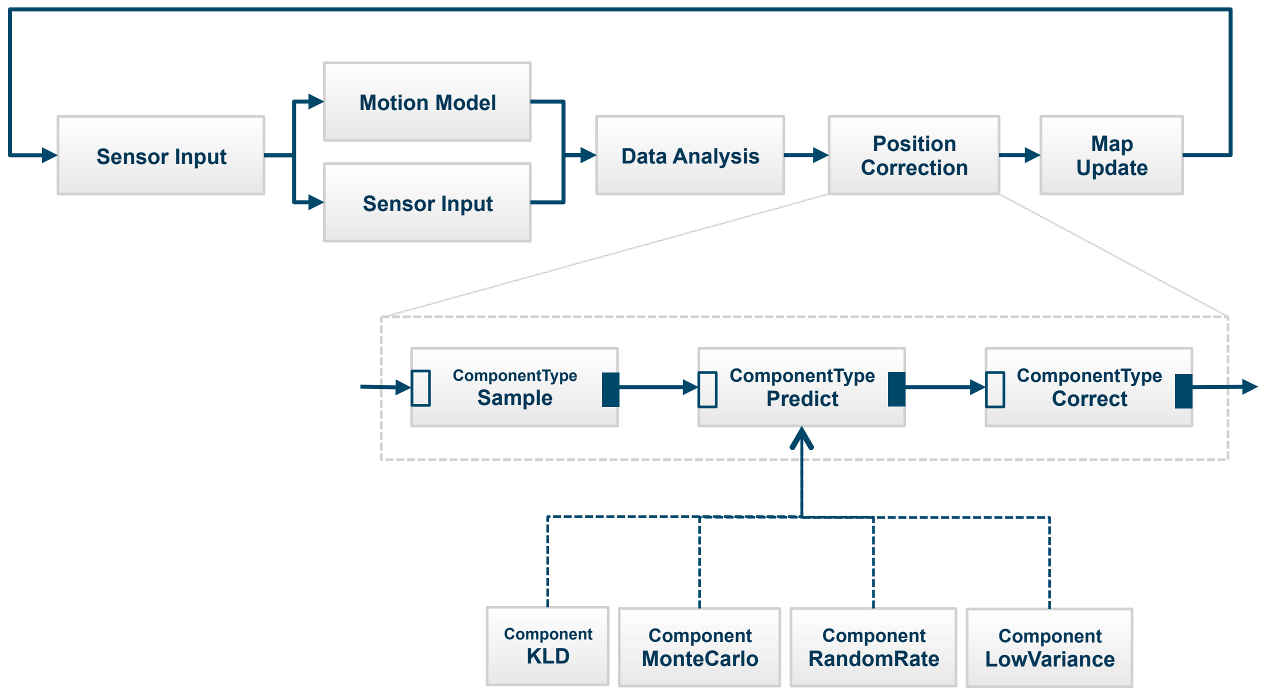


Abstract Process

Variant with Particle Filtering

Alternative algorithms for prediction

MQuAT Modeling of the SLAM Process



Abstract Process

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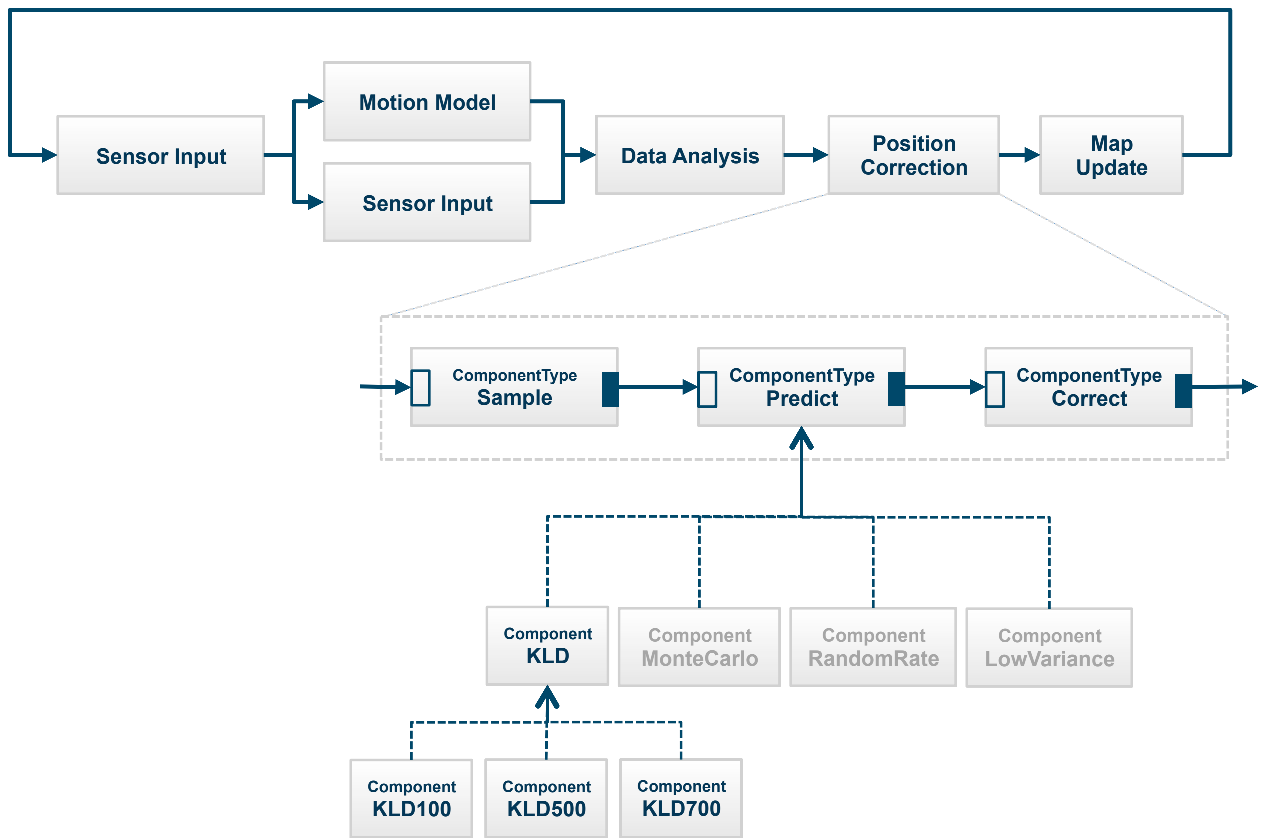
MQuAT Modeling of the SLAM Process



Abstract Process

Variant with Particle Filtering

Alternative algorithms for prediction

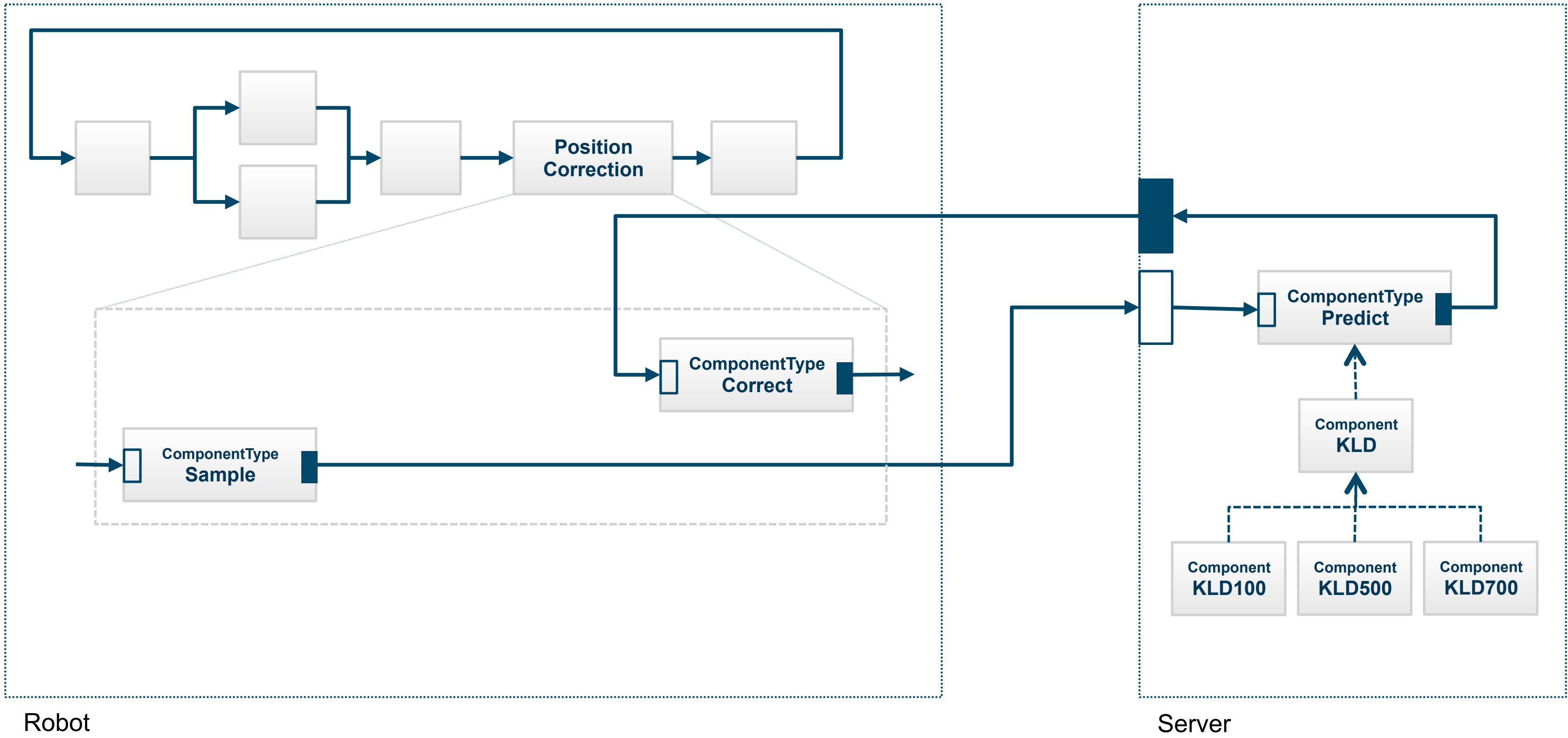
Variants by parameterization
(e.g., number of particles)

SLAM as a Service

- Battery is a very limited resource in mobile robotic systems
  - Predicition of particles is a computation intensive task

    → Prediction consumes much energy
- Outsourcing of the prediction logic
- **Hosting the prediction calculation on a server as a service**

SLAM as a Service



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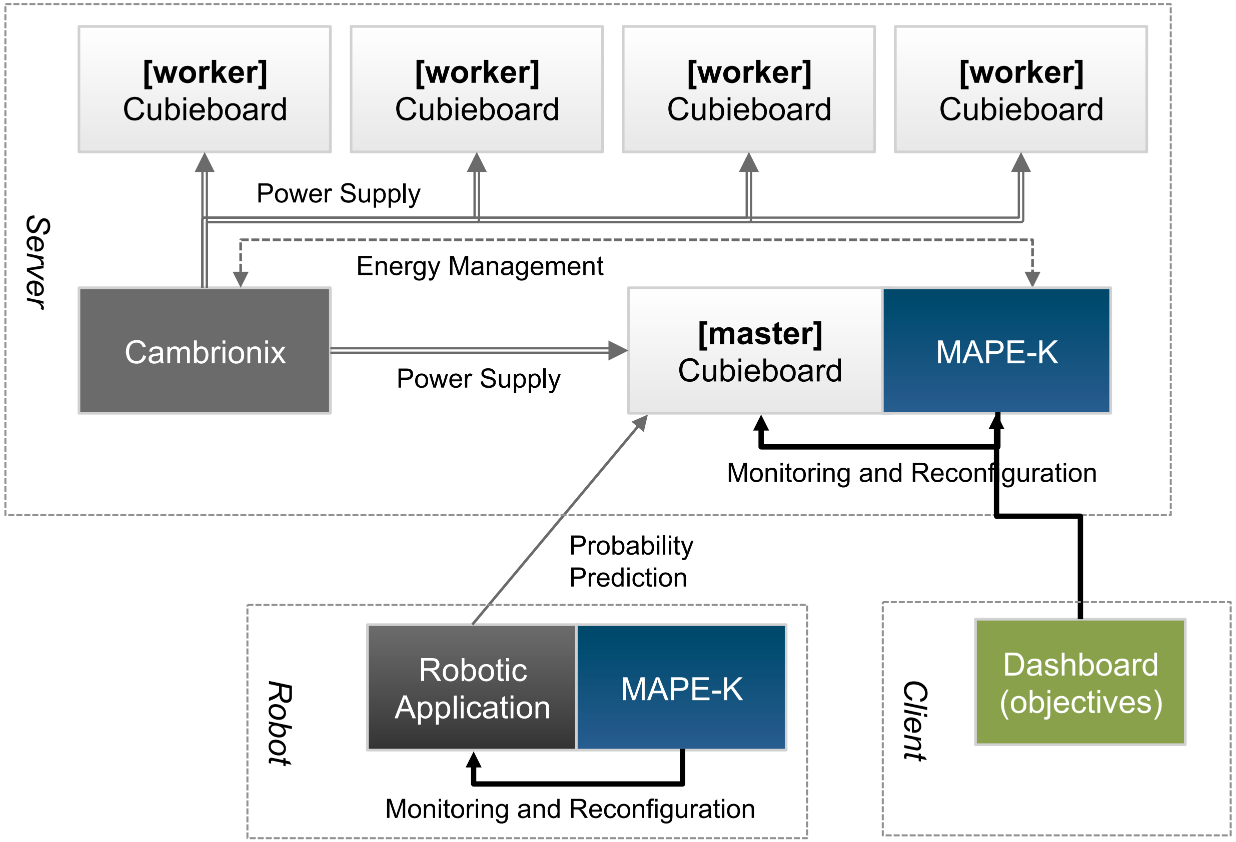
EVALUATION

SLAM PARTICLE PREDICTION AS A SERVICE

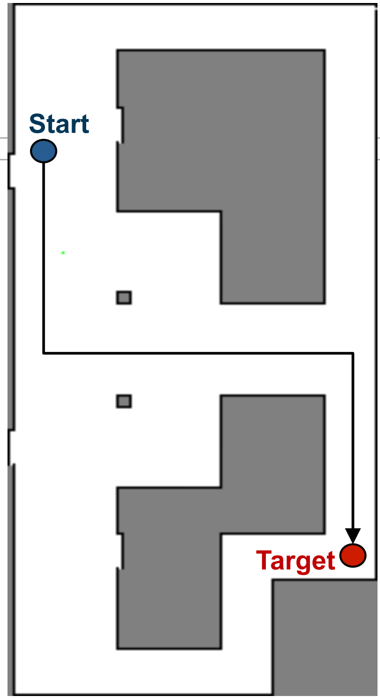
Hardware setup



Cubieboard

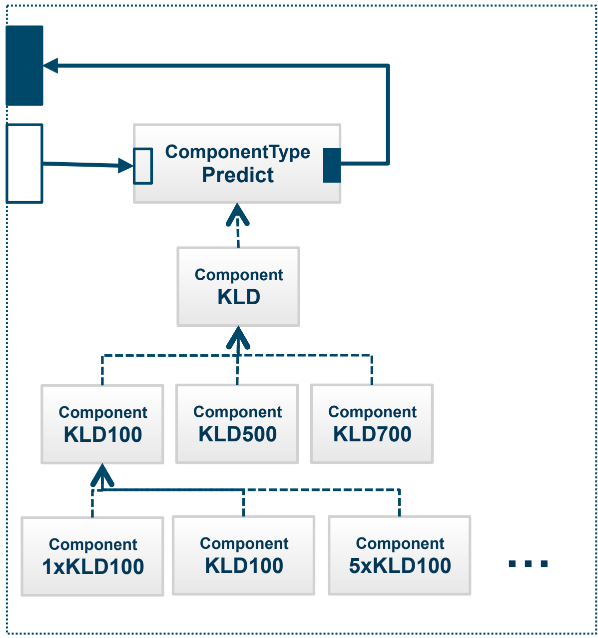
Cambrionix USB Power Supply

SLAM as a Service with Parallelization



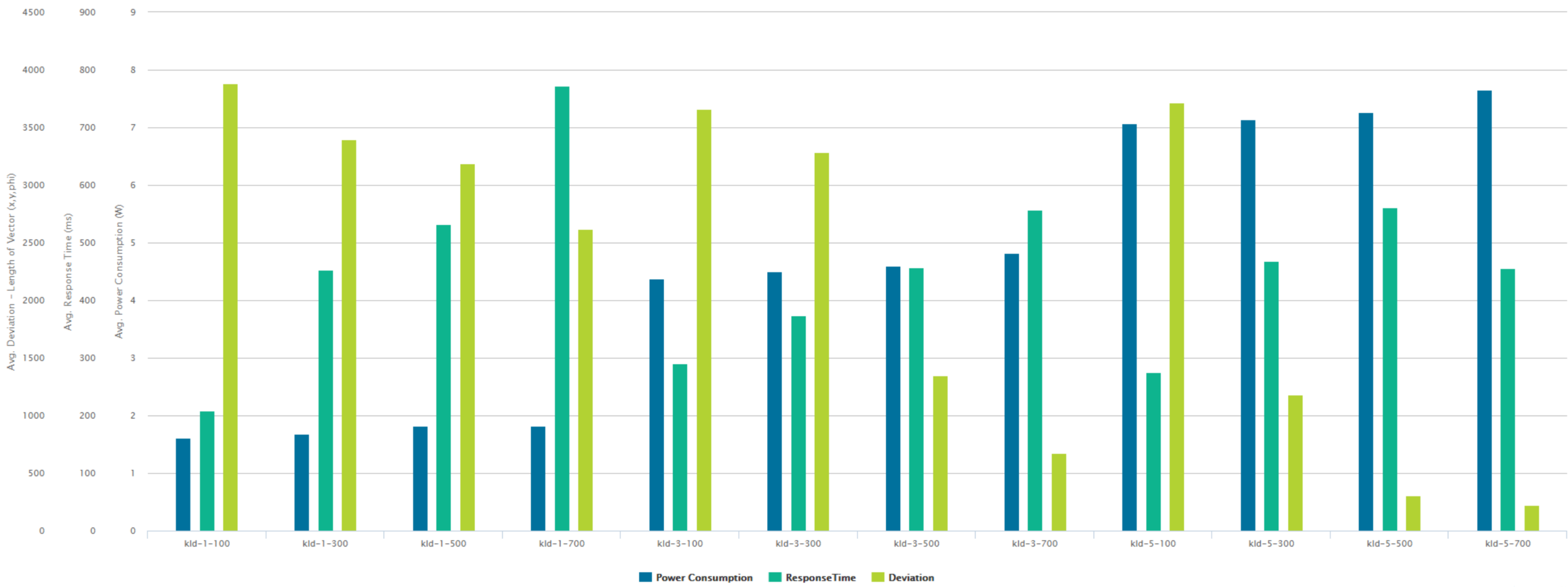
- Robot driving from the start to the target position
- **Simbad** simulation environment
- **GeneralRobot** target framework
- **MQuAT SLAM optimizer**
  - Prediction is done for each particle in isolation → Can calculated in parallel
  - 1-5 boards with 2 cores, max. 10 parallel threads
  - Kullback-Leibler Divergence with n*100 particles
- For each variant, measure:
  - **PC:** Server power consumption in ms
  - **T:** Response time of the service in Watt
  - **D:** Deviation between real and estimated position as length of the vector (Δx; Δy; ΔΦ)

    x,y = Position, Φ = rotation



Server

Result



Avg. Deviation - Length of Vector (x,y,phi)
Avg. Response Time (ms)
Avg. Power Consumption (W)
4500 4000 3500 3000 2500 2000 1500 1000 500 0
900 800 700 600 500 400 300 200 100 0
9 8 7 6 5 4 3 2 1 0
kld-1-100
kld-1-300
kld-1-500
kld-1-700
kld-3-100
kld-3-300
kld-3-500
kld-3-700
kld-5-100
kld-5-300
kld-5-500
kld-5-700
Power Consumption
ResponseTime
Deviation

Result

particles	1 cubie 100	1 cubie 500	1 cubie 700	3 cubies 100	3 cubies 500	3 cubies 700	7 cubies 100	7 cubies 300	7 cubies 700
T (ms)	208.6	532.2	772.7	290.2	457.2	557.4	275.3	361.6	456.2
PC (W)	1.6	1.8	1.8	4.4	4.6	4.8	7.1	7.3	7.7
D	338.4	318.7	261.9	365.9	134.6	67.6	371.3	30.6	22.4

particles	1 cubie 100	1 cubie 500	1 cubie 700	3 cubies 100	3 cubies 500	3 cubies 700	7 cubies 100	7 cubies 300	7 cubies 700
T (ms)	**208.6**	**532.2**	**772.7**	**290.2**	**457.2**	**557.4**	**275.3**	**361.6**	**456.2**
PC (W)	1.6	1.8	1.8	4.4	4.6	4.8	7.1	7.3	7.7
D	338.4	318.7	261.9	365.9	134.6	67.6	371.3	30.6	22.4

- **Response time depends on both parameters**

  → More boards = lower response time

  → More particles = higher response time

particles	100	500	700	100	500	700	100	300	700
	1 cubie			3 cubies			7 cubies		
T (ms)	208.6	532.2	772.7	290.2	457.2	557.4	275.3	361.6	456.2
PC (W)	**1.6**	**1.8**	**1.8**	**4.4**	**4.6**	**4.8**	**7.1**	**7.3**	**7.7**
D	338.4	318.7	261.9	365.9	134.6	67.6	371.3	30.6	22.4

- **Power consumption** mainly depends on number of boards

  → More boards = higher power consumption

  → More particles = slightly higher power consumption

	1 cubie			3 cubies			7 cubies		
particles	**100**	**500**	**700**	**100**	**500**	**700**	**100**	**300**	**700**
T (ms)	208.6	532.2	772.7	290.2	457.2	557.4	275.3	361.6	456.2
PC (W)	1.6	1.8	1.8	4.4	4.6	4.8	7.1	7.3	7.7
D	**338.4**	**318.7**	**261.9**	**365.9**	**134.6**	**67.6**	**371.3**	**30.6**	**22.4**

- **Deviation** depends on both parameters

  → More boards = lower deviation

  → More particles = lower deviation

Result

	1 cubie			3 cubies			7 cubies		
particles	**100**	**500**	**700**	**100**	**500**	**700**	**100**	**300**	**700**
T (ms)	**208.6**	532.2	772.7	290.2	457.2	557.4	275.3	361.6	**456.2**
PC (W)	**1.6**	1.8	1.8	4.4	4.6	4.8	7.1	7.3	**7.7**
D	**338.4**	318.7	261.9	365.9	134.6	67.6	371.3	30.6	**22.4**

- **Real trade-off between response time, power consumption and deviation**
- Lower response time leads to high deviation
- Lower power consumption leads to high deviation
- Lower deviation leads to:

    higher power consumption (with low response time)

    higher response time (with low power consumption)

Objective function of ILP important

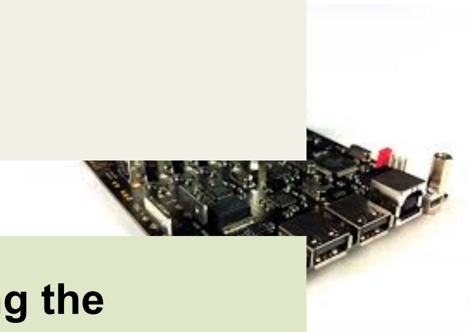
MQuAT Optimizer Follows Change of Objective Function of ILP

[worker] [worker] [worker] [worker]

Server

- **Real trade-off between response time, power consumption and deviation**
- Lower response time leads to high deviation
- Lower power consumption leads to high deviation
- Lower deviation leads to:
    - higher power consumption (with low response time)
    - higher response time (with low power consumption)

Probability Prediction



er Supply

- **MQuAT Optimizer dynamically adapts SLAM by following the changes of Objective Functions**

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CONCLUSION AND FUTURE WORK

Conclusion

- SLAM has a high degree of variation based on varying requirements (also @run.time)
- **State**: Poor reuse of SLAM-code and adaptation logic
- **Assumption**: Component Modeling + Code Generation decreases development time and increases maintainability
- MQuAT for runtime optimization of architectures with Quality Contracts
  - Applicable for SLAM processes

- Benchmarks show that trade-offs exist **(only for one small step within a complex process)**
- **Energy-consumption can be decreased, when lower response time or lower quality is accapable**
- **MQuAT optimizer follows changes of objectives**

Future Work

- Include benchmarks of the other variants of the prediction algorithm
- Model and migrate existing implementations for whole SLAM process
- Develop SLAM-Toolbox for static and dynamic variant generation
- Integration in standard-platforms (e.g., ROS)

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