

# Mixed Reality in the Context of a Smart Mobile System

Sebastian Rockel

rockel@informatik.uni-hamburg.de

May 14th, 2013  
Hamburg



# Outline

- 1** The RACE Project
- 2** State of the Art
- 3** Scientific Achievements
- 4** Outlook

- 1** The RACE Project
  - Introduction
  - Demo Domain
  - Architecture
  - Concepts and Instances
- 2 State of the Art
- 3 Scientific Achievements
- 4 Outlook

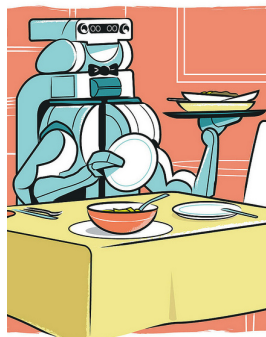
# The RACE Project

## RACE

### Robustness by **A**utonomous **C**ompetence **E**nhancement

#### Focus:

- framework and methods for learning from experiences
- conceptualizing stored experiences
- adapt plans and behavior



# The RACE Project

## RACE

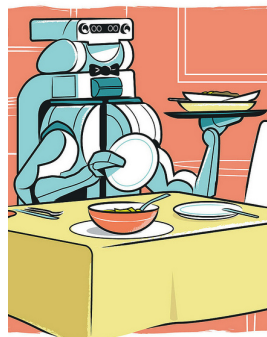
### Robustness by **A**utonomous **C**ompetence **E**nhancement

#### Focus:

- framework and methods for learning from experiences
- conceptualizing stored experiences
- adapt plans and behavior

#### *Experiences: execution traces that...*

- integrate sub-symbolic and symbolic representations
- provide a detailed account of success/failure



# Demo Domain

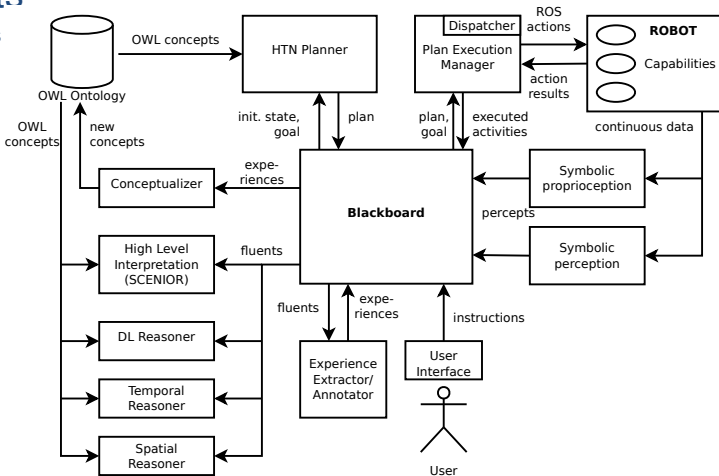
PR2 as Waiter in a Restaurant Environment

Demo: ServeACoffee

<http://youtu.be/uqoBXbBtm2E>

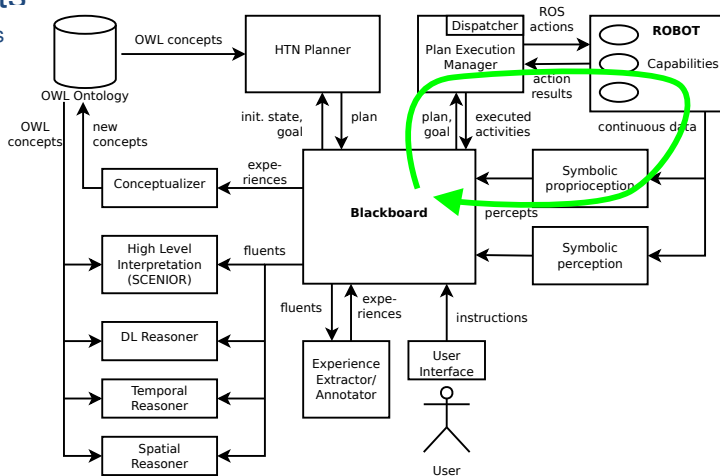
# Comparative Evaluation of competence-enhanced Robots

## Objectives



# Comparative Evaluation of competence-enhanced Robots

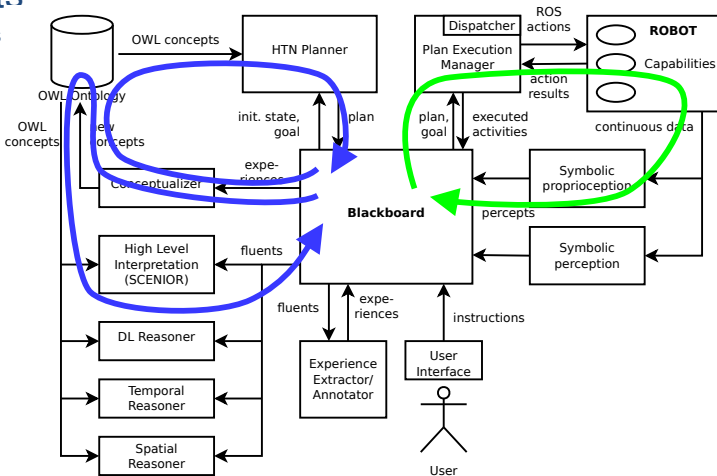
## Objectives





# Comparative Evaluation of competence-enhanced Robots

## Objectives



# Representing Concepts and Instances

## OWL-DL Ontology (T-Box):

Class: MoveObjectFromTo

EquivalentTo:

RobotActivity

AND (hasObject EXACTLY 1 PhysicalEntity)

...

AND (hasGetObjectFrom EXACTLY 1 GetObjectFrom)

AND (hasMoveObjectTo EXACTLY 1 MoveObjectTo)

AND (hasOverlap SOME Overlaps)

AND (hasBefore SOME Before)

## Representing Concepts and Instances II

Blackboard (A-Box) instances:

- basic data type: Fluent
- exchanged through ROS messages
- all fluents are instances of concepts in the ontology

!Fluent

```
Class_Instance: [MoveArmToSide, moveArmToSide1]
```

```
StartTime: [61.142, 61.142]
```

```
FinishTime: [66.306, 66.306]
```

```
Properties:
```

- [hasArm, RobotArm, leftArm]
- [hasResult, ActivityResult, succeeded]

## 1 The RACE Project

## 2 State of the Art

- Planning
- Evaluation
- Reasoning
- Learning

## 3 Scientific Achievements

## 4 Outlook

# Continual vs. Conditional Planning

- Conditional planning widely employed (RACE, currently)
  - computationally hard, limited to smaller domains

## Continual vs. Conditional Planning

- Conditional planning widely employed (RACE, currently)
  - computationally hard, limited to smaller domains
  
- (really) open-ended domains require continual planning (Off et al. 2011)
  - 1 what information to look for
  - 2 how to acquire necessary information

## Continual vs. Conditional Planning

- Conditional planning widely employed (RACE, currently)
  - computationally hard, limited to smaller domains
  
- (really) open-ended domains require continual planning (Off et al. 2011)
  - 1 what information to look for
  - 2 how to acquire necessary information
  
- example:
  - *Tidyup-Robot Project*, Freiburg (Dornhege, Hertle 2013)
  - ACogPlan, Hamburg (Off. et al. 2011)

# Evaluation of a planning System

- generally not a trivial task (Brenner and Nebel, 2009)
- example: *ACogSim* (*Off et al. 2012*)
  - evaluate overall system behavior for several domains
  - focus on continual planning
  - metrics:
    - is the planner (always) able to perform the given task?
    - how often switch between planning and acting?
    - how much time is necessary for the whole planning and reasoning process
    - how long is the average planning phase?
    - how does the performance change with a decreasing amount of initial knowledge?



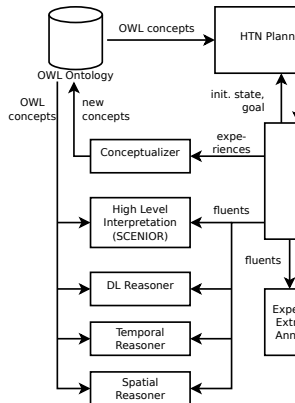
## Evaluation of a planning System

- generally not a trivial task (Brenner and Nebel, 2009)
- example: *ACogSim (Off et al. 2012)*
  - evaluate overall system behavior for several domains
  - focus on continual planning
  - metrics:
    - is the planner (always) able to perform the given task?
    - how often switch between planning and acting?
    - how much time is necessary for the whole planning and reasoning process
    - how long is the average planning phase?
    - how does the performance change with a decreasing amount of initial knowledge?
- another example: *RACE Deliverable 5.1 – Evaluation Infrastructure*

# Reasoning

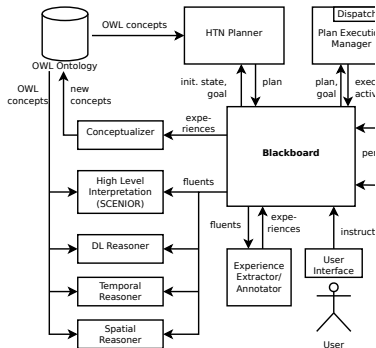
## ■ RACE:

- hybrid-reasoning: spatial, temporal, causal
- dedicated reasoner feed the blackboard (finally the planner)
- dependent on initial knowledge and perception (during execution)



# Learning

- RACE:
  - supervised
  - (human) instructor gives tasks and “teaches” concepts
  - (Experience Extractor and Conceptualizer planned)

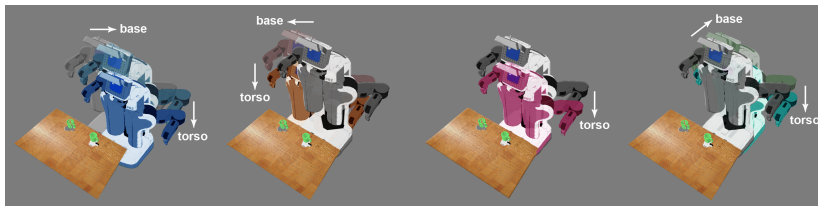


- 1 The RACE Project
- 2 State of the Art
- 3 Scientific Achievements**
  - MR for Evaluation
  - MR as Reasoner
  - MR for Learning
  - First Evaluation Results
- 4 Outlook

# Evaluation

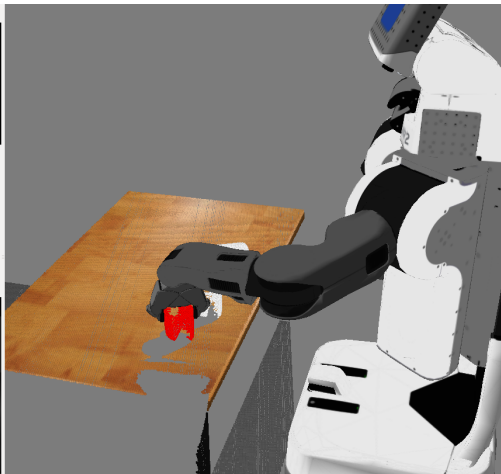
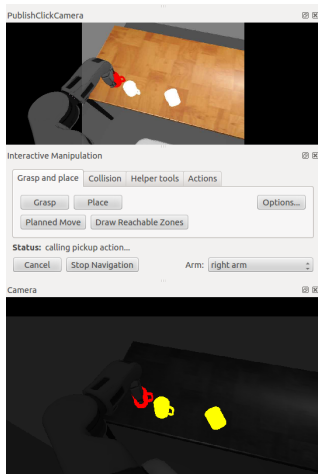
Mixed Reality (Rockel et al. 2013)

- improving object recognition and grasping quality of the robot



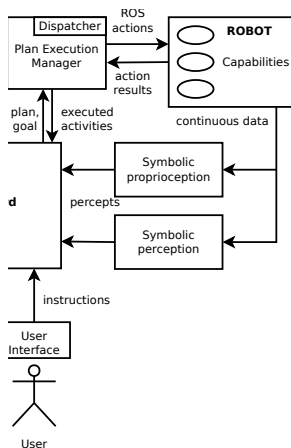
# Evaluation II

## Thermal Camera

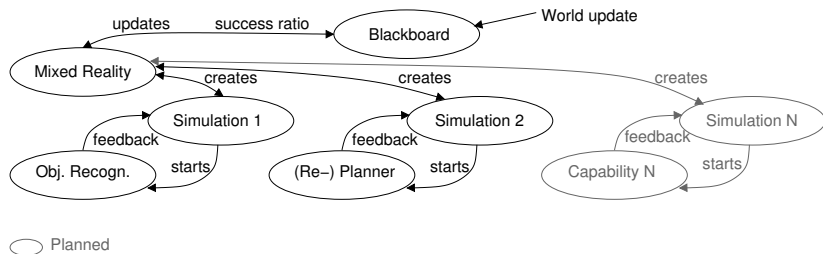


# Evaluation III

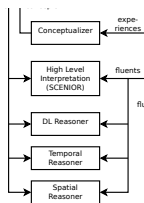
- evaluates
  - parts of the system (manipulation, perception, navigation etc.)
  - the complete system (time, distance, efficiency, failure, accuracy etc.)



# Mixed Reality as Modality for Reasoning



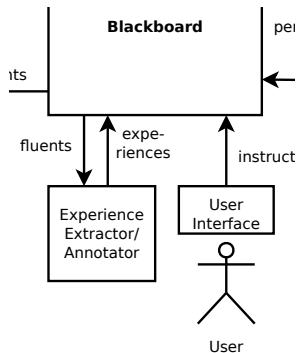
- Mixed Reality gives recommendation about actions the robot should take to improve robot capabilities
- can be considered as reasoner
- feeds the blackboard (eventually the planner)





# Learning

- enables unsupervised learning
  - creates different scenarios and executes the system
  - automatic recognition of failure or success cases
  - creates experiences



# First Results and Summary

## Mixed Reality

- benefits
  - automatic change in simulation
  - without sensor noise (ideal sensors)
  - new sensors objects (not yet in reality available)

# First Results and Summary

## Mixed Reality

- benefits

- automatic change in simulation
- without sensor noise (ideal sensors)
- new sensors objects (not yet in reality available)

- first results

- object recognition in torso down pose improved by 10 %
- grasping in torso up pose improved by 32.5 %

- 1 The RACE Project
- 2 State of the Art
- 3 Scientific Achievements
- 4 Outlook**
  - Open Points
  - Questions

# Open Points

- unsupervised learning by automated scenario execution
- MR as Reasoner
- MR for Evaluation (of the whole system)

# Any Questions?



Universität Hamburg  
 DER FORSCHUNG | DER LEHRE | DER BILDUNG



UNIVERSITY OF LEEDS



ÖREBRO  
 UNIVERSITET



*HITec*

# Thank You!

## Further Reading I



D. Klimentjew, S. Rockel, L. Einig, J. Zhang. **Mixed Reality to Evaluate and Optimize Complex Mobile Systems for Improved Robustness Exemplified by Object Recognition, Re-planning and Parallelization**. IROS2013, November 3-7, 2013, Tokyo Big Sight, Japan (submitted)



D. Klimentjew, S. Rockel, J. Zhang. **Towards Scene Analysis based on Multi-Sensor Fusion, Active Perception and Mixed Reality in Mobile Robotics**. In Proceedings of the IEEE First International Conference on Cognitive Systems and Information Processing (CSIP2012), 15-17 December, Beijing, China, 2012.



S. Rockel, D. Klimentjew, J. Zhang. **A Multi-Robot Platform for Mobile Robots – A Novel Evaluation and Development Approach with Multi-Agent Technology**. In Proceedings of the IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems (MFI), University of Hamburg, Hamburg, Germany, 2012.



S. Rockel, B. Neumann, J. Zhang, K. S. R. Dubba, A. G. Cohn, Š. Konečný, M. Mansouri, F. Pecora, A. Saffiotti, M. Günther, S. Stock, J. Hertzberg, A. M. Tomé, A. J. Pinho, L. S. Lopes, S. v. Riegen and L. Hotz. **An Ontology-based Multi-level Robot Architecture for Learning from Experiences**. In: Proc. Designing Intelligent Robots: Reintegrating AI II, AAAI Spring Symposium, March 25-27, Stanford (USA), 2013.



L. Zhang, S. Rockel, F. Pecora, L. Hotz, Z. Lu, J. Zhang. **Evaluation Metrics for an Experience Based Mobile Artificial Cognitive System**. IROS2013, November 3-7, 2013, Tokyo Big Sight, Japan (submitted)



D. Off, J. Zhang. **Continual HTN Robot Task Planning in Open-Ended Domains: A Case Study**. In Proc. AAAI-11 Workshop, San Francisco, USA, August, 2011



D. Off, J. Zhang. **Continual HTN Planning and Acting in Open-Ended Domains**. In Proc. ICAART 2012, Vilamoura, Portugal, February, 2012

## Further Reading II



C. Dornhege, A. Hertle. *Integrated Symbolic Planning in the Tidyup\_robot Project*. In: Proc. Designing Intelligent Robots: Reintegrating AI II, AAAI Spring Symposium, March 25-27, Stanford (USA), 2013.