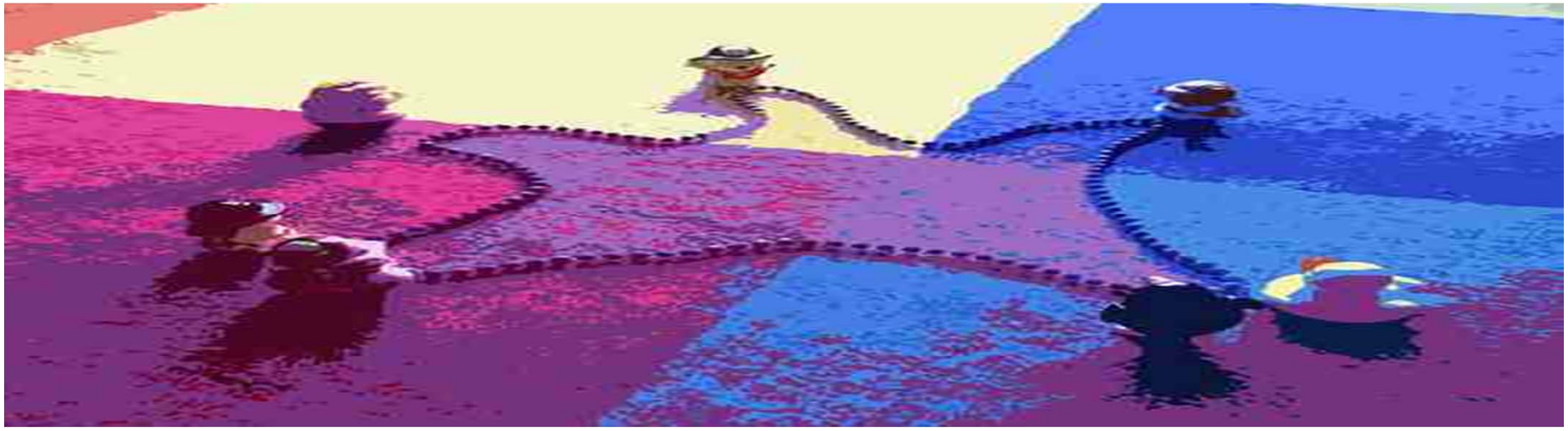
10th Colloquium SPP OC
Observation and Control of Collaborative Systems (OCCS)

Learning Architectures for Collaborative Systems



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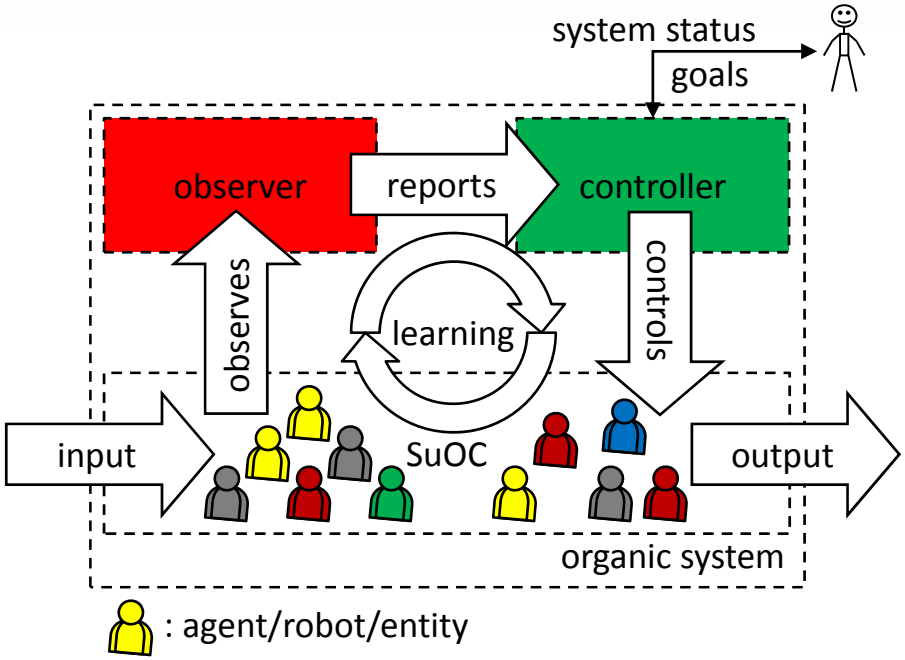
Generic O/C Architecture

- From the Phase I
  - Development of the generic observer/controller architecture
  - **Observer**: Monitors system state and dynamics and quantifies them
  - **Controller**: Influences the system under observation and control (SuOC)



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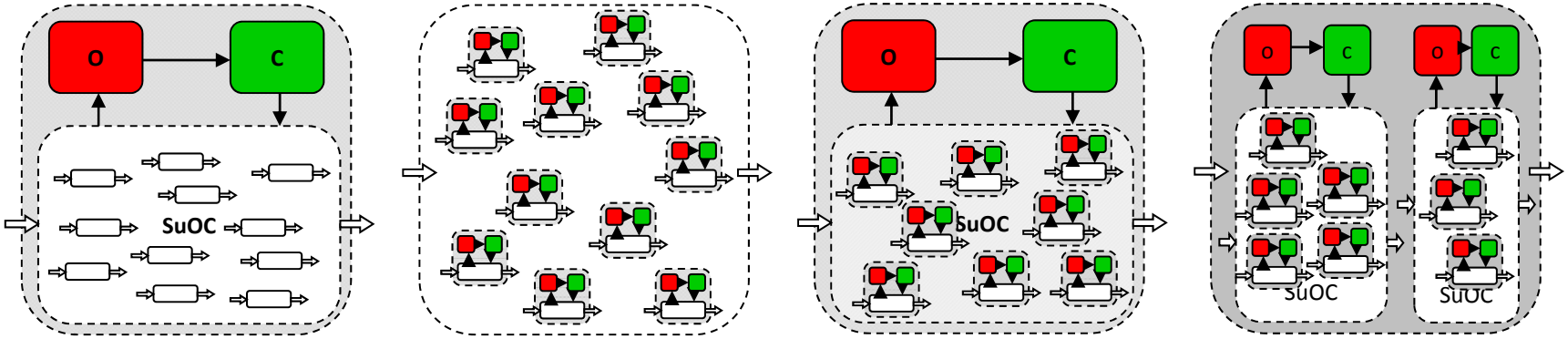
O/C Architectural Variants

- From the Phase II



  - **Central**: One observer/controller for the whole system
    - *Example scenarios: chicken, elevator, or off-highway machines*
  - **Distributed**: An observer/controller on each agent
    - *Example scenarios: Indian junction, predator/prey pursuit, or cleaning robots*
  - **Hierarchical or multi-level**: Multi-observer/controllers on each technical unit and at the higher level (or levels)
    - *Example: Regional manager for organic traffic control*

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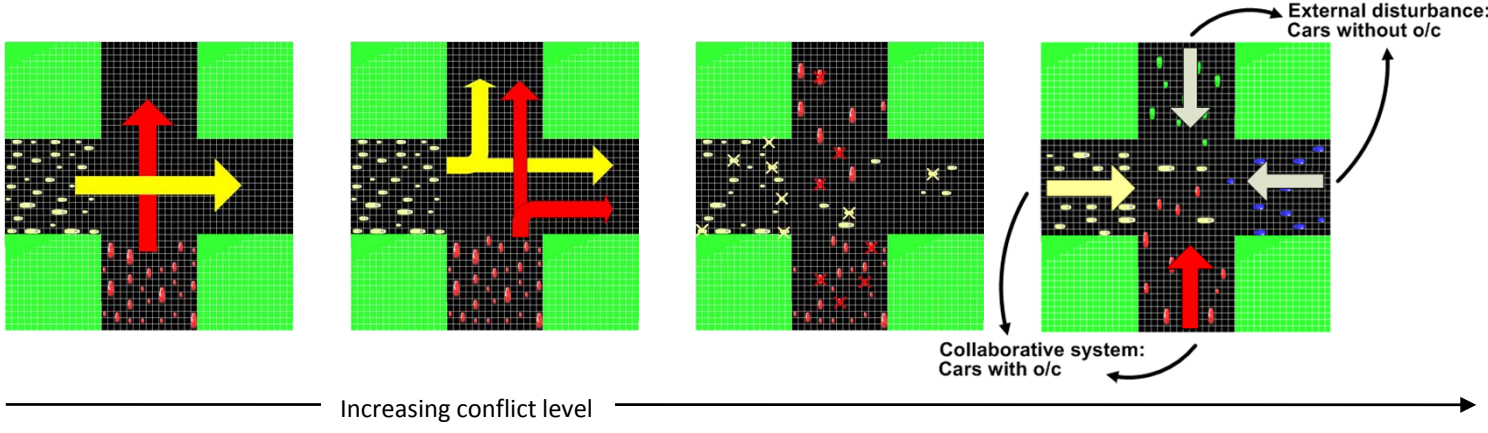
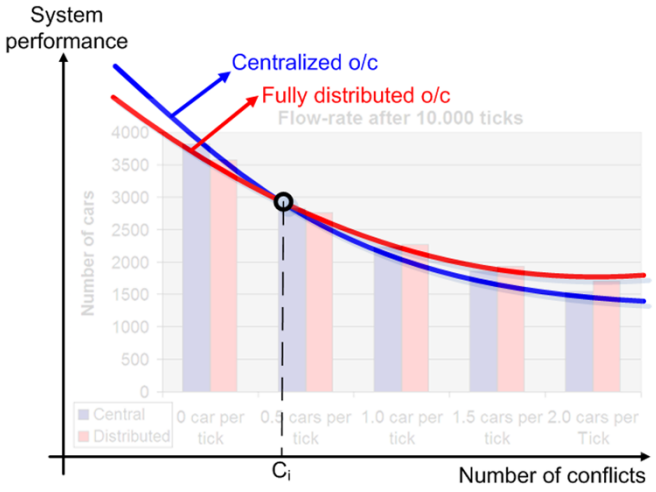
Centralised vs. Distributed

- System performance is measured by traffic-flow rate.



- Neither the centralised nor on the distributed architecture leads to optimal collaboration.
- Adaptive architecture that switches between the two architectures depending on the conflict level.



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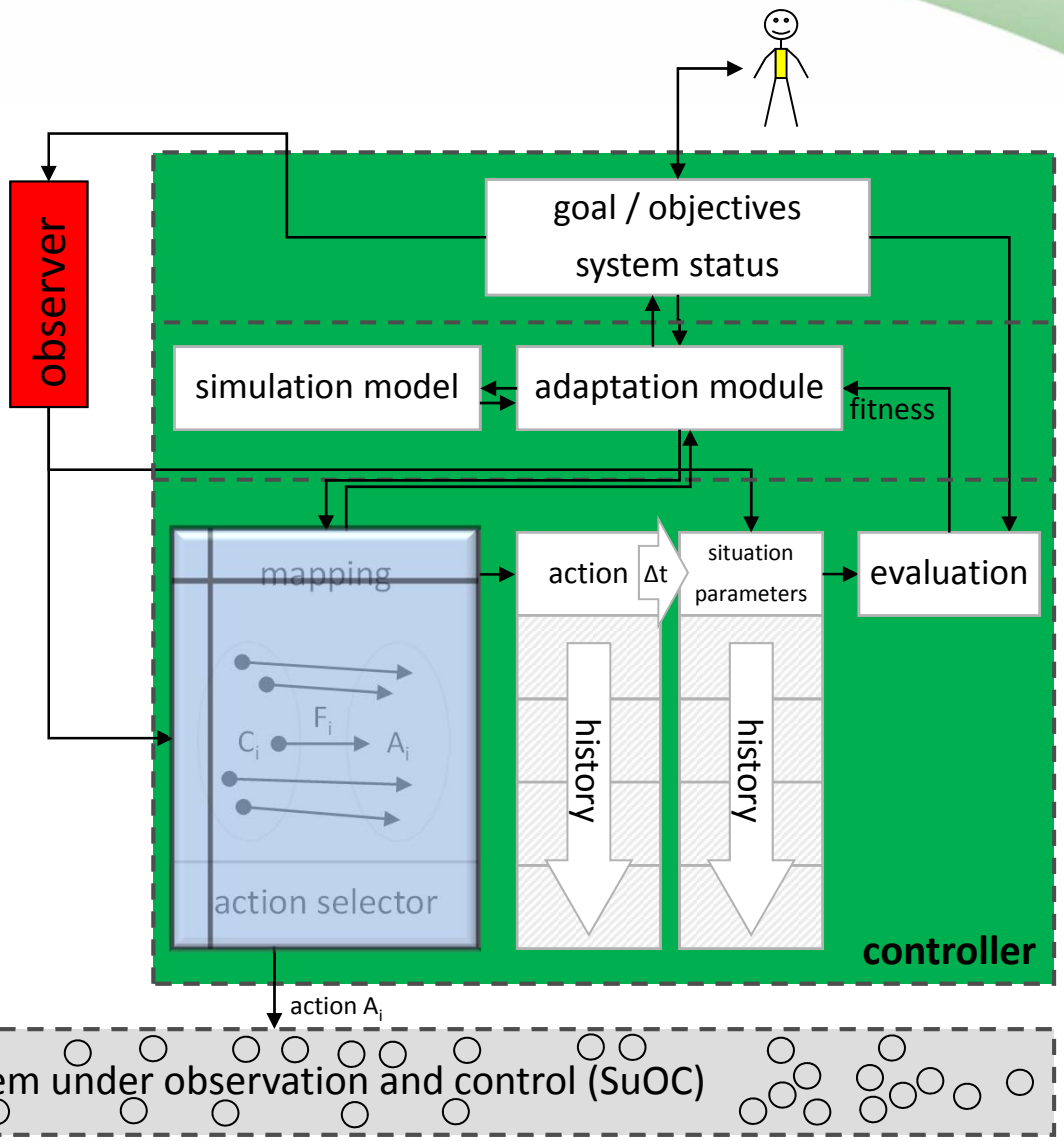
Learning

- Focus on learning as part of the generic controller
- Two-level learning approach (on-line vs. off-line)
- Learning architecture as action selector in form of a rule base



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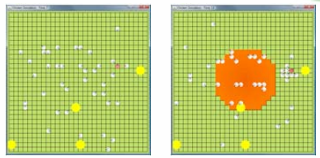
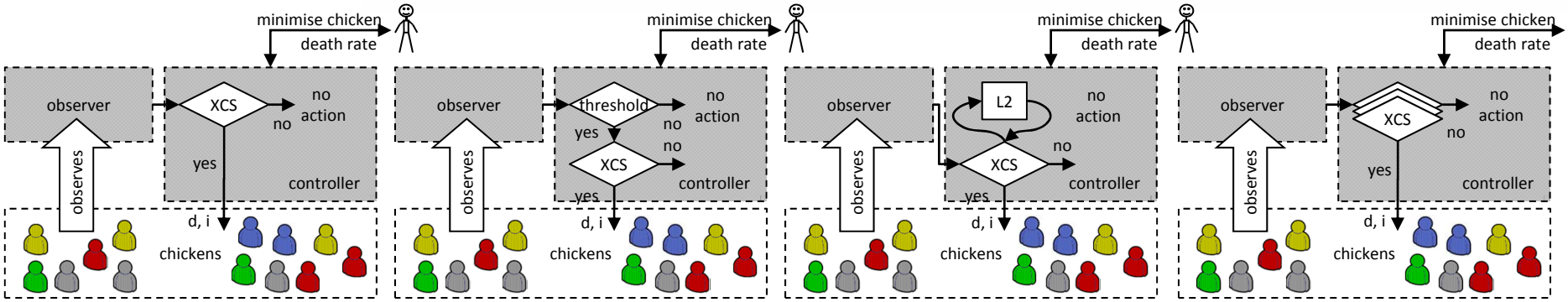
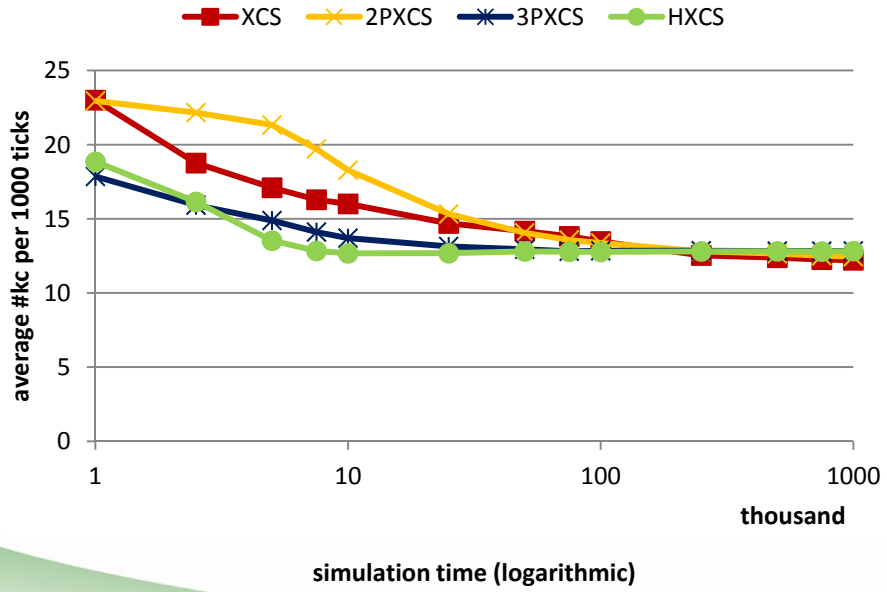
Single-Agent Learning





All situations | Only critical situations | On-line learning and off-line planning | Parallelism



+ Significant improvements in performance and learning speed
– Parallelism is limited by the size of the problem.
– The task of decomposing a task into subtasks is static and predefined.

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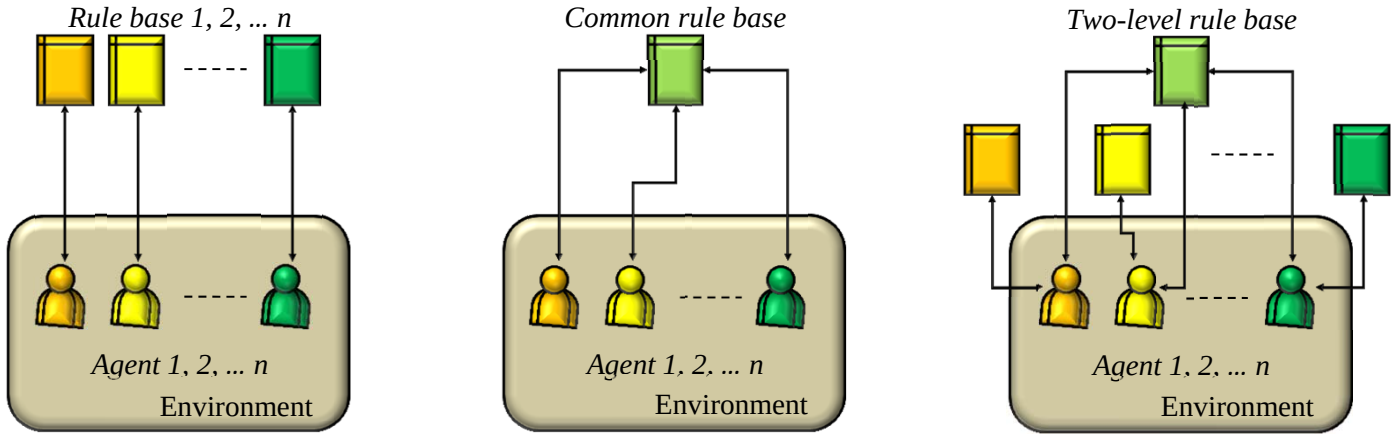
Multi-Agent Learning

- Three different architectures
  - ***Individual rule base approach:*** Every agent stores its learned knowledge in an individual rule base.
  - ***Common rule-base approach:*** Agents store their experience in a centralized rule base and get advantages from the shared knowledge.
  - ***Two-level rule-base approach:*** A combination of ***common*** and ***individual rule base*** which both are available to be used.



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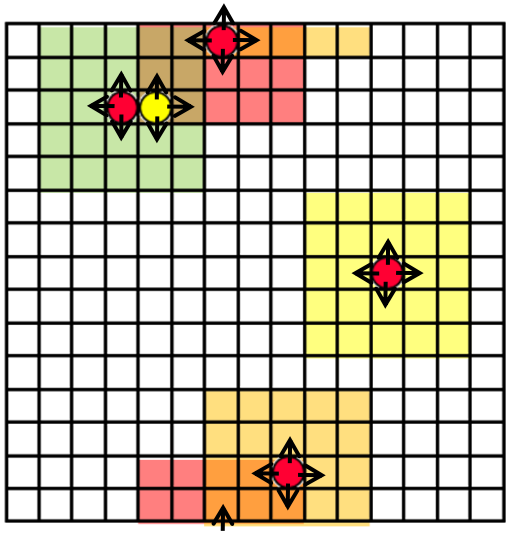
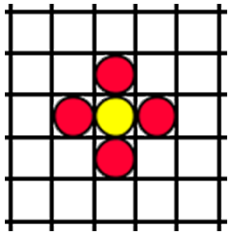
Testbed: Predator/Prey Pursuit Scenario

(Benda et. al., 1986)

- Scenario
  - Two-dimensional borderless (torus) grid-world
  - Four predators (red dots) and a prey (yellow dot)
  - The predators' team goal: Capture the prey
- Predators
  - Observe local environment
  - Communicate each other
  - Make decisions autonomously
  - Move themselves closer to the prey
- Simulations
  - Limited to 1 million ticks
  - A new prey appears at random location of the grid, after the previous one is captured and eliminated
  - The average number of capture times denotes the system performance.
- Simulations are tested using two different prey settings: *static* (not moving) and *moving*.





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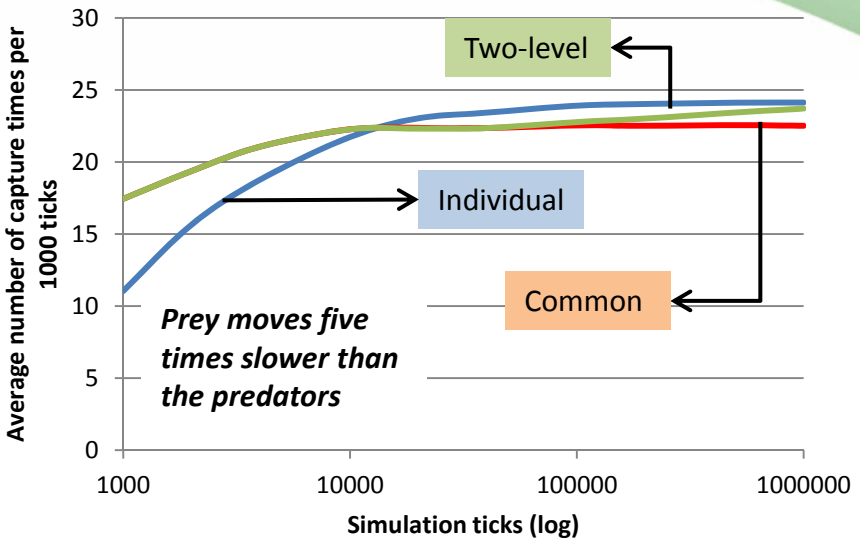
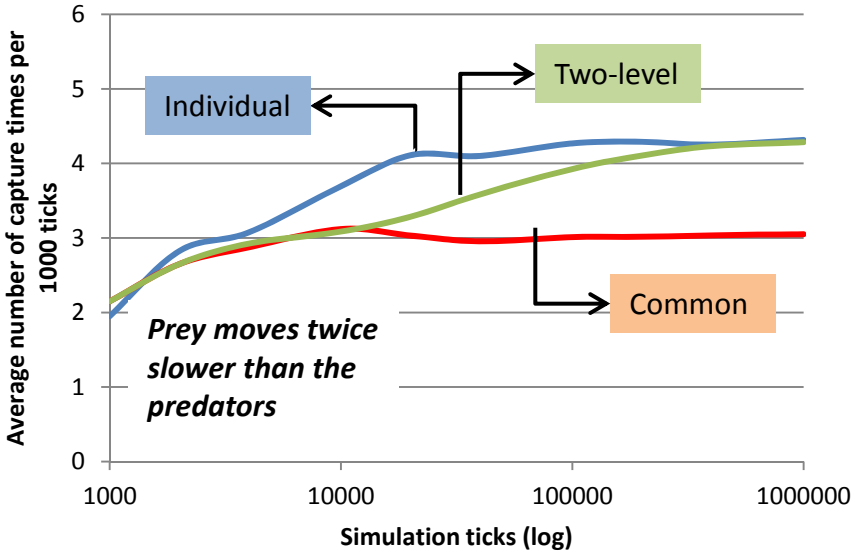
Simulation Results

+ The ***common rule base*** learning architecture succeeds in increasing the learning speed at the beginning of the simulations, although it is inferior to the ***individual rule base*** afterwards.

+ The ***two-level rule base*** combines both advantages of quicker learning as shown by the ***common rule base*** and better results in the long run as ***individual rule base*** gives.





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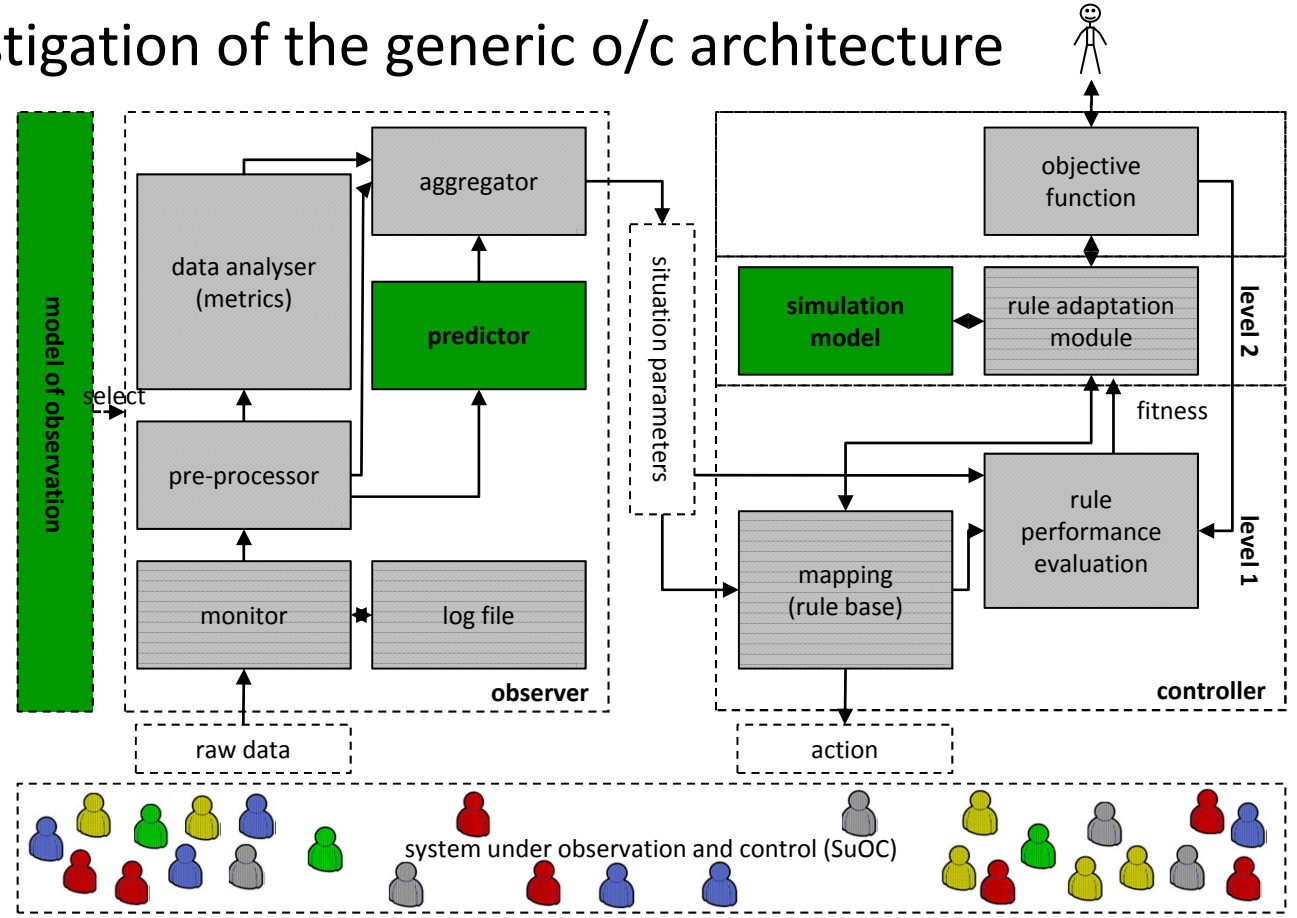
Outlook on the O/C Architecture

- Extended investigation of the generic o/c architecture
- Quantitative definitions of robustness and flexibility
- Complex and adaptive cooperation and collaboration mechanisms



- Demonstration of the achievements (OTC^3)

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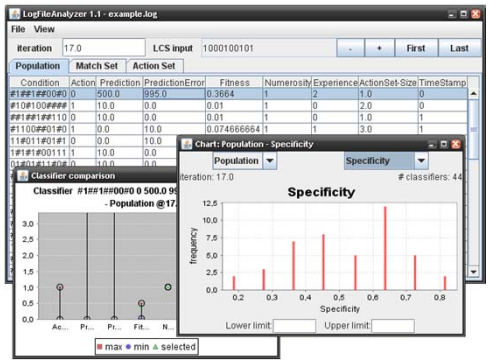
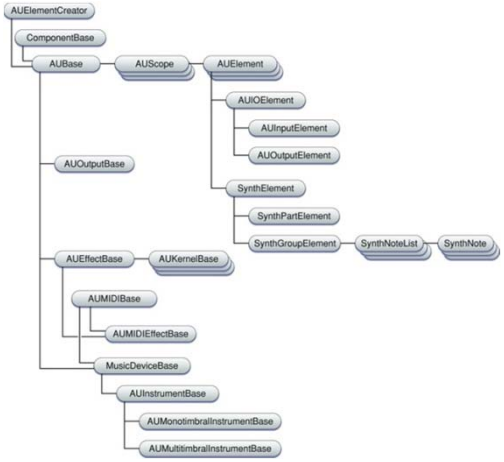
Tools

LogFileAnalyzer



- Supports the analysis of Learning Classifier System (LCS) experiments
- Visualisation of classifier populations
- Written in JAVA
- Available at http://www.aifb.uni-karlsruhe.de/EffAlg/Projekt/otcqe/publ/software.htm

Reference implementation of the abstract OTC architecture



- Written in JAVA
- Defining interfaces and (abstract) classes
- Prototypical implementation

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