

# Multi-robot Exploration with Limited Communication in the RoboCup Rescue

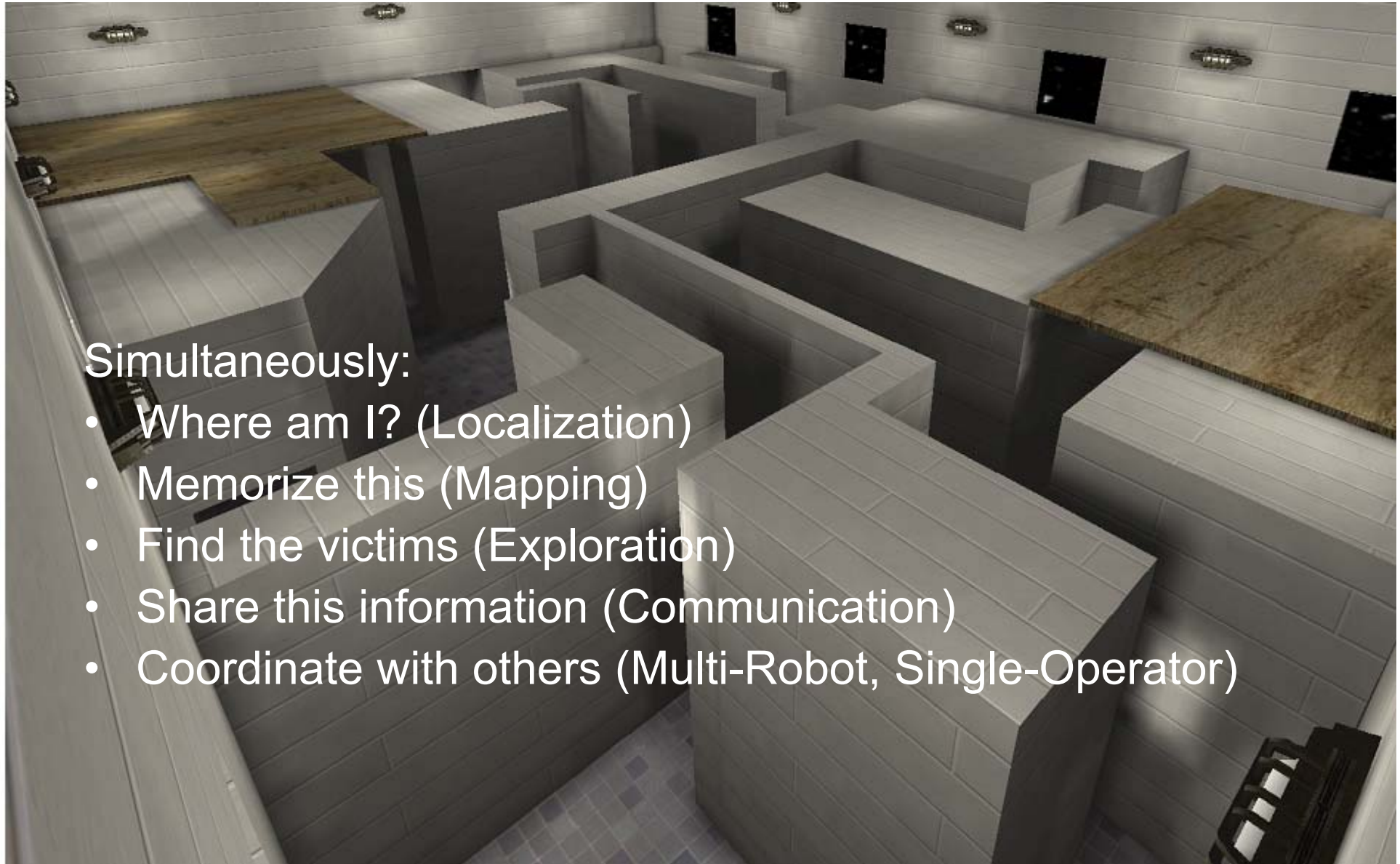
Arnoud Visser

Lisbon Workshop on New Challenges for Cooperative Robotics,  
Lisbon, Portugal, October 24, 2008



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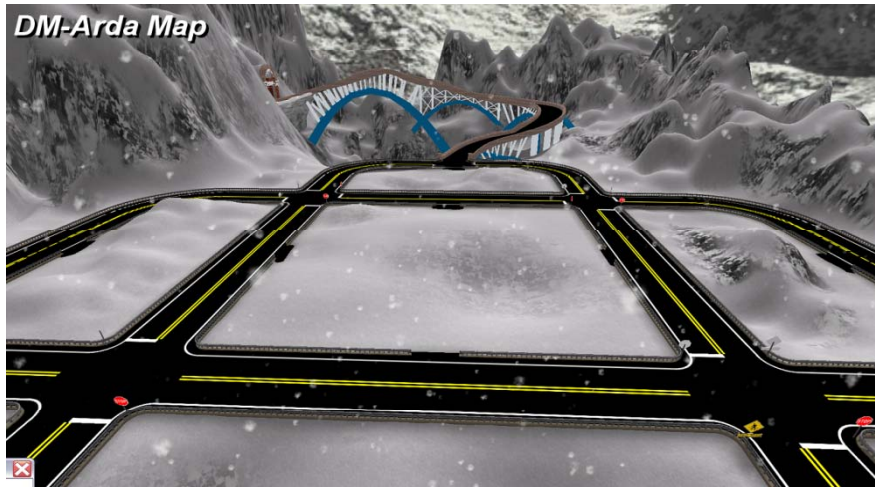
# Virtual Rescue League



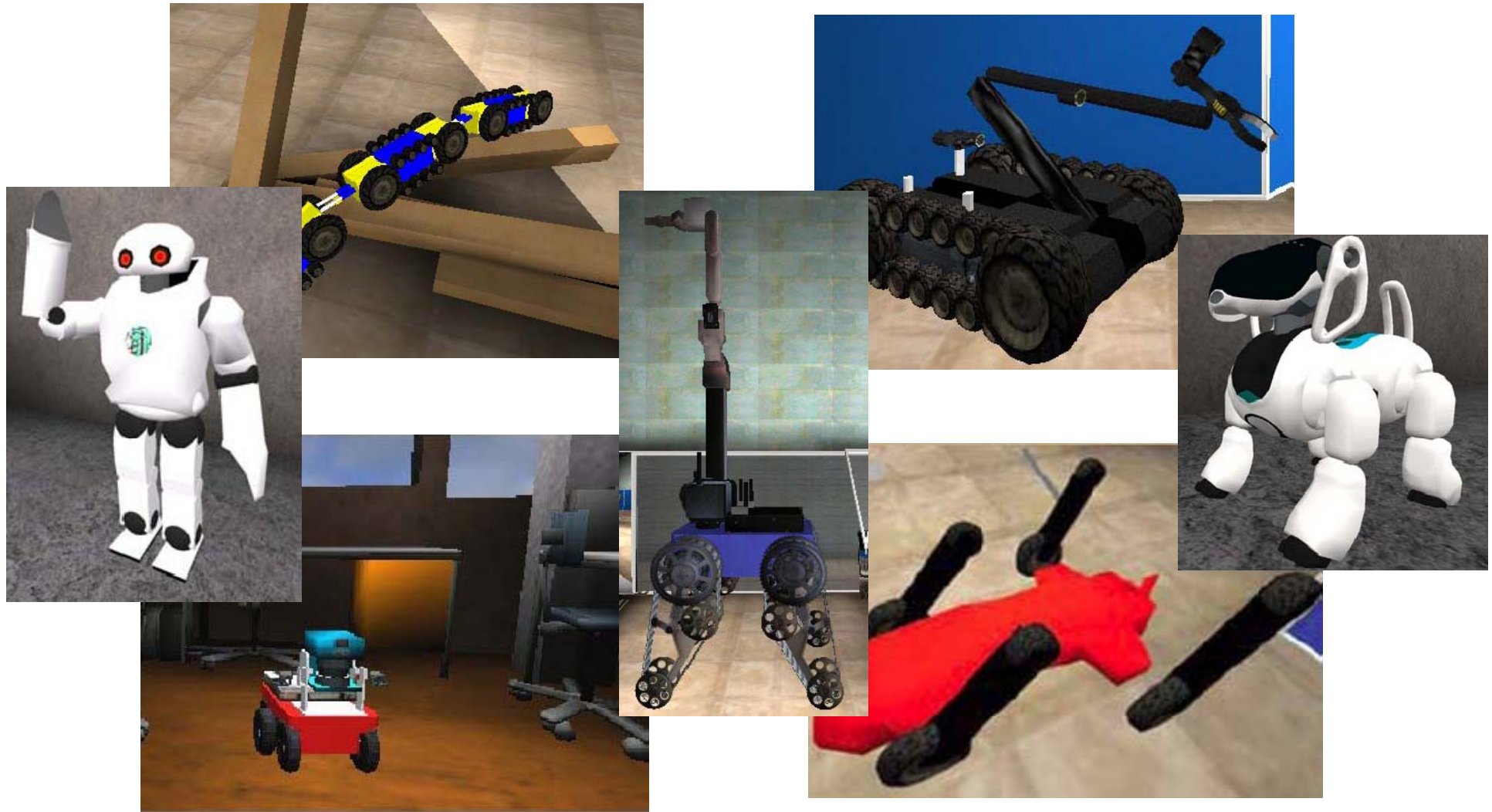
Simultaneously:

- Where am I? (Localization)
- Memorize this (Mapping)
- Find the victims (Exploration)
- Share this information (Communication)
- Coordinate with others (Multi-Robot, Single-Operator)

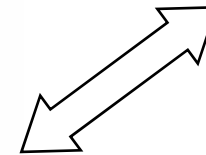
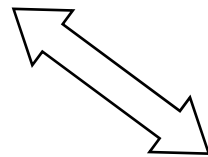
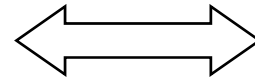
# A wide variety of simulated worlds



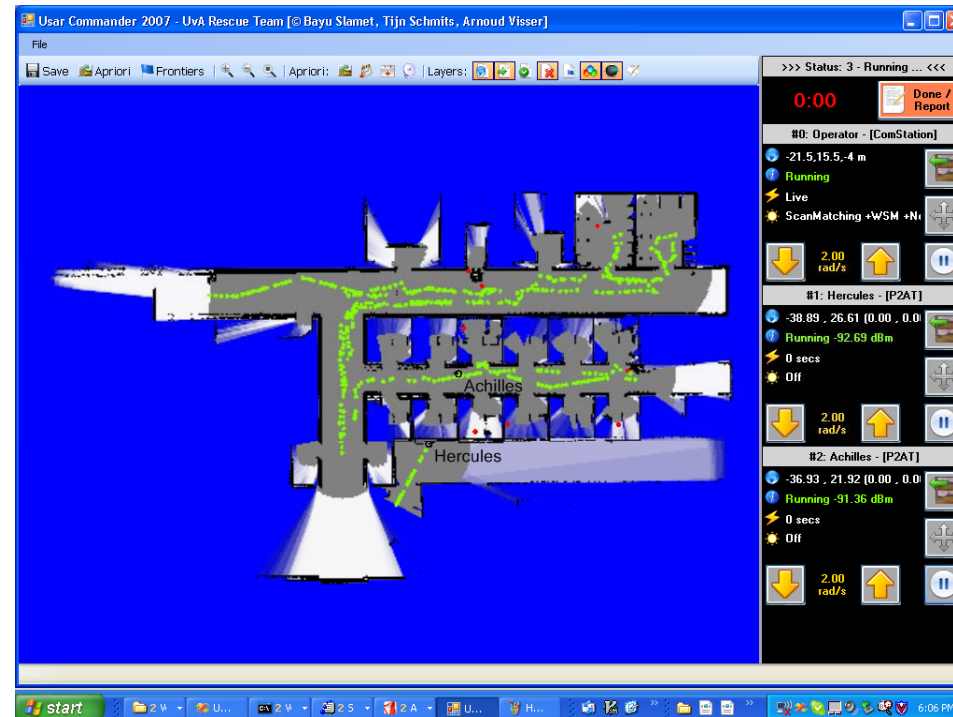
# A wide variety of Robotic platforms



# Networked robot team



# UsarCommander



- User Interface can be used to teleoperate the robots and monitor the shared map.
- Here, the robots are autonomous exploring on a distributed map (each with a partial view).

Localization and Mapping challenge:  
Combination of Manifold SLAM  
with Weighted Scan Matching  
algorithm

Bayu Slamet and Max Pfingsthorn

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# Pose estimation



**Agent Configuration - [Hercules]**

Config File: PlyWoodStartInside.cfg

Spawn Configuration

Robot Model: P2AT

Robot Number: 1

Start Location: -21.5,17.5,-4 m

Start Rotation: 0,0,-3.3 rad

Behavior Configuration

Behavior: AutonomousExploration

Cost/Gain Balance: 1

Slam Configuration

Localization Mode: ScanMatching

Scan Matcher: WSM

Pose Seed Mode: WSM, IDC, MblCP, MultlCP, QuadWSM, QuadIDC

Skindetector Configuration

Skindetector Mode: Detection

Teacher Mode: SkinOnly

Detector Theta:

Agent Type

User Operator

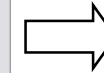
User SLAM

User Skin

User Follow

User Base

Spawn from Commander



Pose & confidence



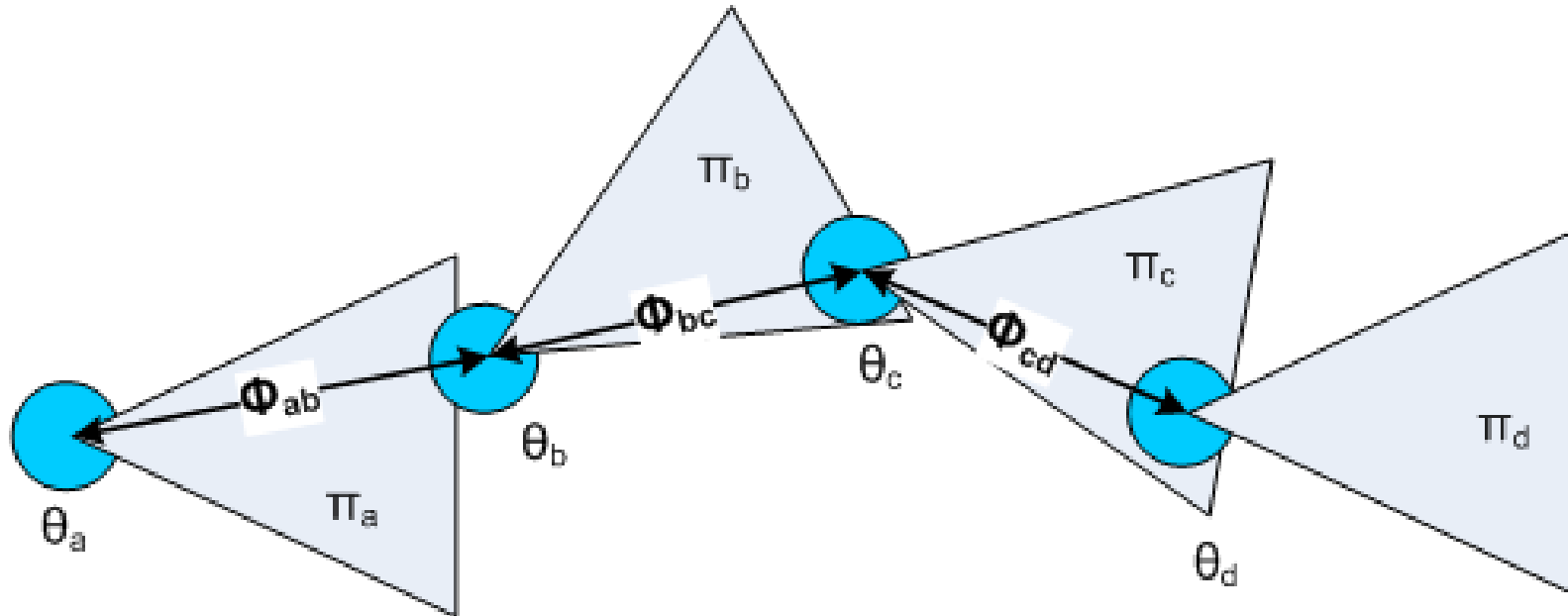
- Several Scan Matching algorithms



# Localization vs Mapping

- When the confidence is good, the current position fits to one of the positions of the local submap  
*(localization, no extension of the map)*
- When confidence drops, a new *patch* is added to the chain  
*(graph based mapping)*

# Chain of patches



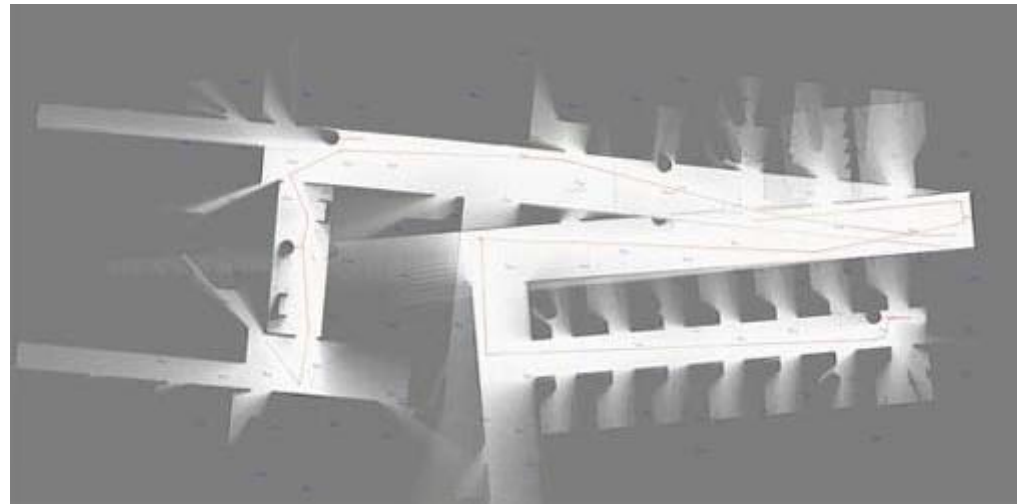
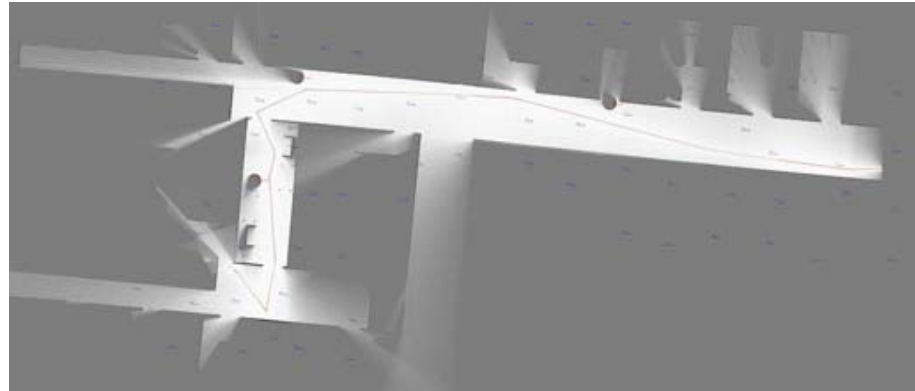
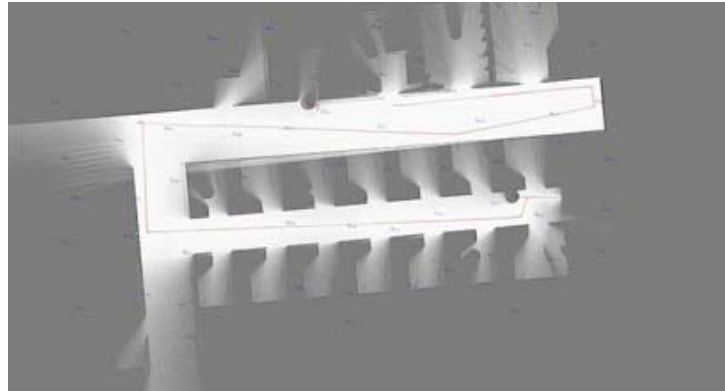
$\pi$  = laser scan

$\theta$  = absolute location (Euclidean)

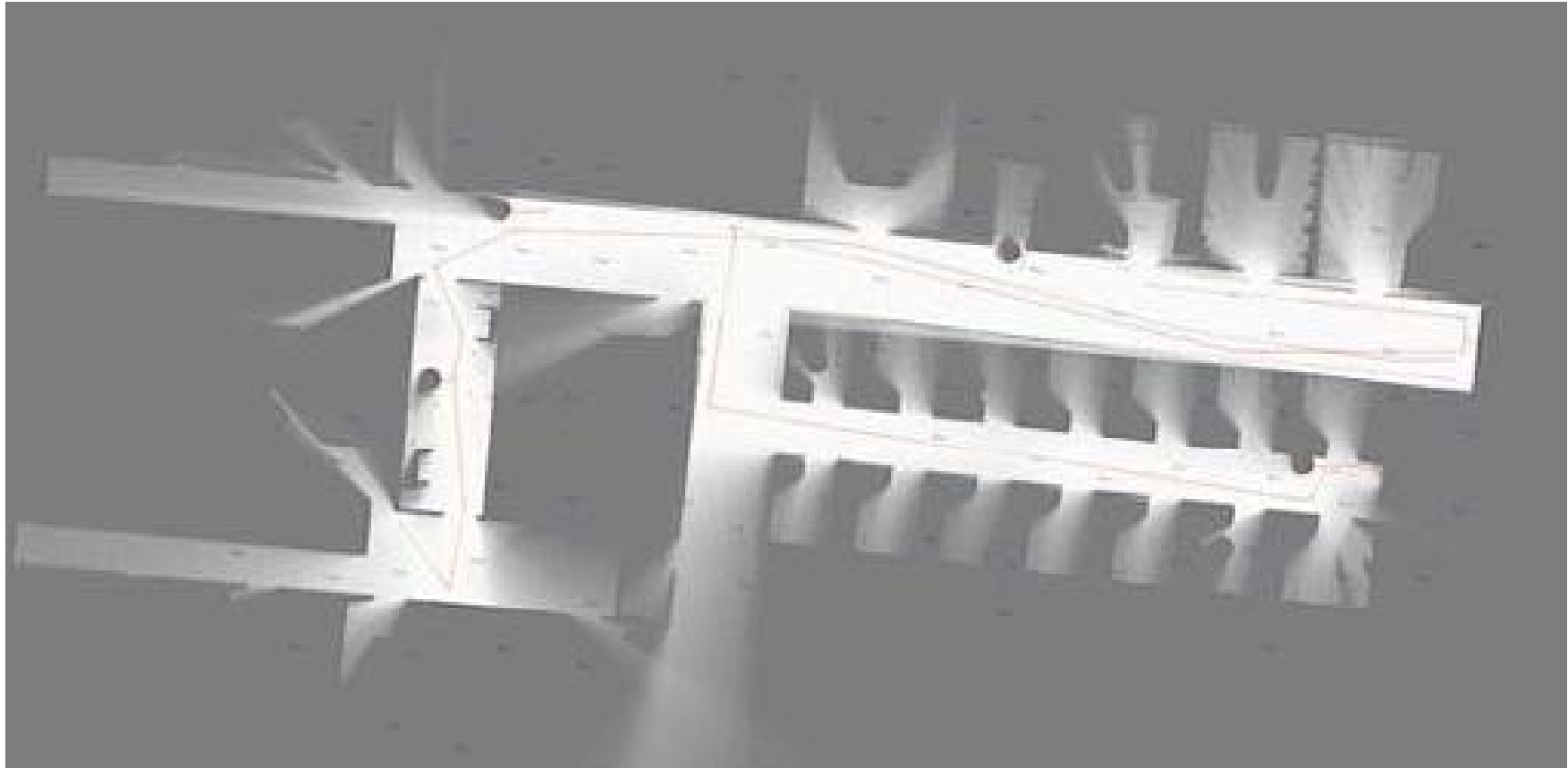
$\Phi$  = relation

= relative location (polar)  $\Delta\theta$  + covariance matrix  $\Sigma$

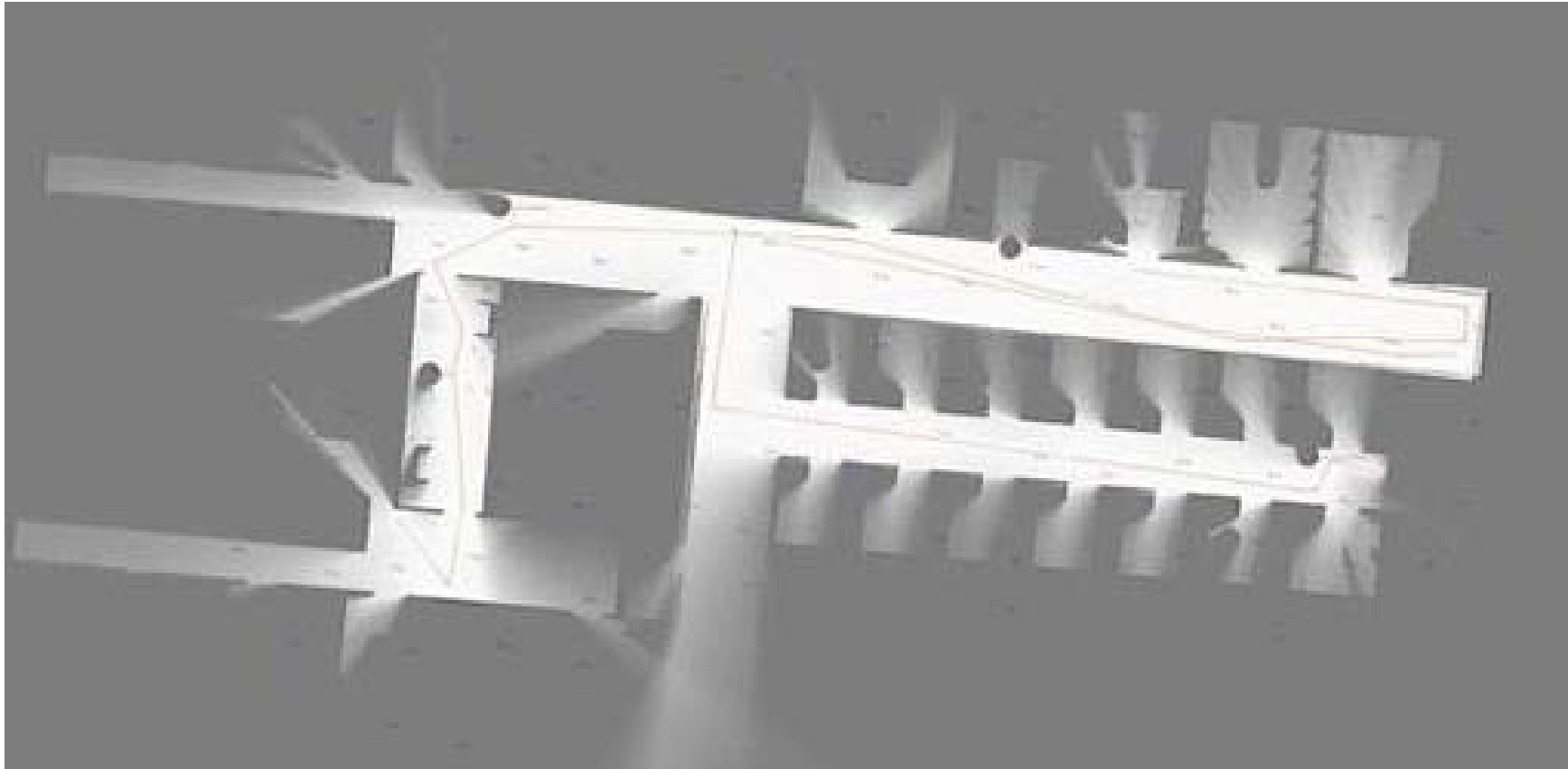
# Island merging



# Rigid body transformation



# Refitting graph-relations



# Corridor



Press Fire to View a different Player

## Localization and Mapping challenge:

### Result

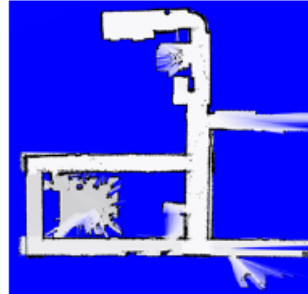
- Distributed approach scales well for multiple robots
- High accuracy maps can be achieved
- Additional data can be added asynchronously
- Results have been validated

See Max Pfingsthorn, Bayu Slamet and Arnoud Visser, "A Scalable Hybrid Multi-Robot SLAM Method for Highly Detailed Maps", Lecture Notes on Artificial Intelligence series.

# Validation on Radish datasets



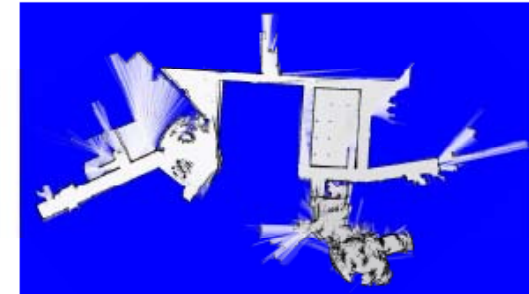
(a) AP Hill



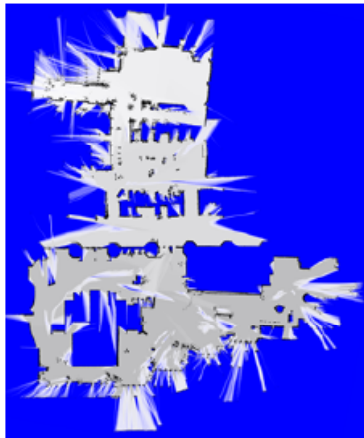
(b) CMU N. Simon Hall



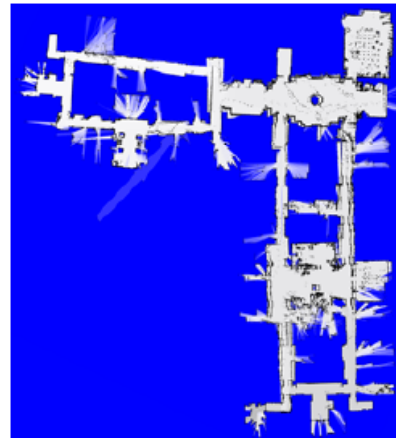
(e) Intel Lab, Seattle



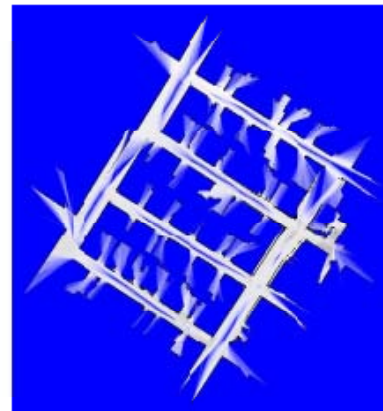
(f) 3rd floor of MIT CSAIL



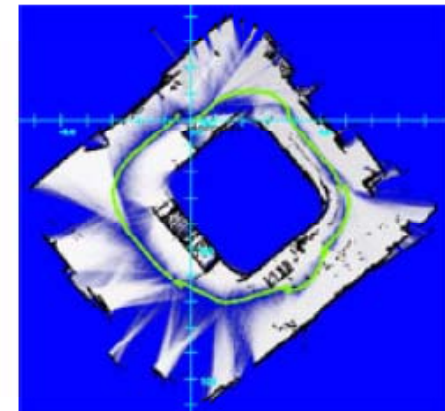
(c) Edmonton Convention



(d) Stanford Gates



(g) Intel Campus, Oregon



(h) NIKHEF Amsterdam



Navigation Challenge:  
Beyond frontier exploration

Merlijn van Ittersum, Xingrui-Ji,  
Luis Gonzalez and Laurentiu Stancu

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# Interpret the map

- Make the information on the map available in a value function to optimize the selection of the next action.
- The value function has to balance the information gain against the cost of the action.

# Information gain

- Active localization can be seen as minimizing the entropy  $H(m)$  of map  $m$

$$H(m) = - \sum_{x \in m} p(x) \log(p(x))$$

- Important is the difference in entropy  $H$  before and after an exploration action  $a$

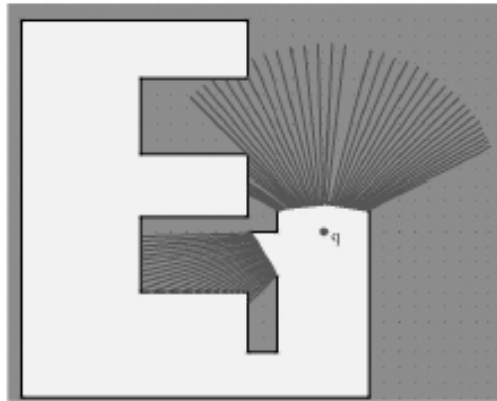
$$\Delta I(a) = H(m|a) - H(m)$$

# Reduction of action space

- At a large map many exploration actions are possible. A finite number of observation points have to be chosen.
- Typically, those observation points are chosen on the boundaries of explored and unexplored areas: frontier based exploration

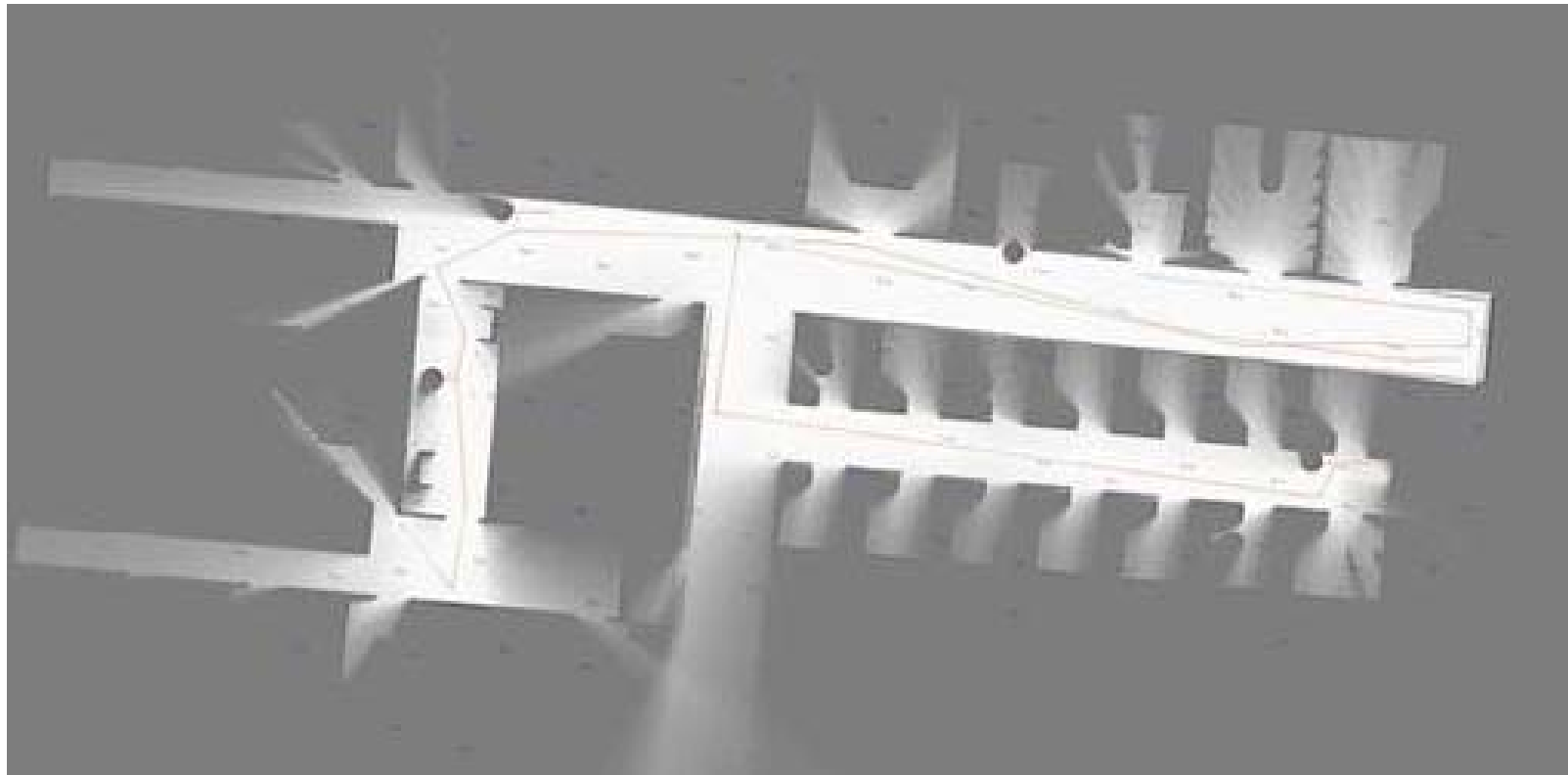
See Yamauchi, B.: A frontier based approach for autonomous exploration. In: Proceedings of IEEE International Symposium on Computational Intelligence in Robotics and Automation, Monterey, CA, July 10-11, 1997. (1997)

# Candidate Observation points

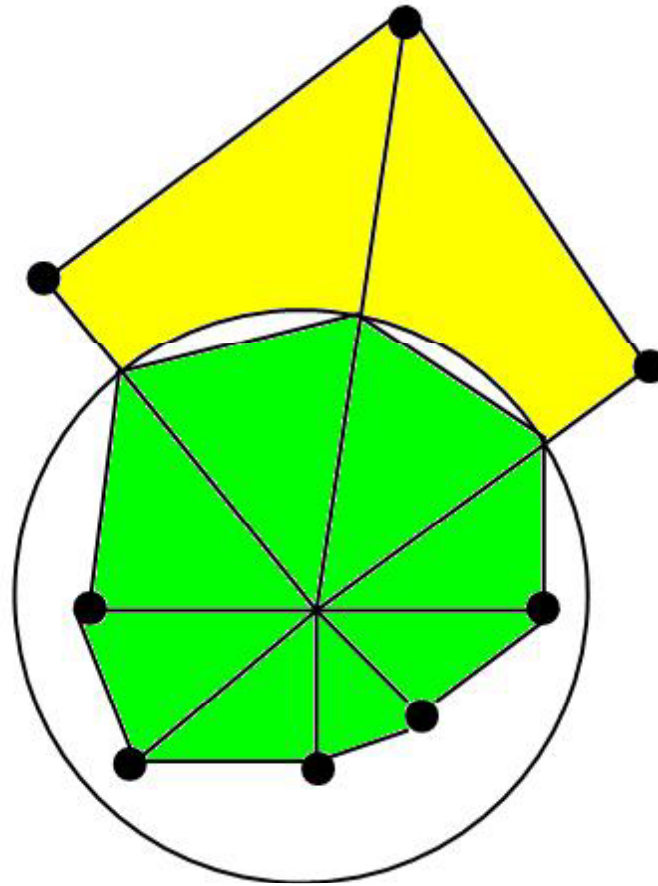


- The potential information gain  $\Delta I(a)$  of a candidate observation point  $q$  is the area  $A(q)$  that may be visible through the two free edges; this area is estimated by casting rays from  $q$ .

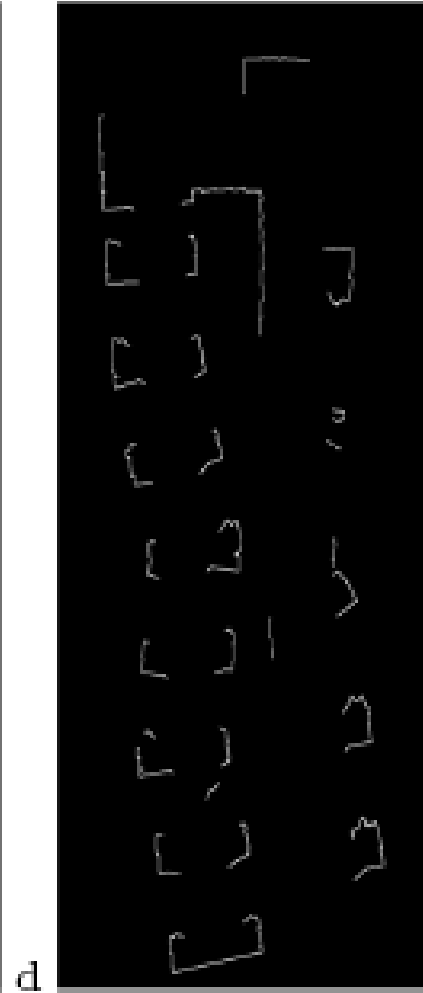
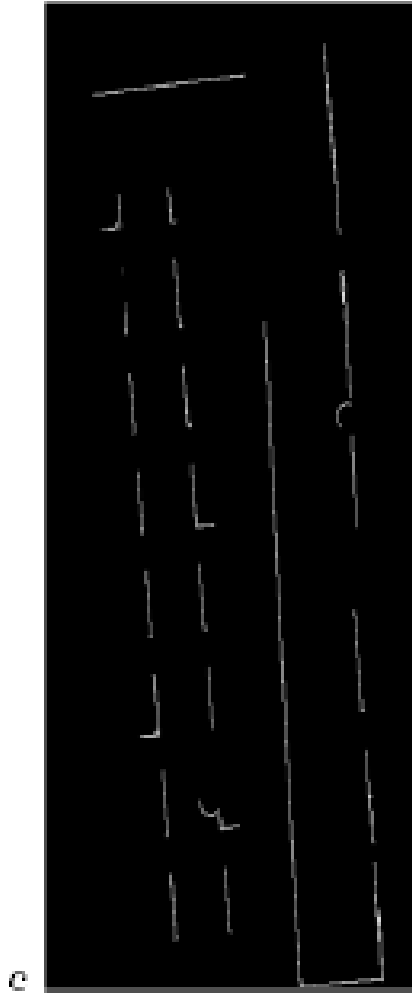
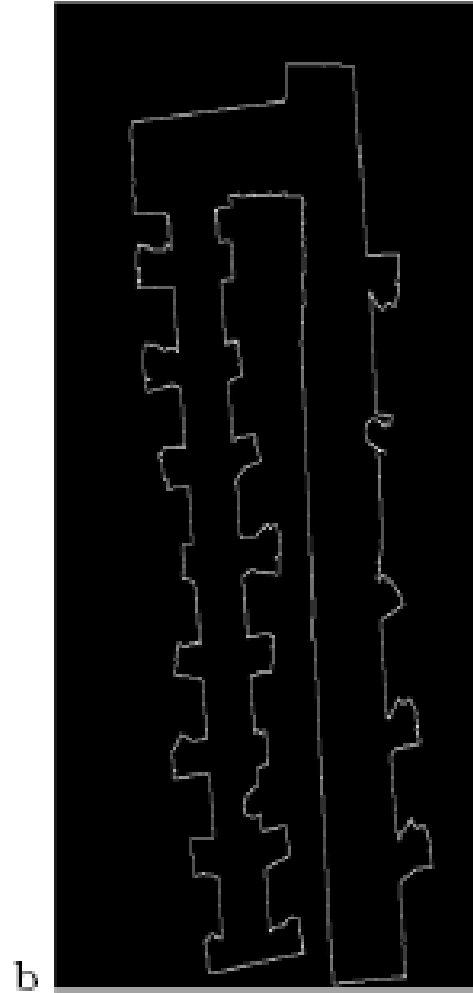
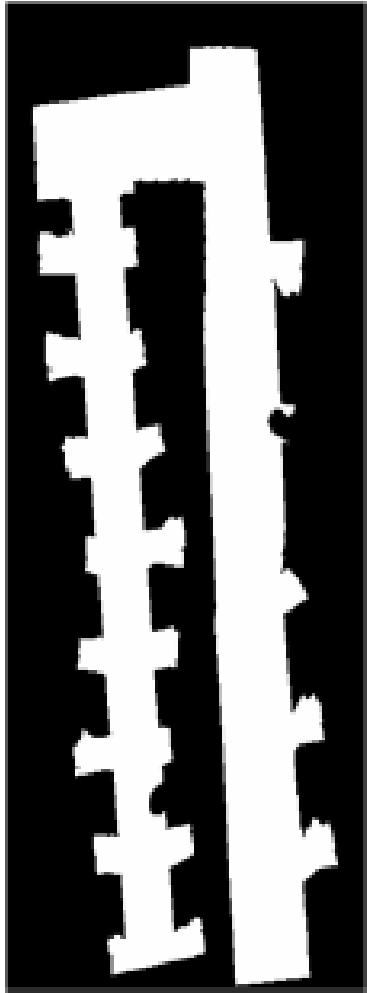
# Probabilistic occupancy map



# Ray-tracing with a long and short maximum range



# How to interpret the map





File

Save Apriori Frontiers | Apriori: Layers:



>>> Status: 3 - Running ...

8:51

#0: Operator - [ComStation]

- 10,10,-1 m
- Ready to Spawn
- Live
- ScanMatching +WSM +N

2.00 rad/s

#1: Hercules - [P2AT]

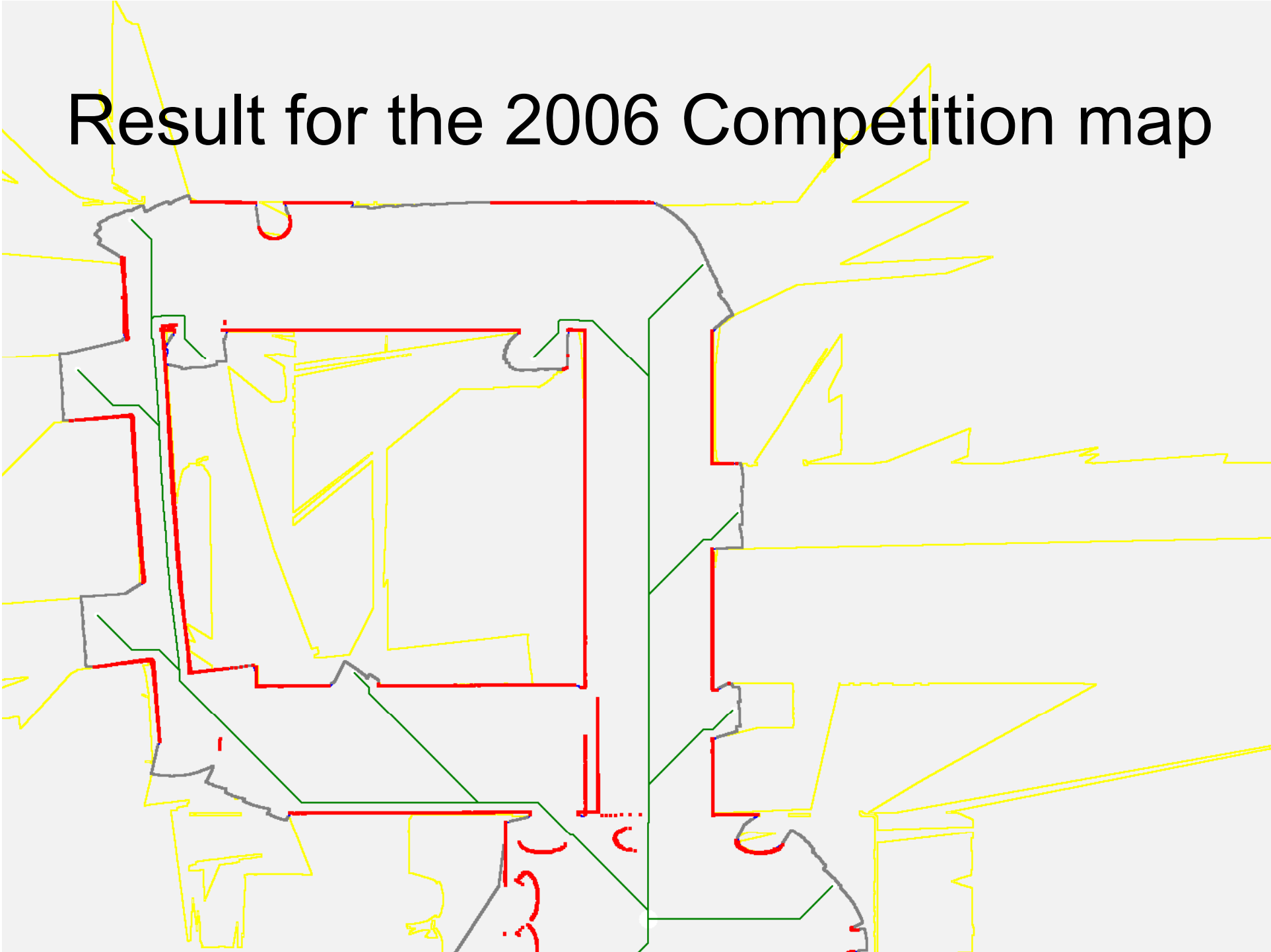
- 0.98 , 6.17 (1.76 , -0.90)
- Running
- 2233 secs
- On

2.00 rad/s



30.96 m<sup>2</sup>

# Result for the 2006 Competition map



# Quantative results

	<i>expected frontiers &amp; observation points</i>	<b>exploration frontiers</b>			<b>observation points</b>		
		<i>false</i>	<i>false</i>	<i>false</i>	<i>false</i>	<i>false</i>	<i>false</i>
		<b>found</b>	<i>positives</i>	<i>negatives</i>	<b>found</b>	<i>positives</i>	<i>negatives</i>
<b>Three corridors</b> (Fig. 2)	22	27	6	1	21	0	1
<b>Lobby loop</b> (Fig. 5)	13	17	5	1	11	0	2
<b>Yellow arena</b> (Fig. 6)	9	17	8	0	9	1	1

## Navigation Challenge:

### Result

- A limited set of candidate exploration locations can be generated from the current map  $m$
- The candidate exploration locations are at the center of exploration frontiers
- The information gain can be estimated from the area beyond the frontiers

# Balancing the information gain against the movement cost for multi-robot frontier exploration

Arnoud Visser and Bayu A. Slamet.

2nd European Robotics Symposium,  
Prague, Czech Republic March 26, 2008



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# Exploration Algorithm

- A greedy algorithm that calculates the utility function  $U(f)$  for each frontier  $f$  based on the  $Area(f)$  and distance  $dist(f)$

$$U(f) = Area(f) / dist(f)$$

- The  $Area(f)$  is a measure for the information gain, and the  $dist(f)$  is a measure for the exploration cost.

# Quantative results

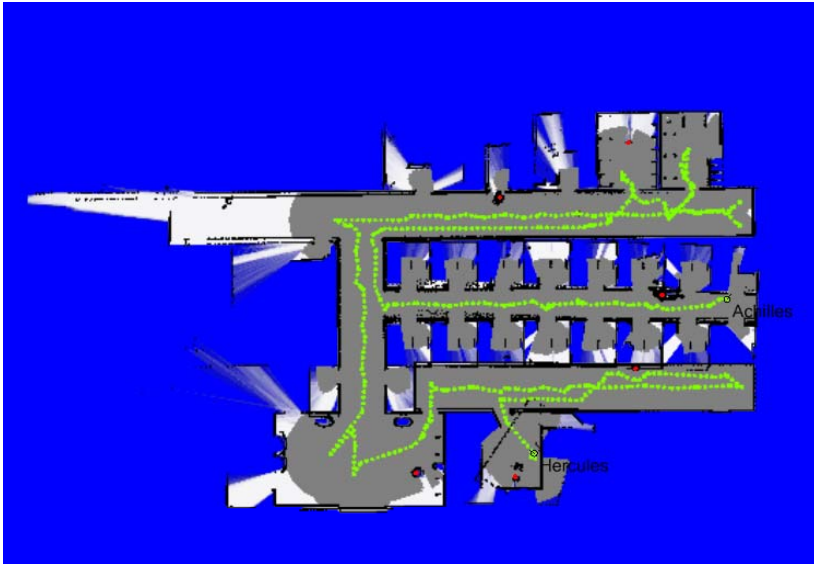
	Single robot	Two robot team	Increase
North-East	416 m <sup>2</sup>	519 m <sup>2</sup>	+25%
North-West	379 m <sup>2</sup>	637 m <sup>2</sup>	+68%
South	498 m <sup>2</sup>	707 m <sup>2</sup>	+42%



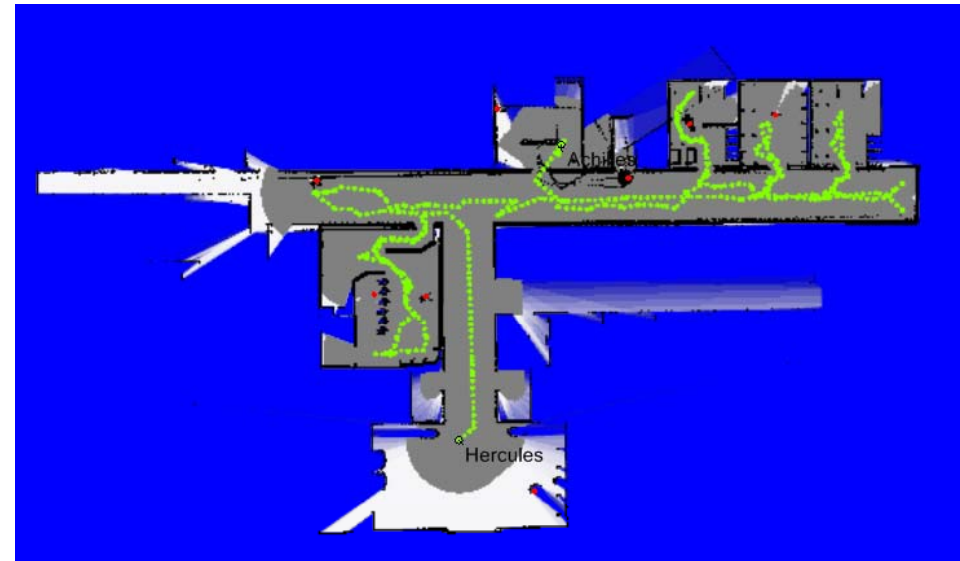
# Three Exploration Algorithms

- A greedy algorithm that uses an utility function  $U(f)$  for each frontier  $f$ . The utility function balances the information gain against the exploration costs.
  - linear:  $U(f) = Area(f) / dist(f)$
  - quadratic:  $U(f) = Area(f) / dist(f)^2$
  - cubic:  $U(f) = Area(f) / dist(f)^3$
- The  $Area(f)$  is a measure for the information gain, and the  $dist(f)$  is a measure for the exploration cost.

# Results



A(f)/d(f)  
(629 m<sup>2</sup>, 6 victims)



A(f)/d<sup>3</sup>(f)  
(486 m<sup>2</sup>, 8 victims)

# Conclusion

- The information gain  $A(f)$  and exploration costs  $d(f)$  can in real-time be estimated from the current map
- Tuning the balance between the information gain and exploration costs can change the **overall behavior** from exploring mainly corridors towards concentrating on nearby rooms.

# Including Communication Success in the Estimation of Information Gain for Multi-robot Exploration

Arnoud Visser and Bayu A. Slamet.

1th Workshop on Wireless Multihop Communications  
in Networked Robotics,  
Berlin, Germany, April 4, 2008



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# Including the success of communication into exploration algorithm

- A greedy algorithm that uses an utility function  $U(f)$  for each frontier  $f$ . The utility function balances the information gain against the exploration costs.

$$U(f) = Area(f) \cdot P_{com} / dist(f)$$

- The  $Area(f)$  is a measure for the information gain, is now multiplied with the chance that gained information can be communicated to the ComStation.

# Exploration Algorithm

distributed:

(map  $m$  as known by  $r_c$ )

double loop:

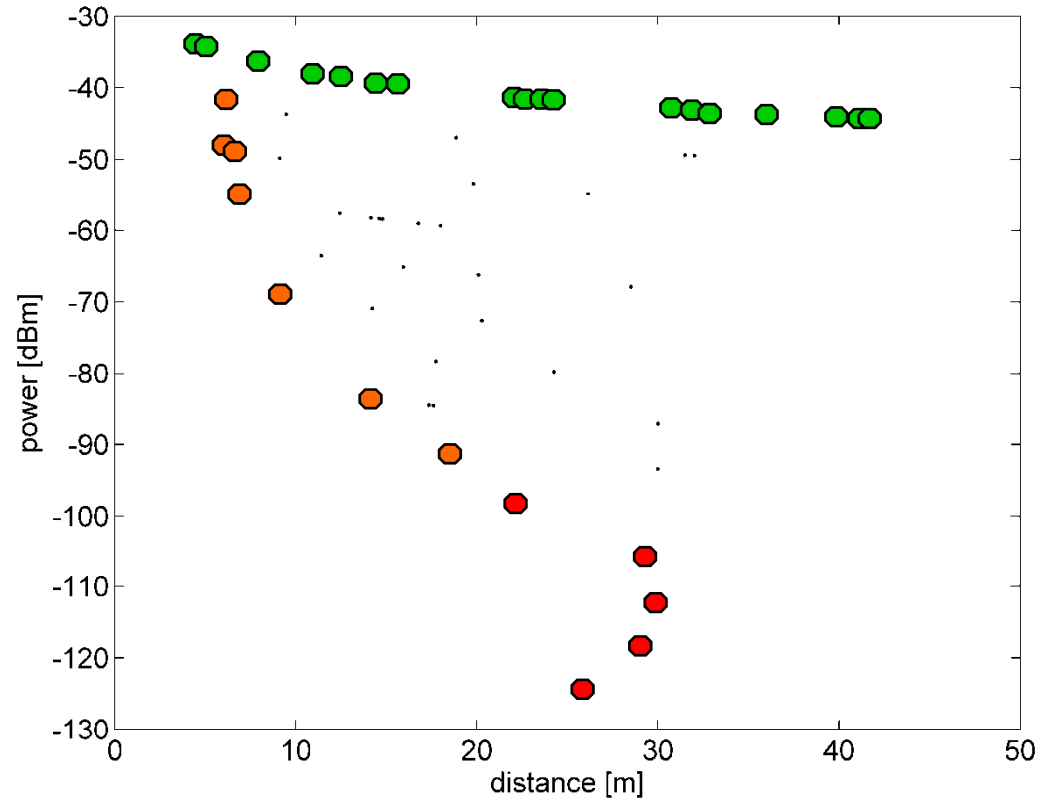
(first Euclidian distance, followed by PathPlanning for  $u_{max}$ )

```

Data: the identity of the current robot  $r_c \in R$  and the
map  $m$  as known by  $r_c$ .
Data: the set of robots  $r_i$  in  $R$ . Each  $r_i$  consist of the
tuple  $(x_{r_i}, y_{r_i}, \theta_{r_i})$ .
Data: the set of frontiers  $f_j$  in  $F$ . Each  $f_j$  consist of the
tuple  $(x_{f_j}, y_{f_j}, A_{f_j}, P_{f_j})$ .
Result: the pair  $r_c, f_c$  and the path  $p_c$  to the location
 $(x_{f_c}, y_{f_c})$ 
for each robot  $r_i$  in  $R$  do
|   for each frontier  $f_j$  in  $F$  do
|   |    $d_{eu} = \sqrt{(x_{f_j} - x_{r_i})^2 + (y_{f_j} - y_{r_i})^2}$ ;
|   |    $u_{ij} = A_{f_j} \dot{P}_{f_j} / d_{eu}$ ;
|   end
end
 $u_{max} = \max u_{ij}$ ;
repeat
|   for robot  $r_i$  and frontier  $f_j$  of  $u_{max}$  do
|   |    $p = \text{PathPlanning}$  from  $(x_{r_i}, y_{r_i})$  to  $(x_{f_j}, y_{f_j})$  on
|   |   map  $m$ ;
|   |    $d_{pp} = \text{length of path } p$ ;
|   |    $u_{ij} = A_{f_j} \dot{P}_{f_j} / d_{pp}$ ;
|   end
|   if  $\max u_{ij} = u_{max}$  then
|   |   Assign  $f_j$  to  $r_i$ ;
|   |   Prune  $U$  from  $i$  and  $j$ ;
|   end
|    $u_{max} = \max u_{ij}$ ;
until robot  $r_c$  is Assigned ;
 $p_c = \text{last path } p$ 

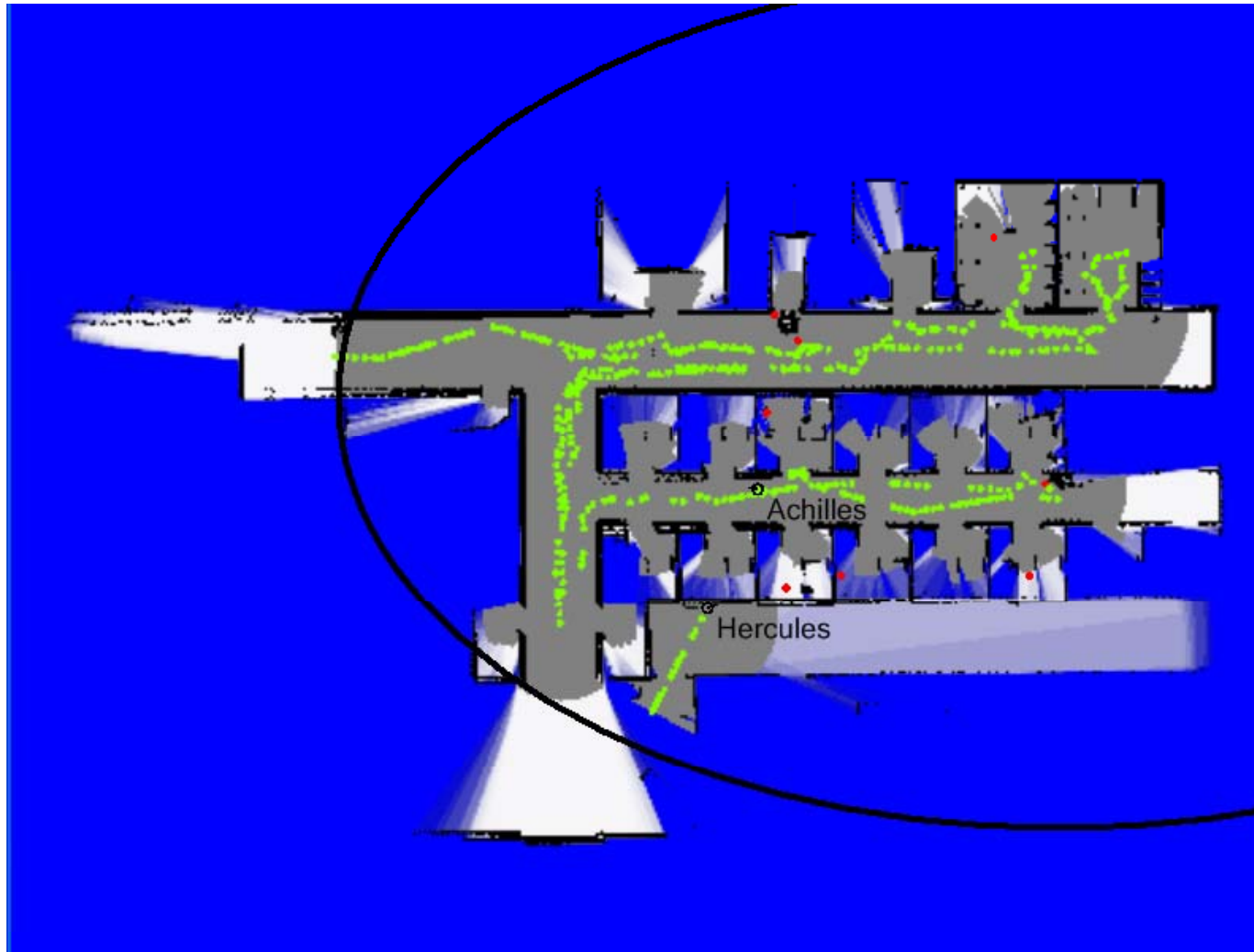
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# Estimating the Success of Communication



- The relation between distance and power is learned while exploring (depended on attenuation of walls)

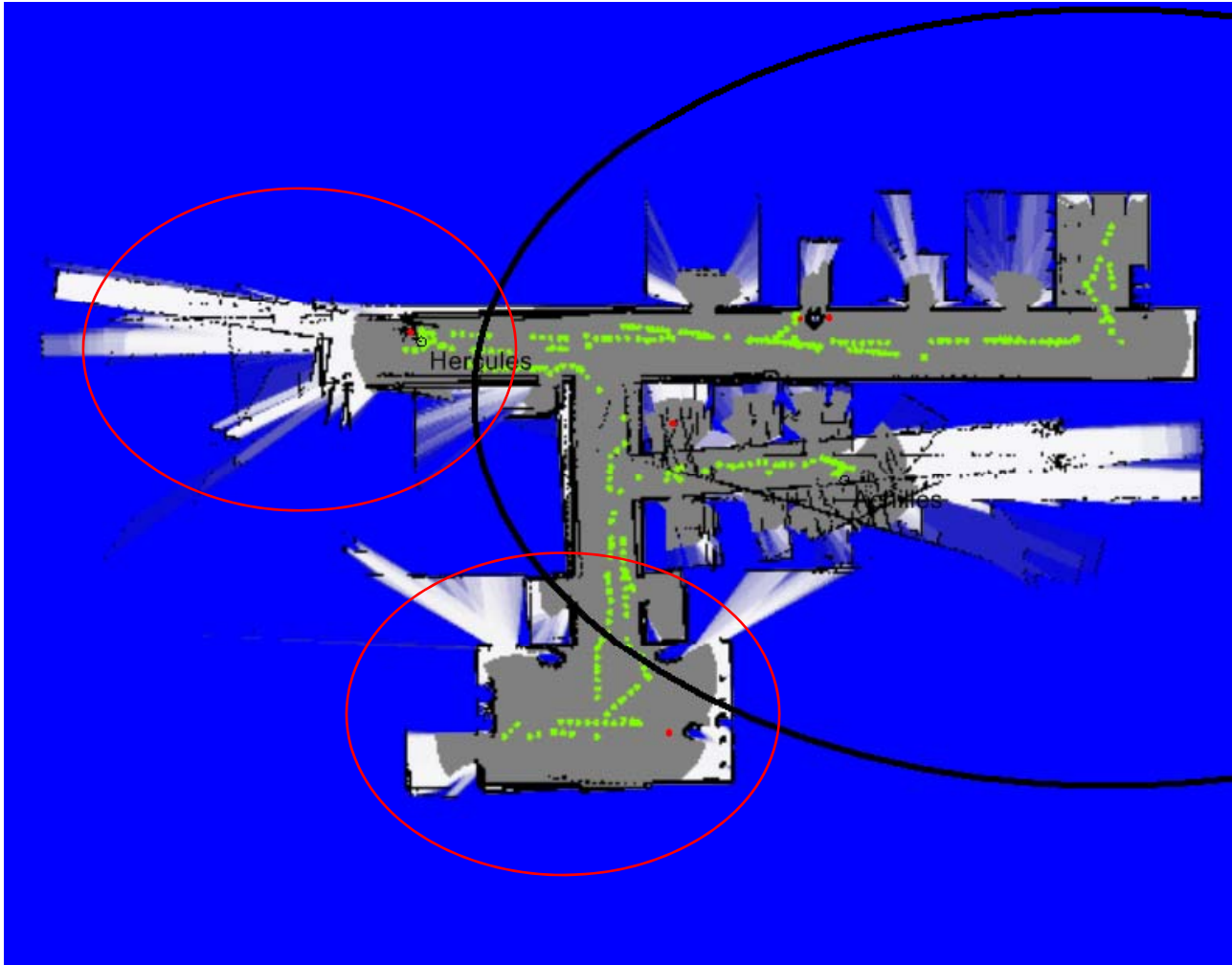
# Results



Two robots with ComStation in North-East corner,  
robots do not share their map (545 m<sup>2</sup>, 6 victims)

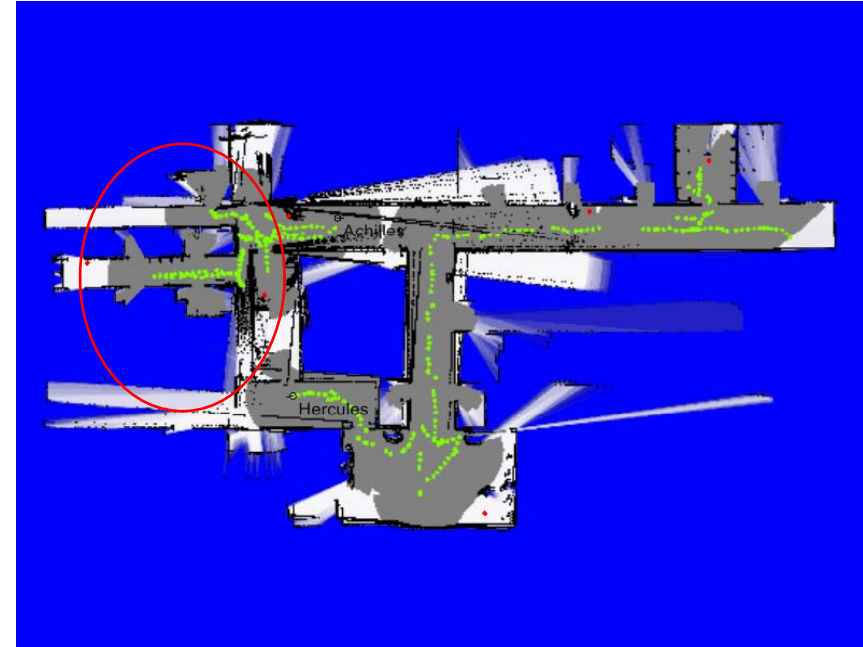
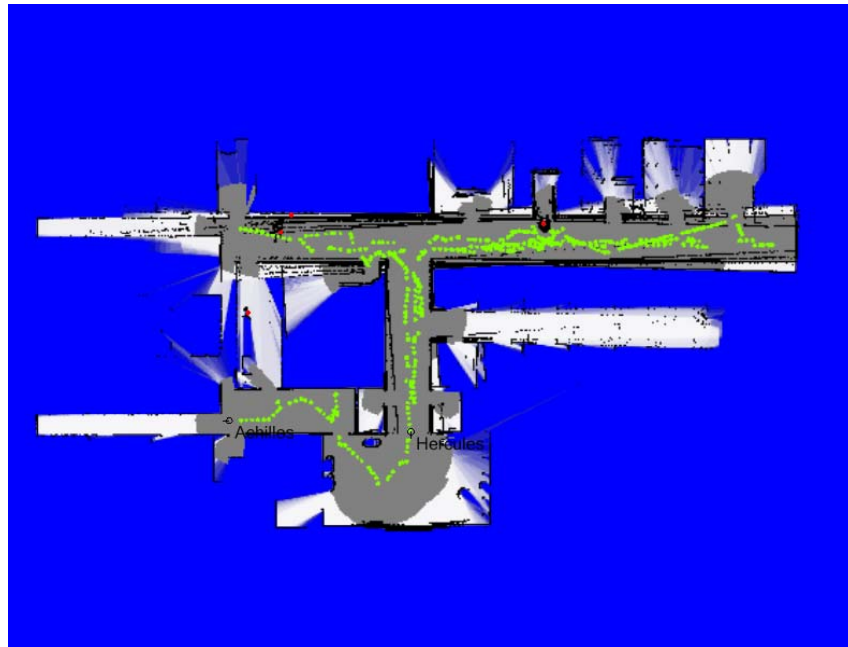


# Results



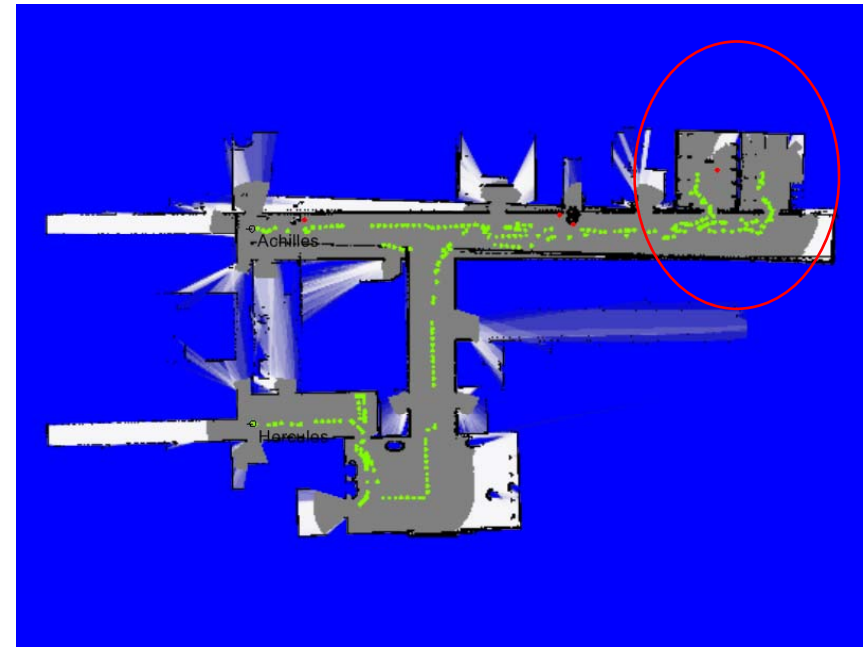
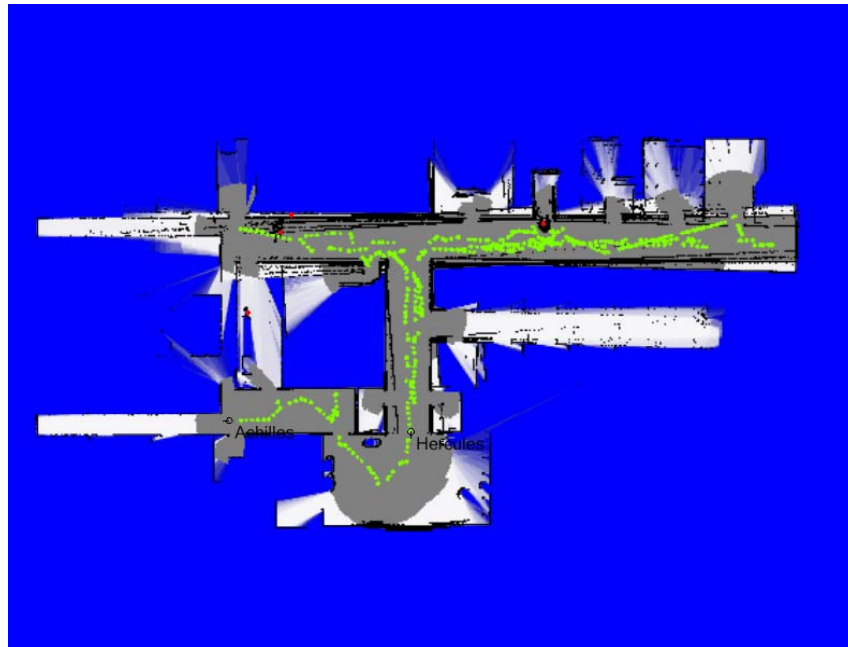
Two robots with ComStation in North-East corner,  
robots share their map (568 m<sup>2</sup>, 4 victims)

# ComStation T-junction



not share their map (556 m<sup>2</sup>, 4 victims), shared (642 m<sup>2</sup>, 5 victims)

# ComStation NW

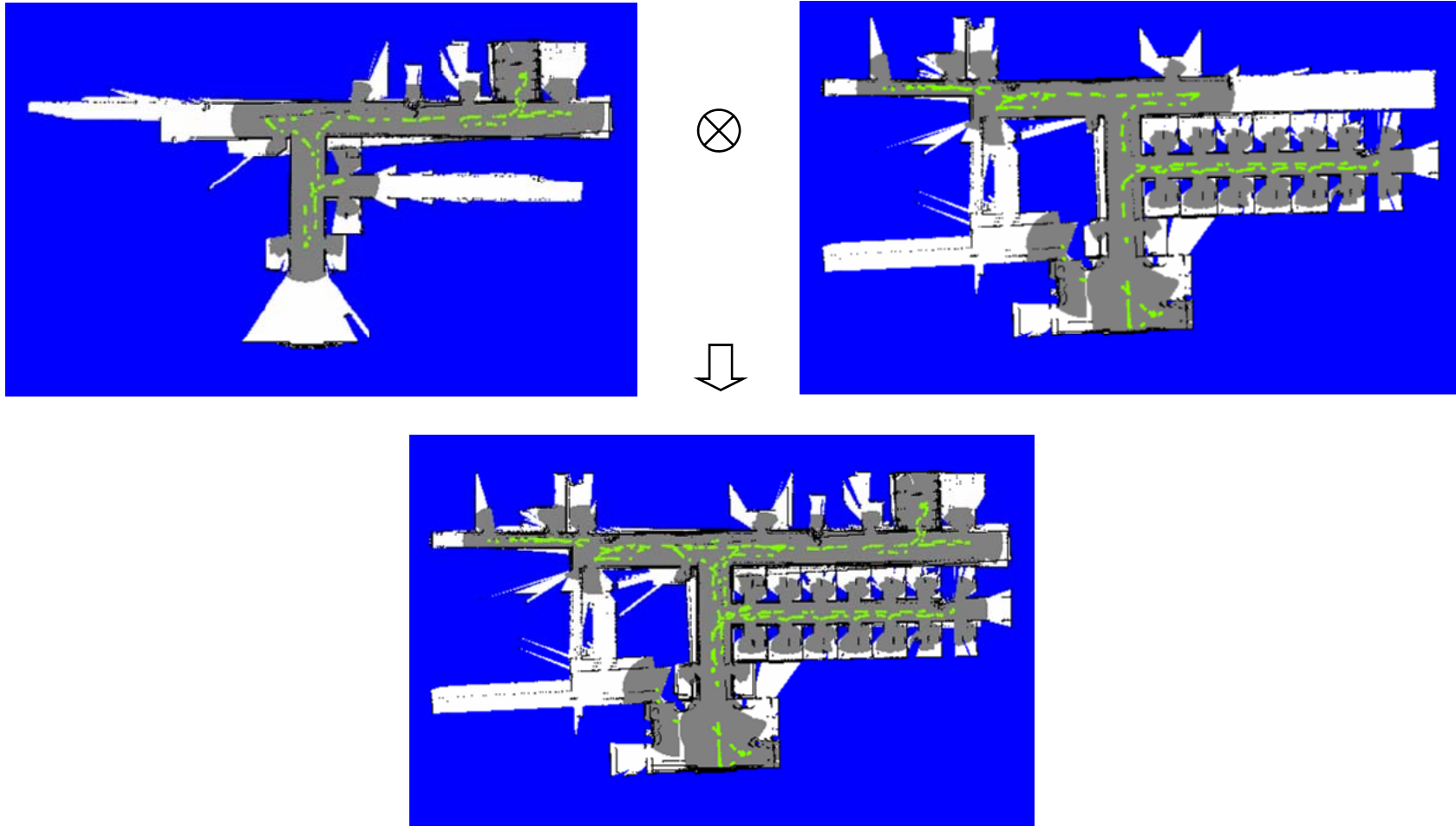


not share their map (535 m2, 3 victims), shared (531 m2, 3 victims)

# Lesson learnt

- With shared maps less area is explored multiple times
- More information is collected in the outer regions, outside the direct communication range.
- More exploration, also means more navigation hazards

# Improved navigation



Shared map (879 m<sup>2</sup>, 5 victims)

# Conclusion

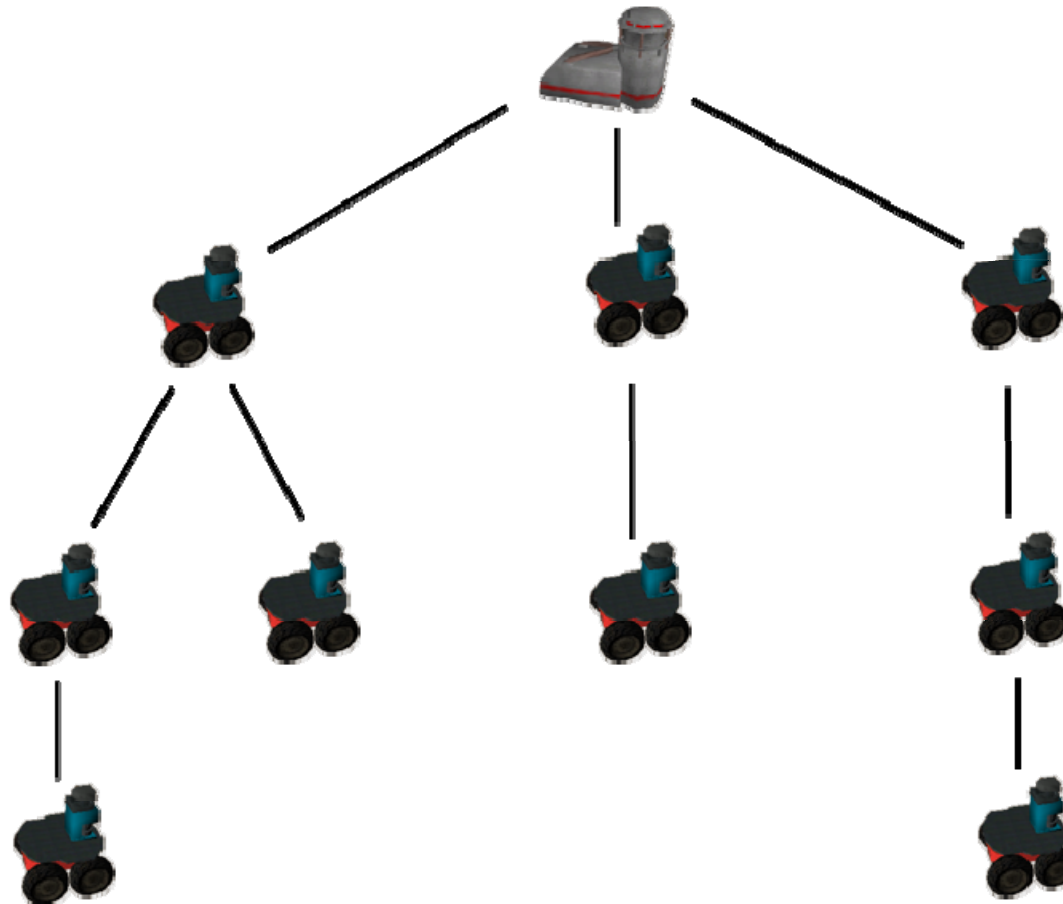
- An exploration algorithm is introduced that includes the probability of communication success in the utility-function
- In a number of experiments, the need to include this probability inside the planning of multi-robot exploration is demonstrated.

# Discussion

- Planning far ahead makes it difficult to estimate the probability of communication success at that distance
- Planning less far ahead could be beneficial for the communication, but not for the exploration
- We had hoped that exploration outside the communication range would occur for both robots at the same time, and that both robots could benefit from each other efforts.
- The limited number of experiments indicates that our hope about the timing could be correct.
- Yet, typically the robots are not near at that moment, so there is no guarantee that both robots could benefit from each other.

# Planned Cooperation

**Assistant communication relay roles have to be planned:**





# Conclusion

- An exploration algorithm is introduced that includes the probability of communication success in the utility-function
- In a number of experiments, the need to include this probability inside the planning of multi-robot exploration is demonstrated.



Tele-operation



RoboCup Brazil Open 2008

Fully autonomous