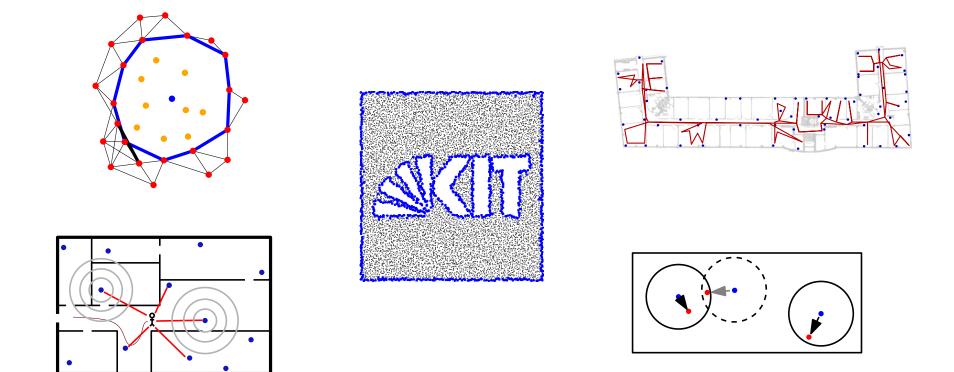
### Scheduling, Boundary Detection, and Localization in Wireless Networks



#### Markus Völker April 20, 2011

Markus Völker · Scheduling, Boundary Detection, and Localization in Wireless Networks Distributed Computing Seminar - April 20, 2011



Institut für Theoretische Informatik Algorithmik I

### About me...



PhD student at Institute for Theoretical Informatics at KIT
 Algorithmics Group (Prof. Dorothea Wagner)



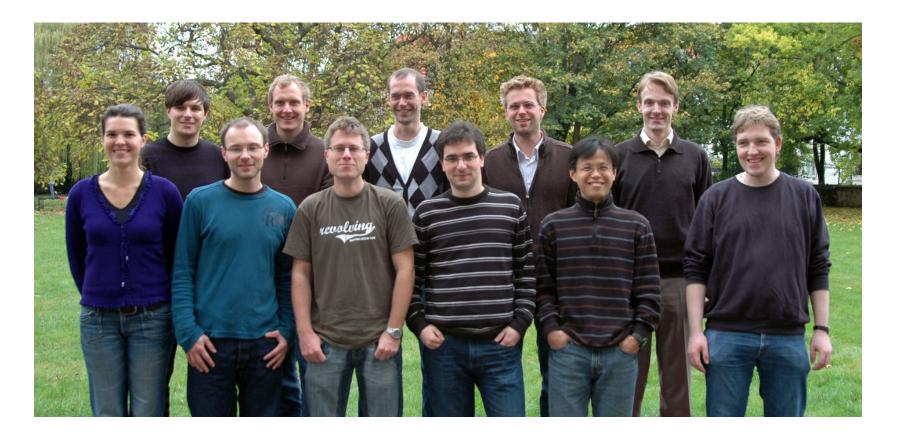


### About me...



Member of DFG Research Training Group 1194

Self-organizing Sensor Actuator Networks



Markus Völker · Scheduling, Boundary Detection, and Localization in Wireless Networks Distributed Computing Seminar - April 20, 2011



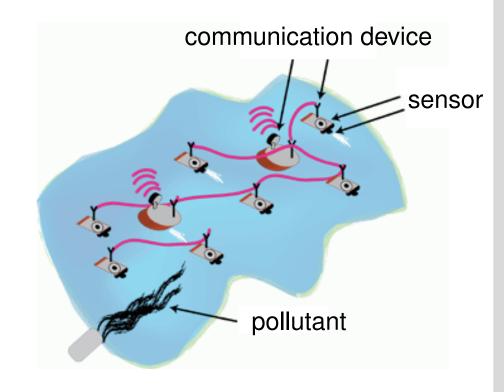
Institut für Theoretische Informatik Algorithmik I

### About me...



#### Research Area: Algorithms for Wireless Sensor Networks

- Wireless Communication
- Localization

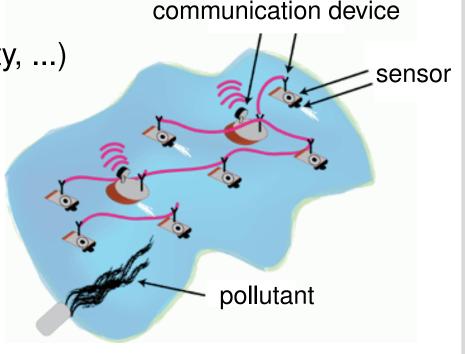




### **About Sensor Networks...**



- Research Area: Algorithms for Wireless Sensor Networks
  - Wireless Communication
  - Localization
- Sensor network
  - network of small devices
  - equipped with sensors
  - collect data (temperature, humidity, ...)
  - communicate with each other
- Applications
  - detection of forest fires
  - intrusion detection
  - automatic watering of fields
  - pollutant detection





## (joint work with Bastian Katz)

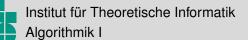
Boundary Detection in Wireless Networks (joint work with Dennis Schieferdecker)

Scheduling of Wireless Transmissions

Localization in Wireless Networks

(joint work with Johannes Schmid)

### **Topics of Today's Talk**











## Schoduling of Miroloss Transm

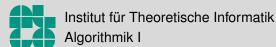
**Topics of Today's Talk** 

Scheduling of Wireless Transmissions (joint work with Bastian Katz)

Boundary Detection in Wireless Networks (joint work with Dennis Schieferdecker)

Localization in Wireless Networks (joint work with Johannes Schmid)

#### Focus on main ideas, details are omitted



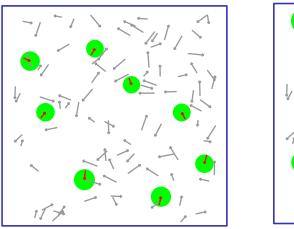


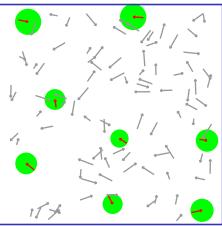












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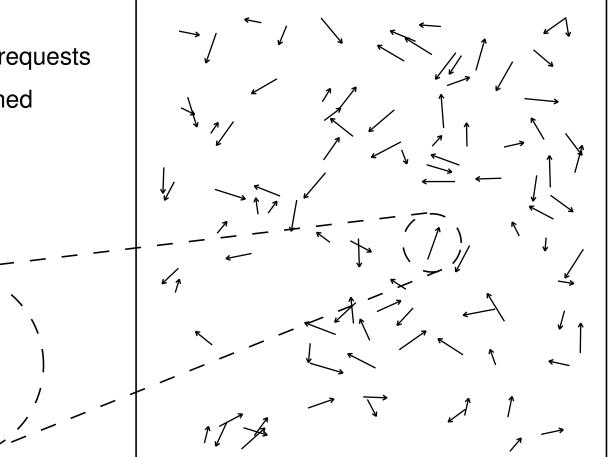


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Given:

- Set  ${\mathcal T}$  of wireless transmission requests
- Transmission  $t = (s_t, r_t)$  is defined by sender  $s_t$  and receiver  $r_t$

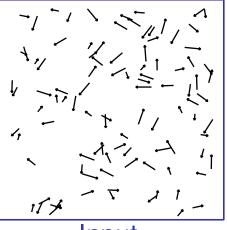




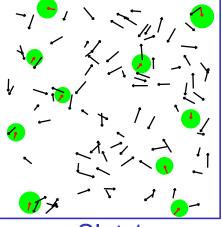


#### Given:

- Set  ${\mathcal T}$  of wireless transmission requests
- Transmission  $t = (s_t, r_t)$  is defined by sender  $s_t$  and receiver  $r_t$



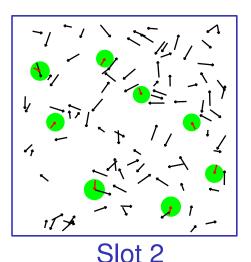
Input

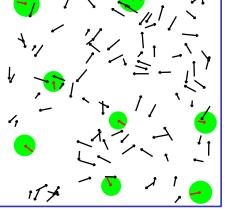


Slot <sup>•</sup>

#### Goal:

- Distribution of transmissions to time slots (TMDA schedule)
- No failures due to interference
- Minimum number of slots





Slot 3

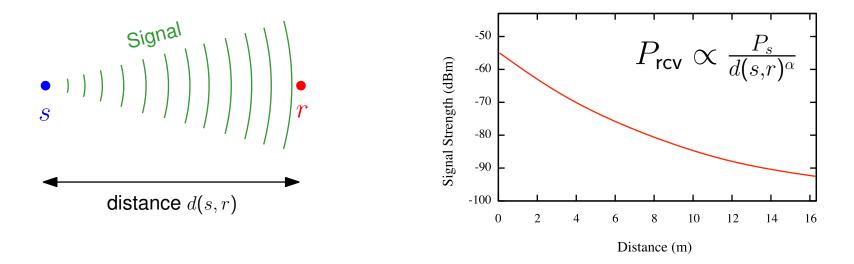








How do we know whether a transmission is successful?

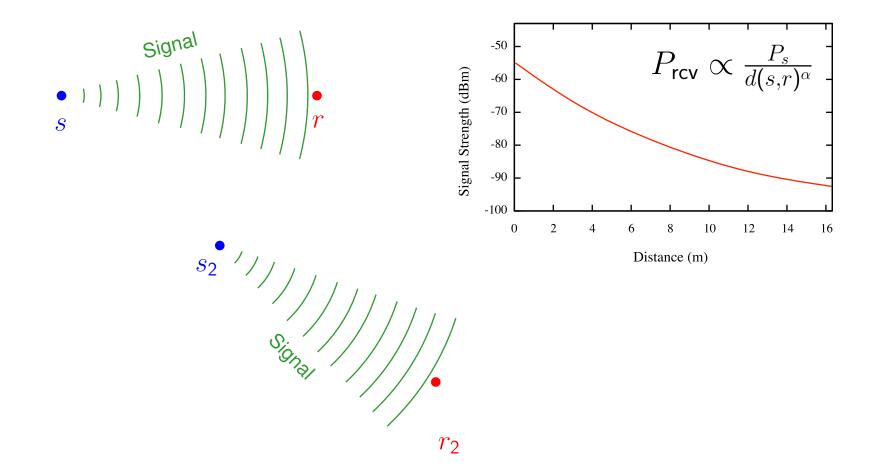


Received signal strength depends on distance between s and r

- Distance dependence is given by a power law
- Path loss exponent  $\alpha$  defines how fast the signal decays ( $\approx$  2 in free space, between 2 and 5 in buildings)

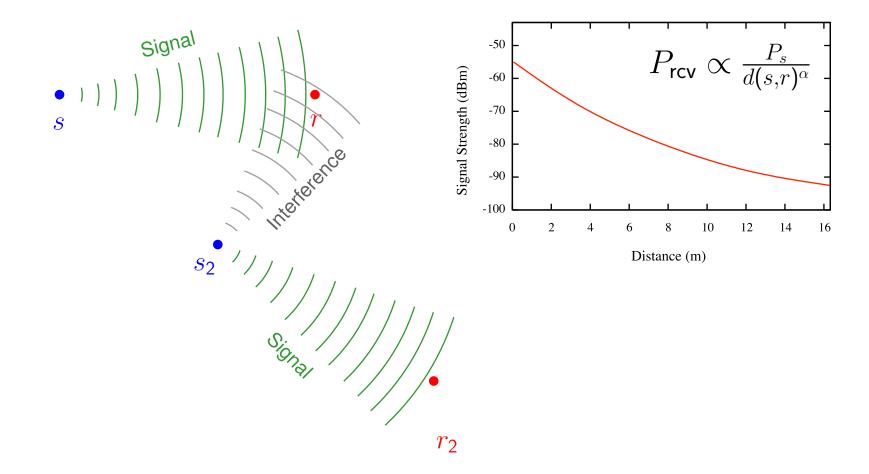


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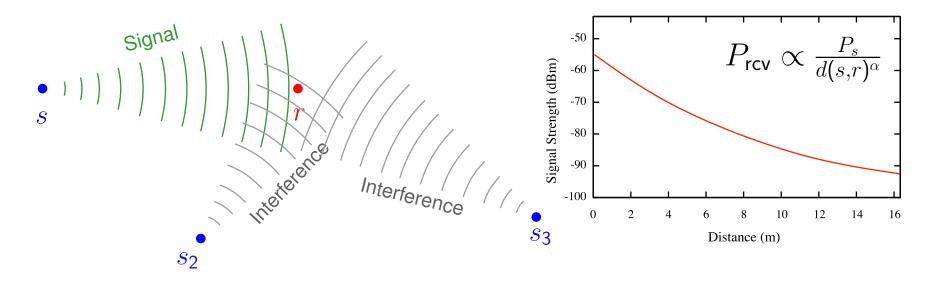




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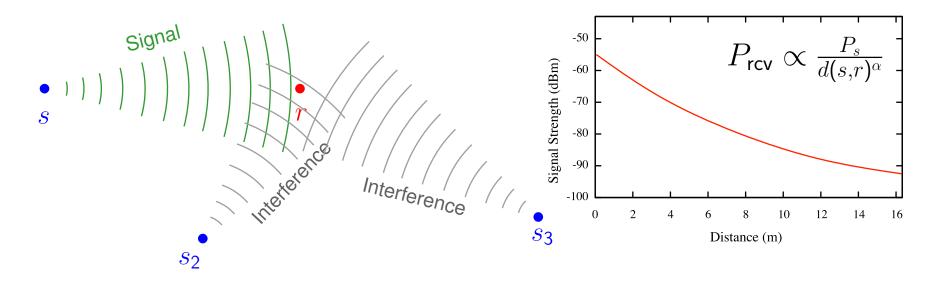








How do we know whether a transmission is successful?



Transmission is successful if SINR exceeds some threshold  $\beta$ 

$$\frac{\text{Signal}}{\sum \text{Interferences + Background Noise}} \geq \beta \qquad (\beta \approx$$

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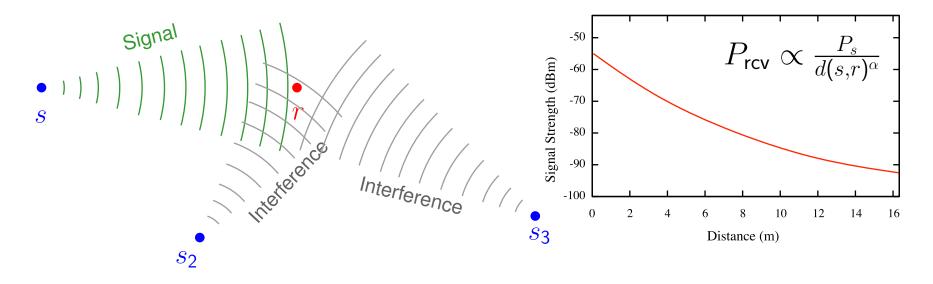
10)





#### **Problem Definition**

Geometric SINR model (SINR<sub>G</sub> model)



Transmission is successful if SINR exceeds some threshold  $\beta$ 

$$\frac{\text{Signal}}{\sum \text{Interferences + Background Noise}} \geq \beta \qquad (\beta \approx$$

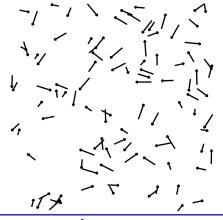
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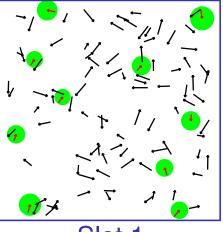
10)



# SINR condition has to be fulfilled!

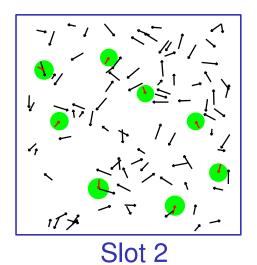


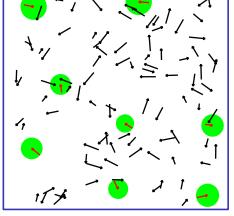
Input



Slot 1

 $\frac{\text{Signal}}{\text{Interference + Background Noise}} \geq \beta$ 





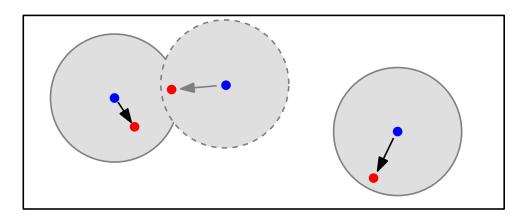
Slot 3



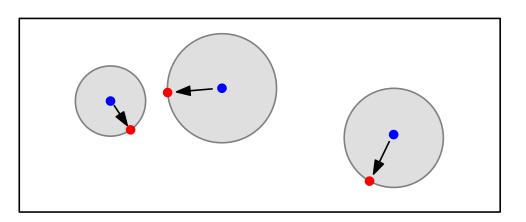


#### **Problem Variants**

Scheduling with fixed transmission powers



Scheduling with power control



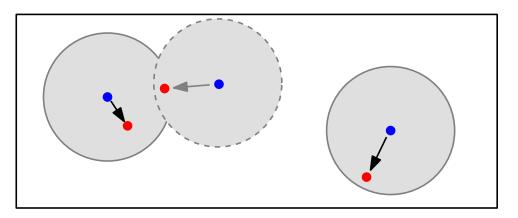


### Transmission Scheduling Complexity



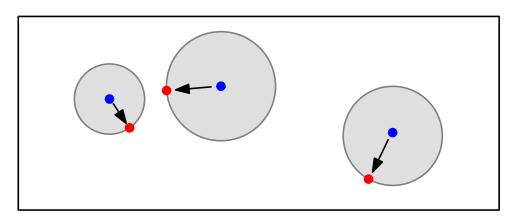
Scheduling with fixed transmission powers

NP-hard (Goussevskaia, Oswald, Wattenhofer, 2007)



Scheduling with power control

#### NP-hard if powers are bounded (Katz, Völker, Wagner, 2009)







**Possible Approaches** 

- Exact solutions for small instances
- Heuristics
- Approximation algorithms
- Randomized algorithms with collision detection





#### **Possible Approaches**

- Exact solutions for small instances
  - Constraint Programming (CP)
  - Integer Linear Programming (ILP)
  - only up to pprox 100 transmissions
- Approximation algorithms
  - Scheduling with local information

#### Heuristics

Heuristic for scheduling with power control





#### Heuristic for Scheduling with Power Control

Usual approach of existing methods

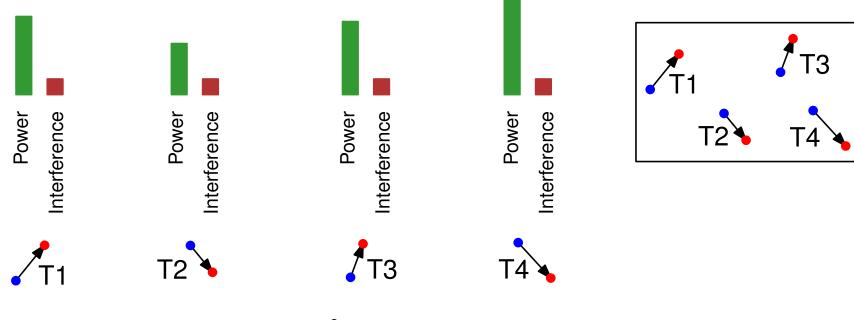
- sort transmissions according to some measure (e.g., sender-receiver-distance or link gain)
- fill time slots greedily
- as soon as a slot is filled, open another slot
- to decide whether a transmission fits into a time slot, use an iterative method for power control





#### Heuristic for Scheduling with Power Control

Iterative Power Control



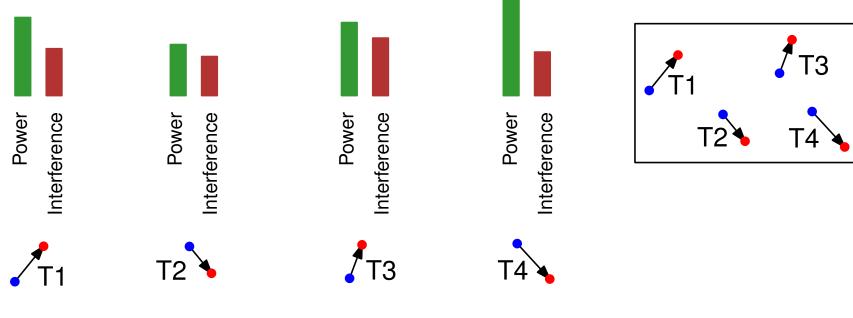
Complexity:  $O(c \cdot n^2)$ , with  $c \approx 20$  number of iterations





### Heuristic for Scheduling with Power Control

Iterative Power Control



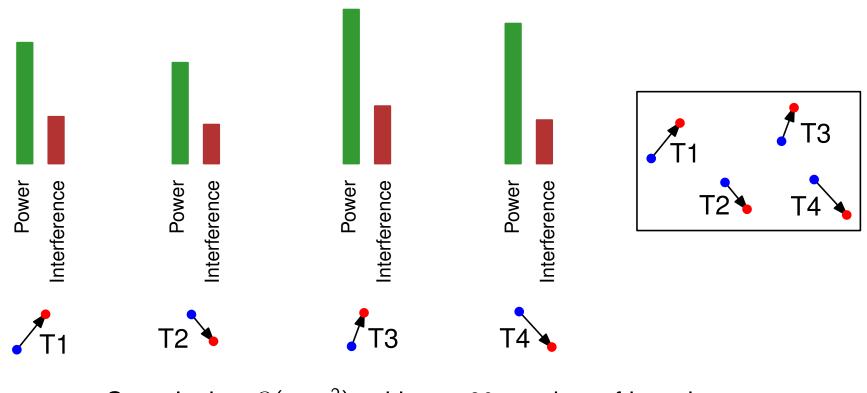
Complexity:  $O(c \cdot n^2)$ , with  $c \approx 20$  number of iterations





#### Heuristic for Scheduling with Power Control

**Iterative Power Control** 



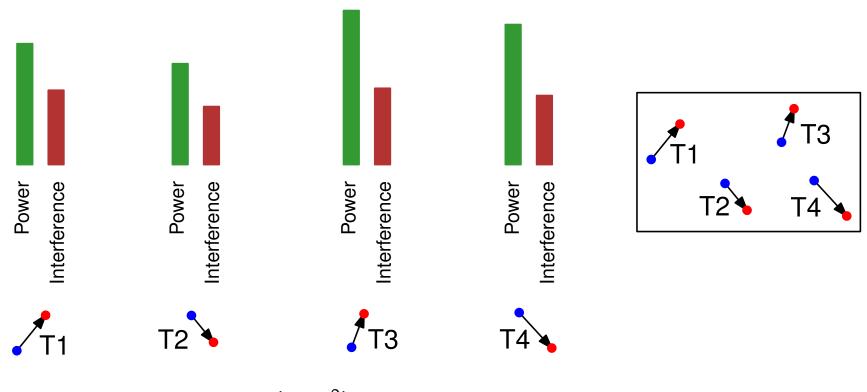
Complexity:  $O(c \cdot n^2)$ , with  $c \approx 20$  number of iterations





#### Heuristic for Scheduling with Power Control

**Iterative Power Control** 



Complexity:  $O(c \cdot n^2)$ , with  $c \approx 20$  number of iterations





#### Heuristic for Scheduling with Power Control

Our approach

- fill several slots simultaneously
- do not add the transmissions in fixed order but choose always the transmission which fits best (= transmissions which minimizes additional power)
- requires frequent updates of transmission powers
  better solution to power control problem necessary

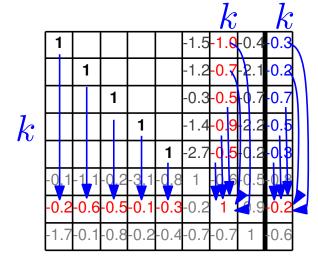


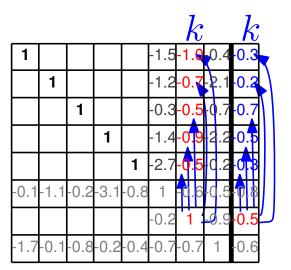


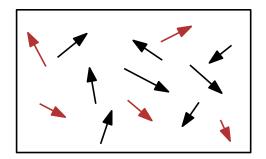
#### Heuristic for Scheduling with Power Control

New method for efficient power control

1					-1.5	-1.0	-0.4	-0.3
	1				-1.2	-0.7	-2.1	-0.2
		1			-0.3	-0.5	-0.7	-0.7
			1		-1.4	-0.9	-2.2	-0.5
				1	-2.7	-0.5	-0.2	-0.3
-0.1	-1.1	-0.2	-3.1	-0.8	1	-0.6	-0.5	-0.8
-0.2	-0.6	-0.5	-0.1	-0.3	-0.2	1	-0.9	-0.2
-1.7	-0.1	-0.8	-0.2	-0.4	-0.7	-0.7	1	-0.6







 $\boldsymbol{k}$  active transmissions

Prediction of optimal transmission powers in O(k) time instead of  $O(ck^2)$  time.

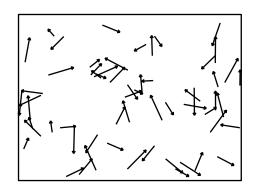
 $\Rightarrow$  better heuristics with same time complexity

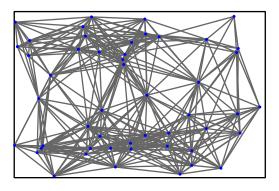


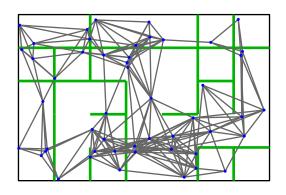


### Heuristic for Scheduling with Power Control Simulation results

- up to 50% higher throughput than existing approaches
- same throughput with transmission power savings of about 30%
- same time complexity as existing approaches thanks to new power control algorithm







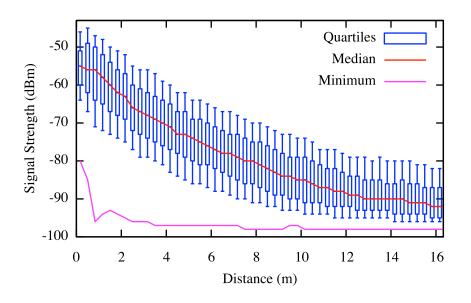




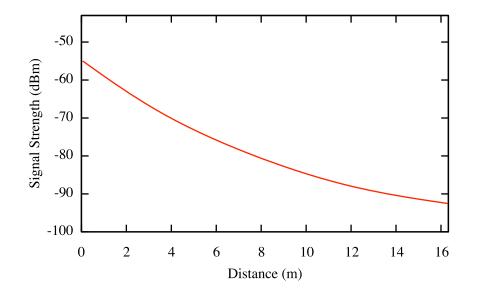


#### Shortcomings of the SINR<sub>G</sub> model

#### Comparison with Reality



Measurement in 60 node sensor network (based on 300.000 packets)



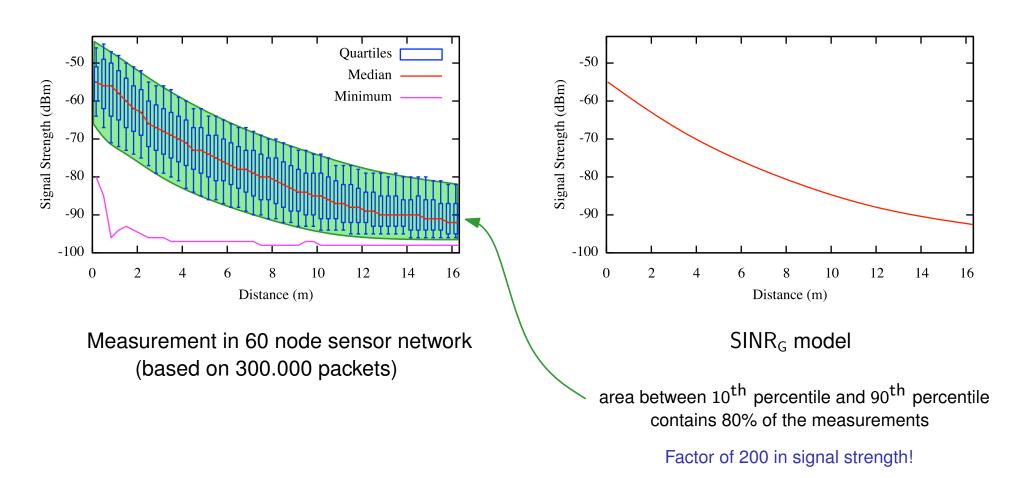
SINR<sub>G</sub> model





#### Shortcomings of the SINR<sub>G</sub> model

#### Comparison with Reality



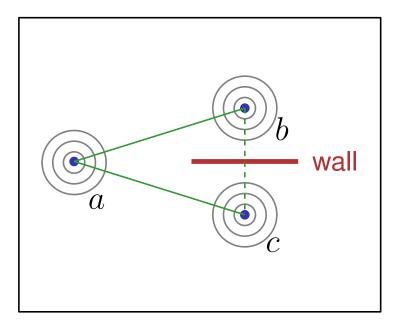




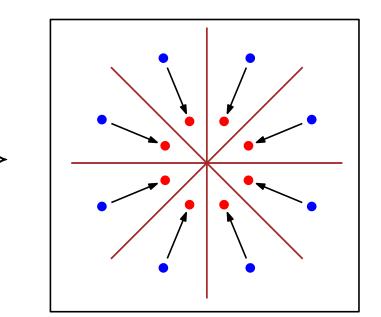


#### Shortcomings of the SINR<sub>G</sub> model

Problems



Individual walls cannot be modeled

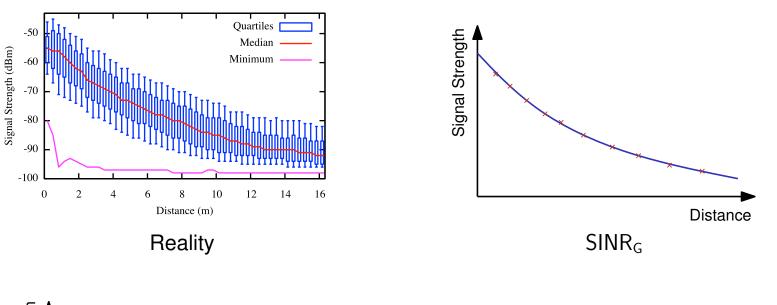


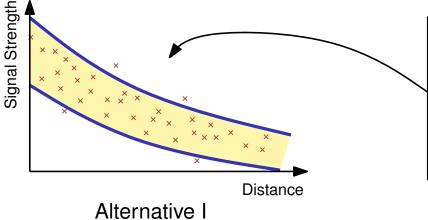
Can make results arbitrarily bad

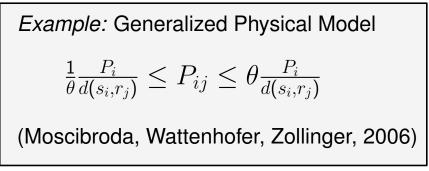




#### Possible alternatives



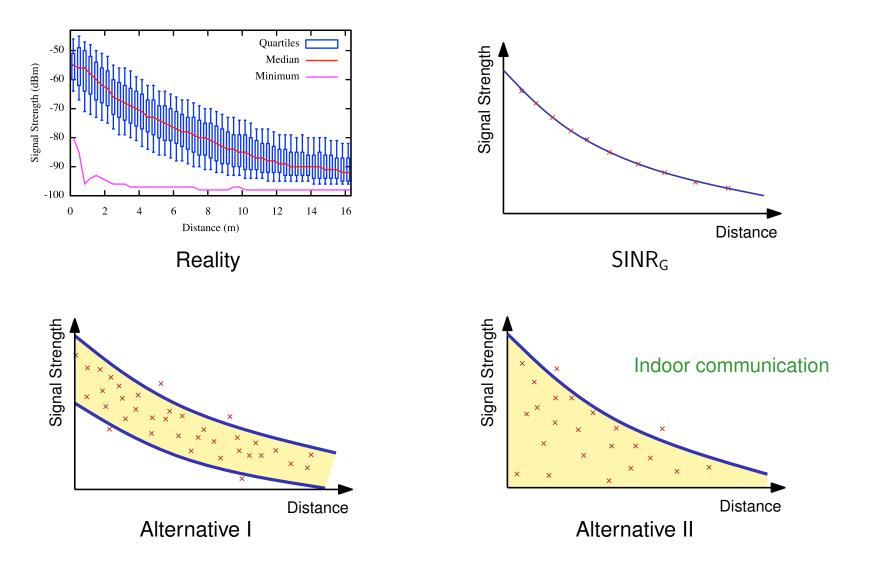


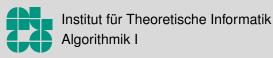






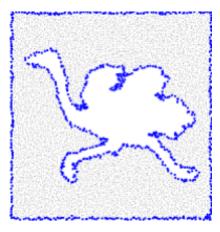
#### Possible alternatives







### **Boundary Detection**



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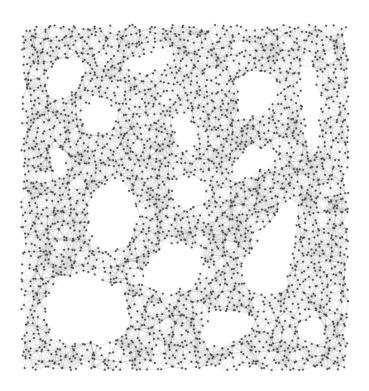


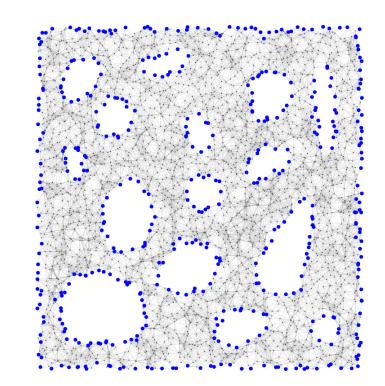
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### **Boundary Detection** Problem Definition



- Recognition of holes and boundaries in WSNs
  - no knowledge about node positions
  - using only connectivity information





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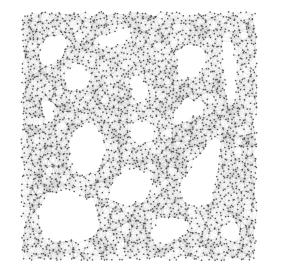


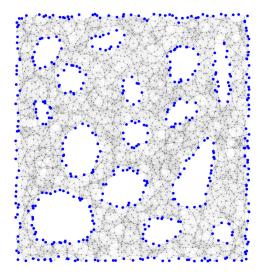
#### **Problem Definition**

- Recognition of holes and boundaries in WSNs
  - no knowledge about node positions
  - using only connectivity information

#### Motivation

- detection of areas of insufficient coverage
- efficient routing
- load balancing

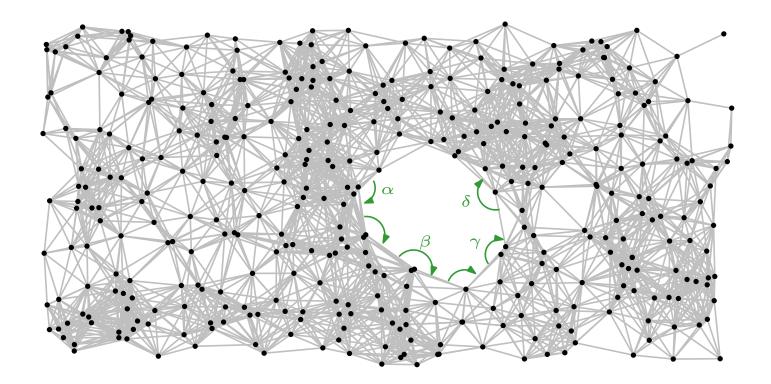






## **Boundary Detection** Existing Approaches

- Geometrical Approaches
  - use information about node positions, distances, or angular relationships





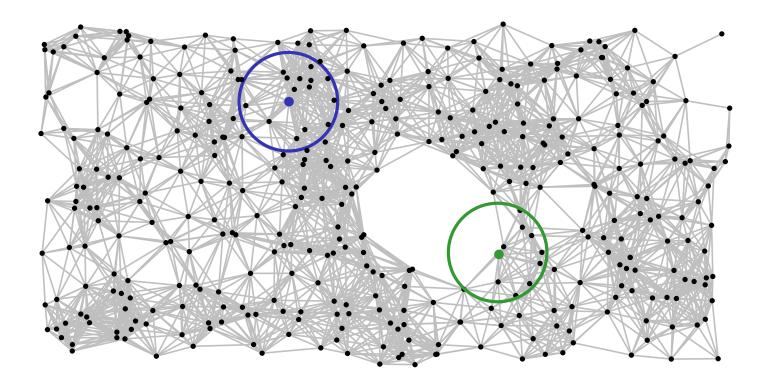


### **Boundary Detection** Existing Approaches



#### Statistical Approaches

use statistical properties such as low node degree, etc.

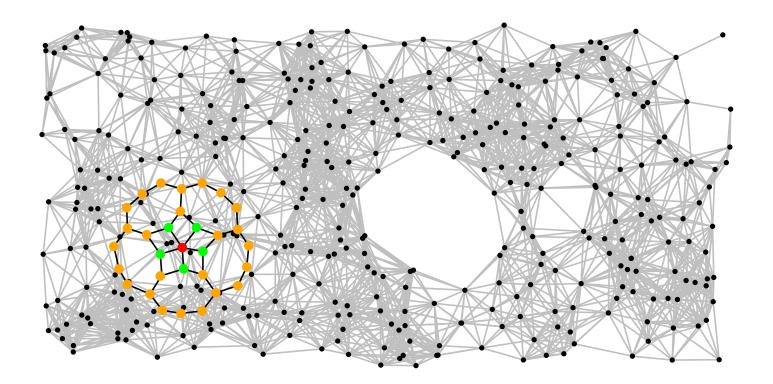






#### Existing Approaches

- Topological Approaches
  - use topological structure of connectivity graph







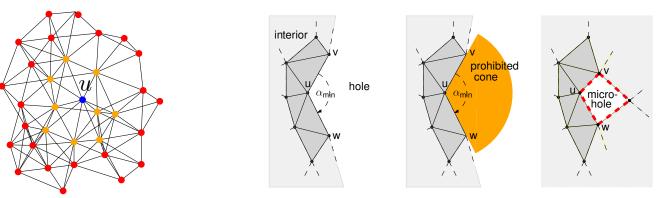
### **Boundary Detection** Design Goals

- simple (easy to understand and implement)
- only connectivity information
- Iittle communication ( $\Rightarrow$  dynamic networks)
- fast computation ( $\Rightarrow$  sensor networks)
- stable with respect to different
  - node degrees
  - node distributions
  - communication models

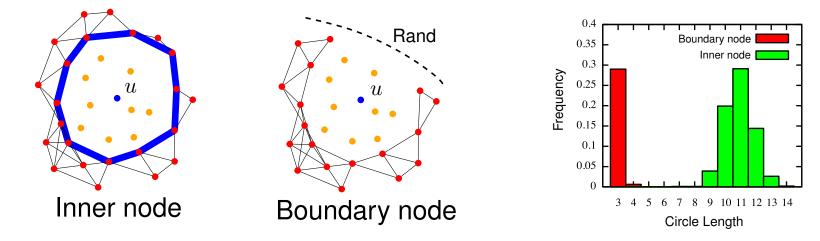


## **Boundary Detection** 2 New Methods

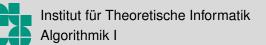
Multidimensional Scaling Boundary Recognition (MDS-BR)



Enclosing Circle Boundary Recognition (EC-BR)



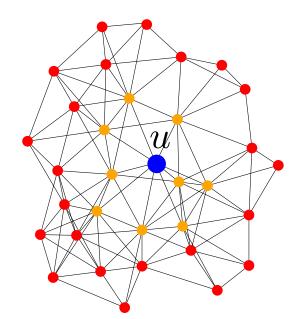
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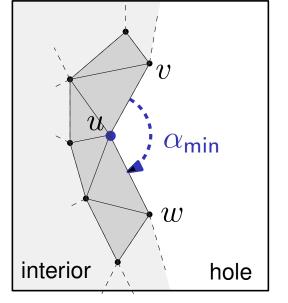


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### Multidimensional Scaling Boundary Recognition Basic Idea





# Estimate relative positions of 2-hop neighborhood

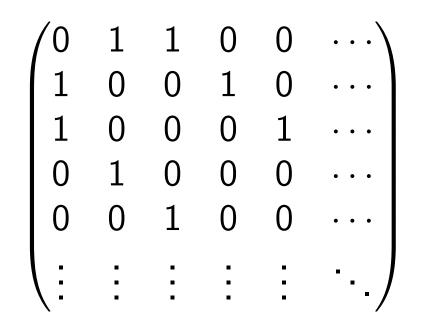
Check some angular conditions



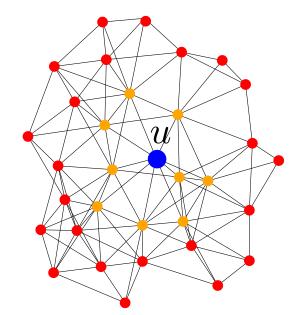


#### Multidimensional Scaling Boundary Recognition

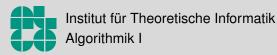
1<sup>st</sup> step: get connectivity information of 2-hop neighborhood



Adjacency matrix of 2-hop neighborhood



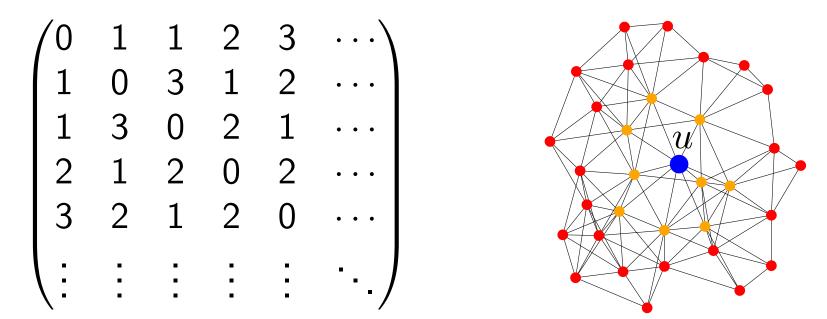
#### (2 messages per node)





#### Multidimensional Scaling Boundary Recognition

2<sup>nd</sup> step: approximate real distances by hop-distances



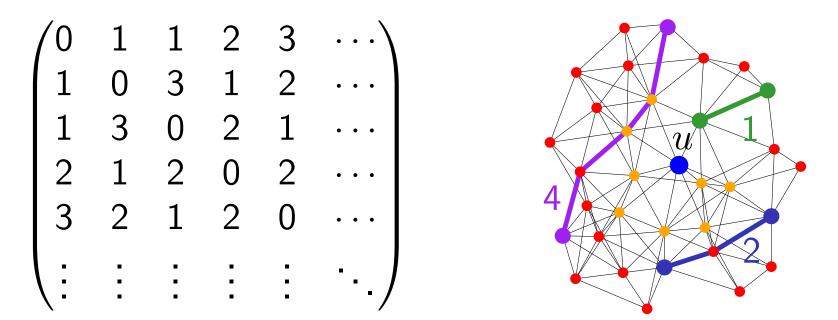
Hop-distance matrix of 2-hop neighborhood





#### Multidimensional Scaling Boundary Recognition

2<sup>nd</sup> step: approximate real distances by hop-distances



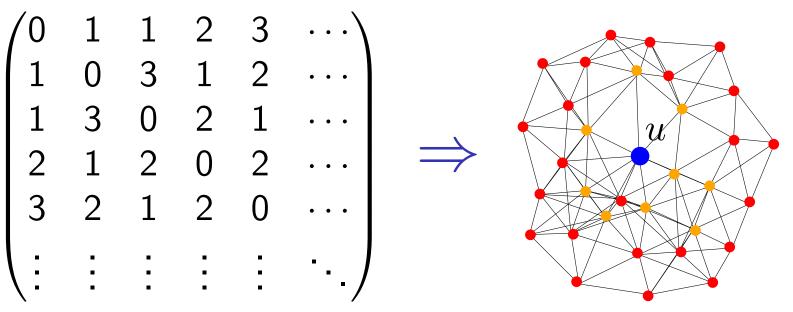
Hop-distance matrix of 2-hop neighborhood





#### Multidimensional Scaling Boundary Recognition

3<sup>rd</sup> step: use MDS to compute embedding from hop-distances



Hop-distance matrix of 2-hop neighborhood

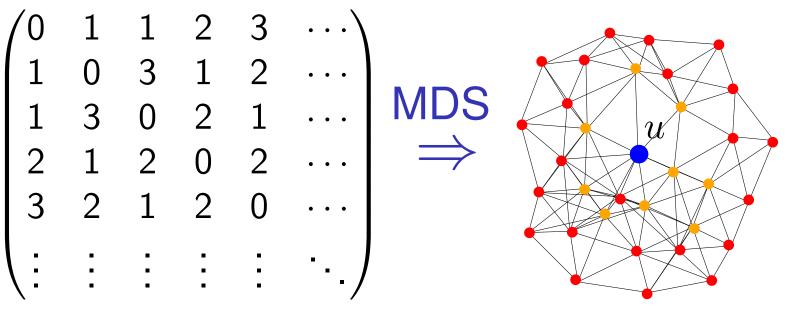
Estimated relative node positions





#### Multidimensional Scaling Boundary Recognition

3<sup>rd</sup> step: use MDS to compute embedding from hop-distances



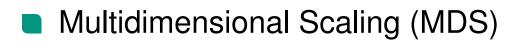
Hop-distance matrix of 2-hop neighborhood

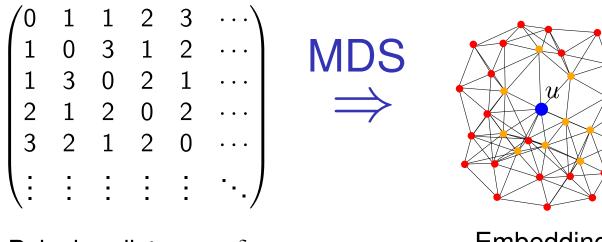
Estimated relative node positions





#### Multidimensional Scaling Boundary Recognition





Pairwise distances  $\delta_{ij}$ 

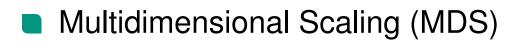
Embedding  $\{x_1, ..., x_n\}$ 

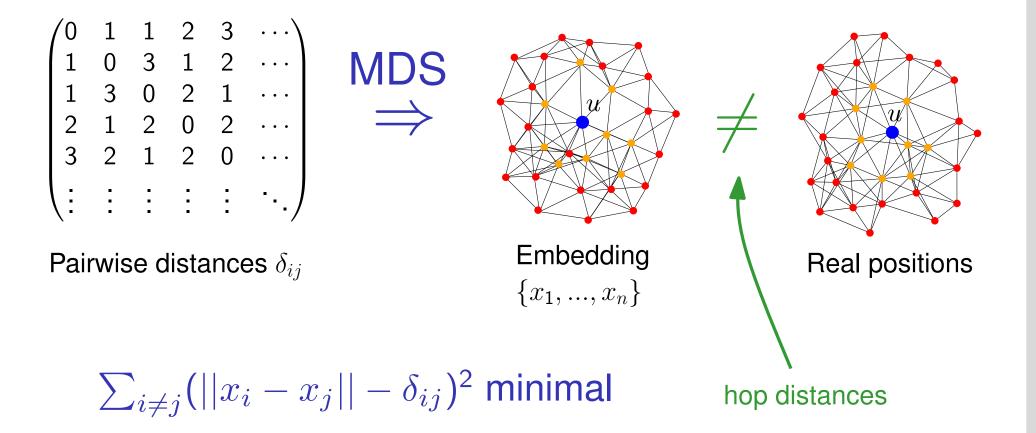
$$\sum_{i \neq j} (||x_i - x_j|| - \delta_{ij})^2$$
 minimal





#### Multidimensional Scaling Boundary Recognition



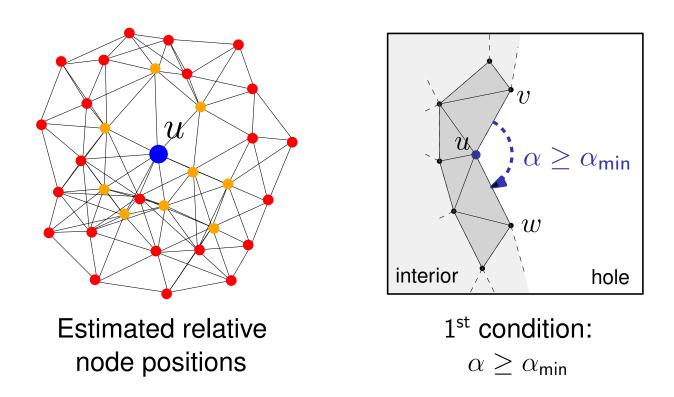






#### Multidimensional Scaling Boundary Recognition

4<sup>th</sup> step: check angular conditions on computed embedding

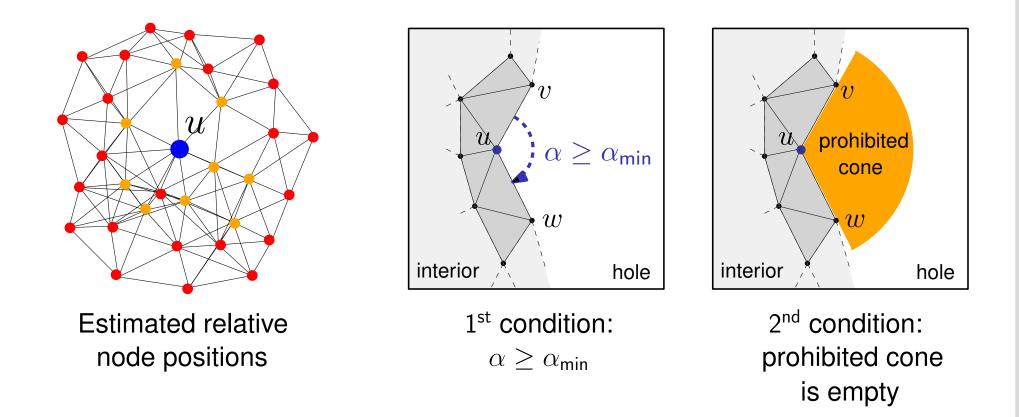






#### Multidimensional Scaling Boundary Recognition

4<sup>th</sup> step: check angular conditions on computed embedding

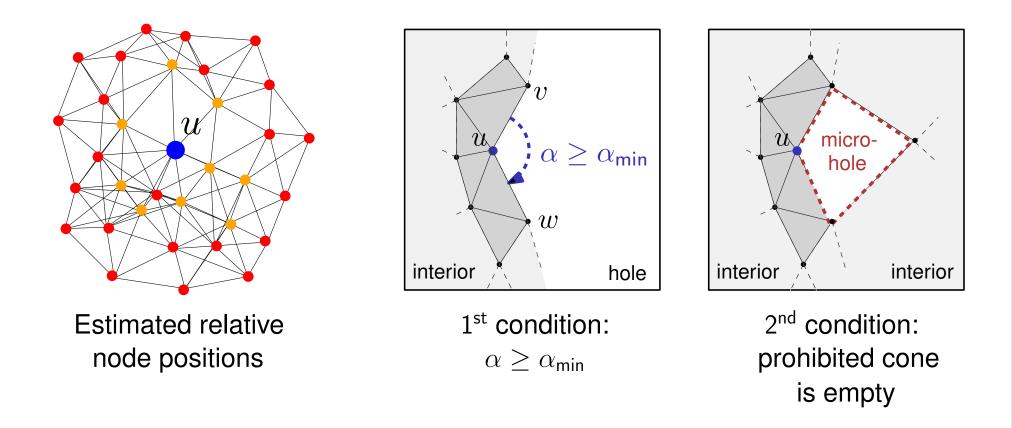






#### Multidimensional Scaling Boundary Recognition

4<sup>th</sup> step: check angular conditions on computed embedding

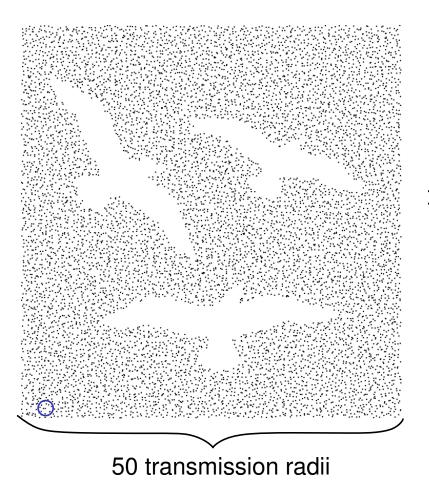


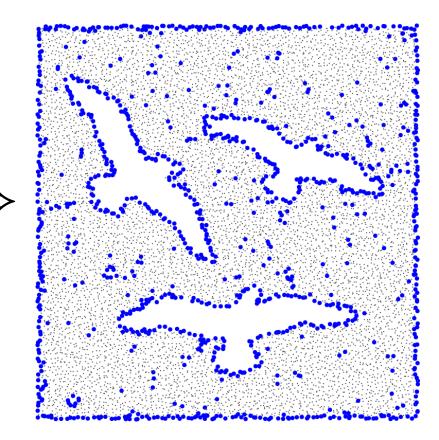




#### Multidimensional Scaling Boundary Recognition

#### Example





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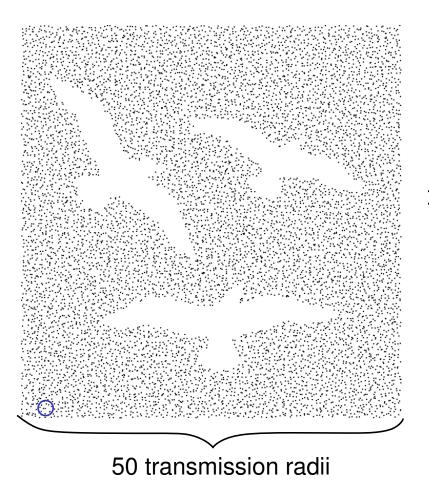


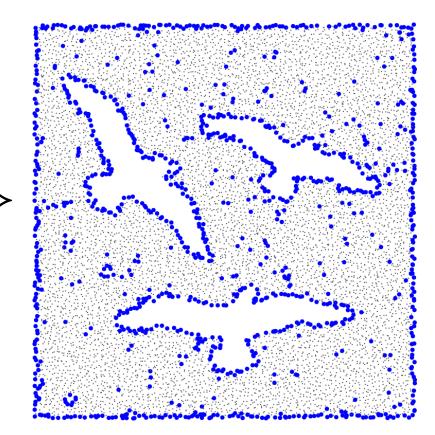
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#### Multidimensional Scaling Boundary Recognition

#### Example





#### $\text{noisy} \Rightarrow \text{filtering step}$

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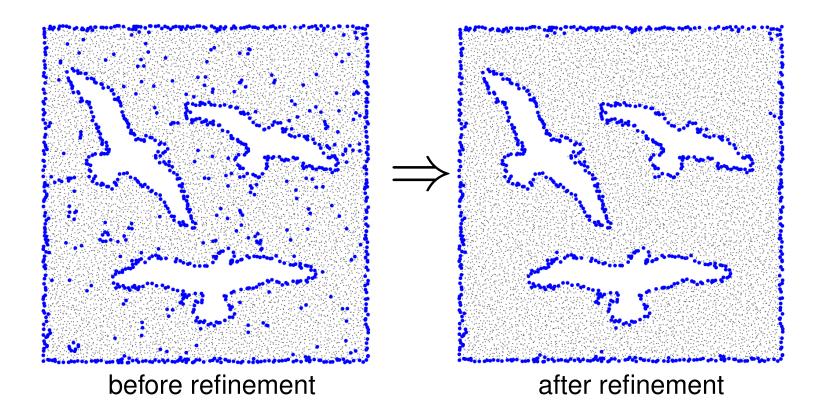


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#### Multidimensional Scaling Boundary Recognition

5<sup>th</sup> step: Refinement

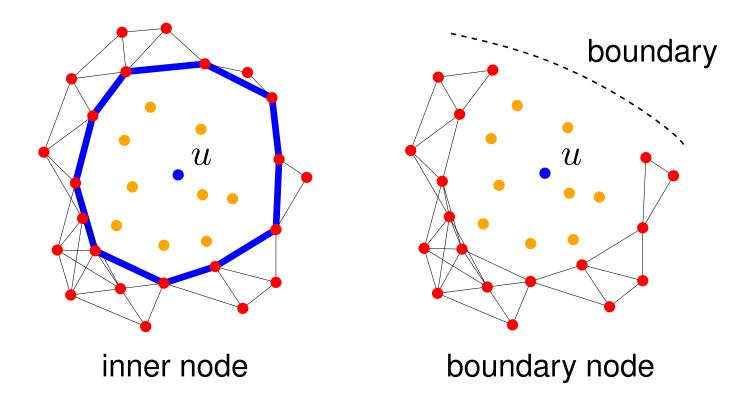


#### reclassify isolated nodes





Enclosing Circle Boundary Recognition (EC-BR) Basic Idea



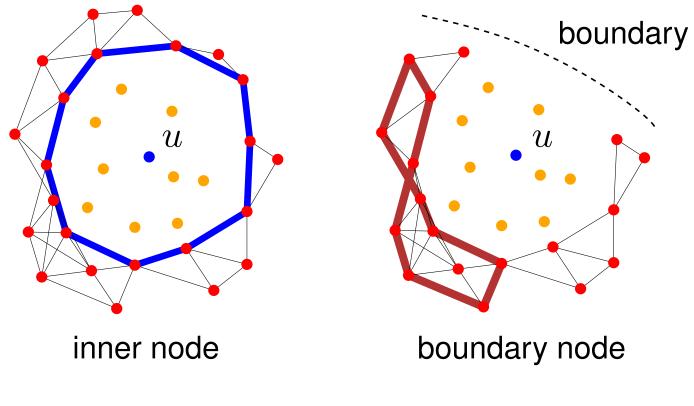
Node checks wheter it is surrounded by a closed circle

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Enclosing Circle Boundary Recognition (EC-BR) Basic Idea



Problem: how to detect enclosing circles?

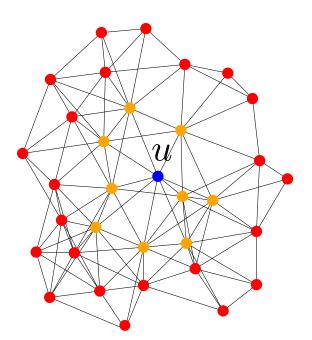
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### Enclosing Circle Boundary Recognition (EC-BR)

1<sup>st</sup> step: collect information about 2-hop neighborhood



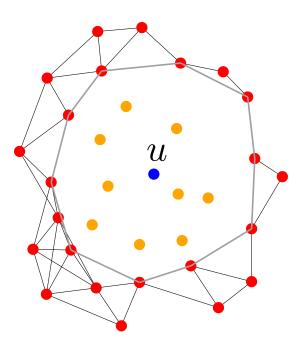
(2 messages per node)





#### Enclosing Circle Boundary Recognition (EC-BR)

2<sup>nd</sup> step: remove 1-hop neighborhood

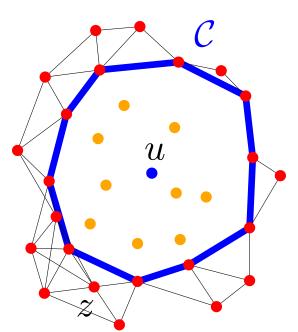




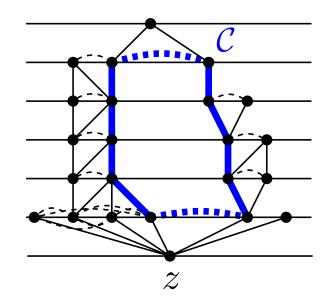


#### Enclosing Circle Boundary Recognition (EC-BR)

3<sup>rd</sup> step: circle detection



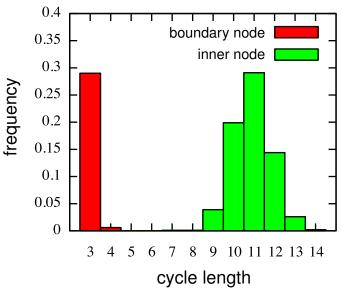
#### Find "tight" cycle of maximum length



modified breadth-first search (in  $\mathcal{O}(|E|)$  time)



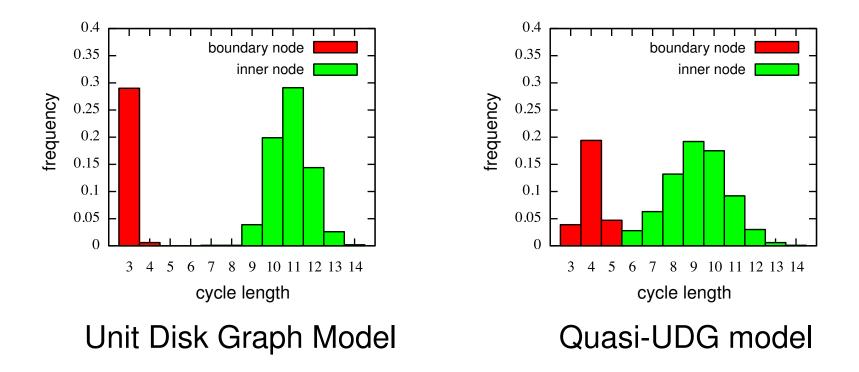
4<sup>th</sup> step: classification according to length of longest cycle found



#### Unit Disk Graph Model

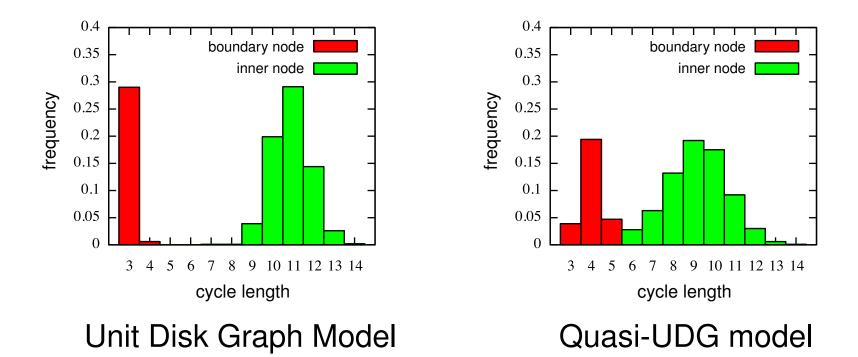


4<sup>th</sup> step: classification according to length of longest cycle found





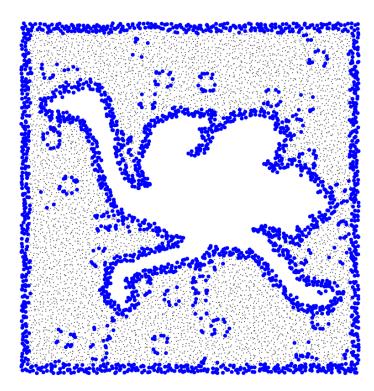
4<sup>th</sup> step: classification according to length of longest cycle found



#### Almost independent of node degree!

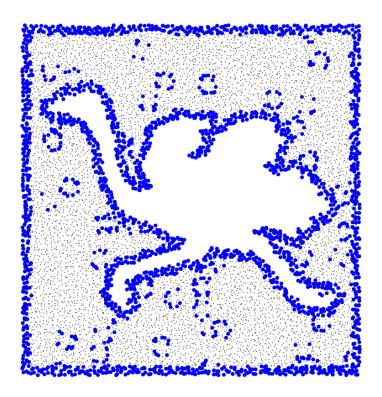


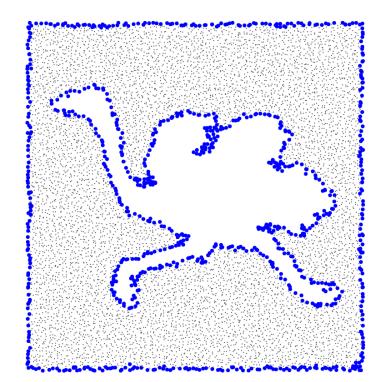
4<sup>th</sup> step: classification according to length of longest cycle found





**5**<sup>th</sup> step: refinement (optional)



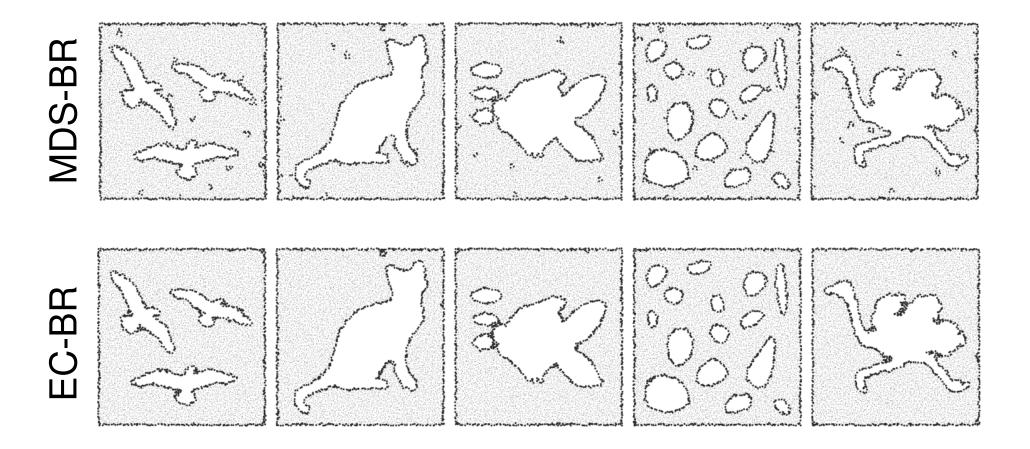


#### reclassify nodes which are not surrounded by other candidates

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### **Boundary Detection** Some examples



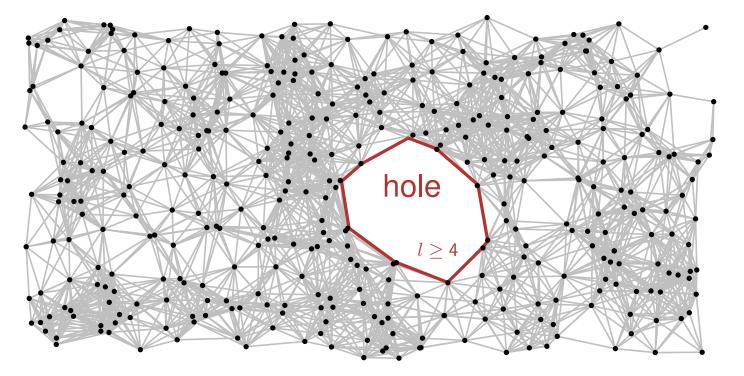
avg. node degree: 12 area: 50x50 transmission radii

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### **Boundary Detection** Quantitative Evaluation Hole Definition



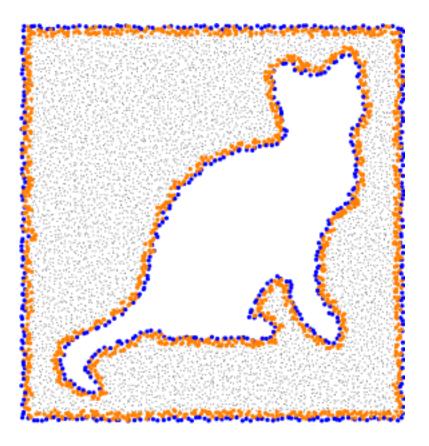
# holes are faces of the connectivity graph with circumference $l \ge 4$

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### **Boundary Detection** Quantitative Evaluation Hole Definition





#### 3 categories

- Mandatory boundary nodes
- Optional boundary nodes
- Inner nodes



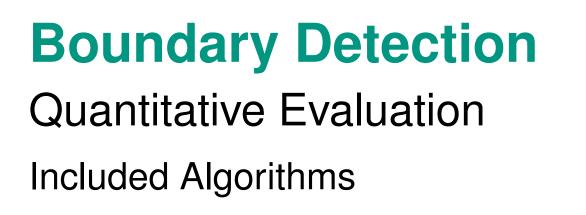


#### Quantitative Evaluation

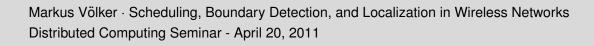
#### Performed Experiments

- network density (avg. degree 9, 12, 15, 18, 21)
- distribution methods (random vs. perturbed grid)
- communication models (UDG, QUDG)
- algorithm variants (e.g., inclusion of signal strength information)
- parameter analysis





- [Fekete, Kröller, Pfisterer, Fischer, Buschmann, 2004]
- [Funke, 2005]
- [Funke, Klein, 2006]
- [Wang, Gao, Mitchell, 2006]
- Saukh, Sauter, Gauger, Marrón, Rothermel, 2010]





In progress



#### **Boundary Detection** Quantitative Evaluation Example: Network Density



	Boundary Nodes					Inner Nodes				
	9	12	15	18	21	9	12	15	18	21
MDS-BR	3.3	3.0	3.7	4.1	4.2	17.3	0.3	0.1	0.1	0.0
EC-BR	4.4	0.4	0.6	1.0	1.3	7.1	0.0	0.0	0.0	0.0
Fekete 04	34.7	14.2	6.7	3.4	1.9	9.8	3.5	7.2	6.9	2.5
Funke 05	16.6	6.3	5.7	5.1	5.0	21.7	3.5	2.0	1.3	0.9
Funke 06	39.7	13.8	16.6	18.9	20.9	13.0	3.4	1.4	0.6	0.3

percentage of false negatives



# **Boundary Detection** Quantitative Evaluation



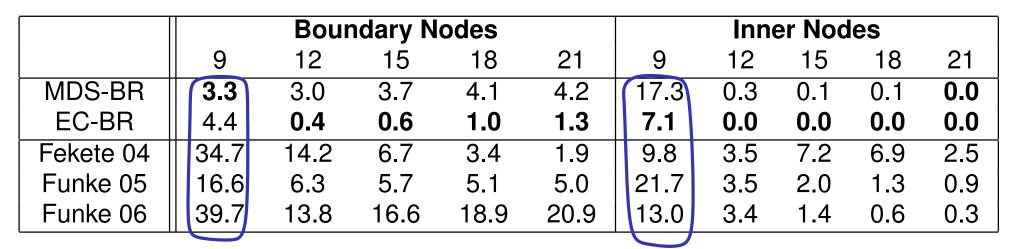
#### Example: Network Density

	Boundary Nodes				Inner Nodes					
	9	12	15	18	21	9	12	15	18	21
MDS-BR	3.3	3.0	3.7	4.1	4.2	17.3	0.3	0.1	0.1	0.0
EC-BR	4.4	0.4	0.6	1.0	1.3	7.1	0.0	0.0	0.0	0.0
Fekete 04	34.7	14.2	6.7	3.4	1.9	9.8	3.5	7.2	6.9	2.5
Funke 05	16.6	6.3	5.7	5.1	5.0	21.7	3.5	2.0	1.3	0.9
Funke 06	39.7	13.8	16.6	18.9	20.9	13.0	3.4	1.4	0.6	0.3

percentage of false negatives



#### **Boundary Detection** Quantitative Evaluation Example: Network Density



percentage of false negatives

all considered algorithms start having problems for avg. degrees below 10



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## **Boundary Detection**



#### Quantitative Evaluation

#### Performed Experiments

- network density (avg. degree 9, 12, 15, 18, 21)
- distribution methods (random vs. perturbed grid)
- communication models (UDG, QUDG)
- algorithm variants (e.g., inclusion of signal strength information)
- parameter analysis

only EC-BR works well with QUDG



## **Boundary Detection**



#### Quantitative Evaluation

#### Performed Experiments

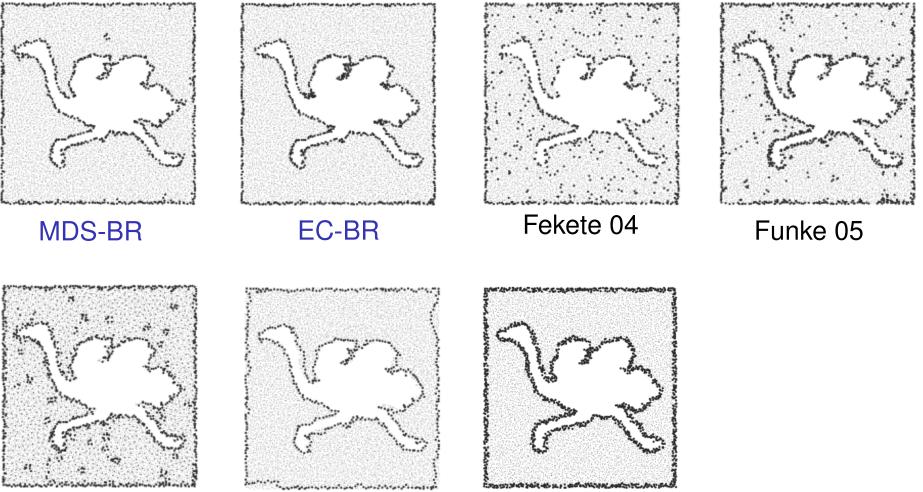
- network density (avg. degree 9, 12, 15, 18, 21)
- distribution methods (random vs. perturbed grid)
- communication models (UDG, QUDG)
- algorithm variants (e.g., inclusion of signal strength information)
- parameter analysis

only EC-BR works well with QUDG

#### Now: visual comparison



# Boundary Detection Comparison with existing approaches



Funke 06

Wang 06

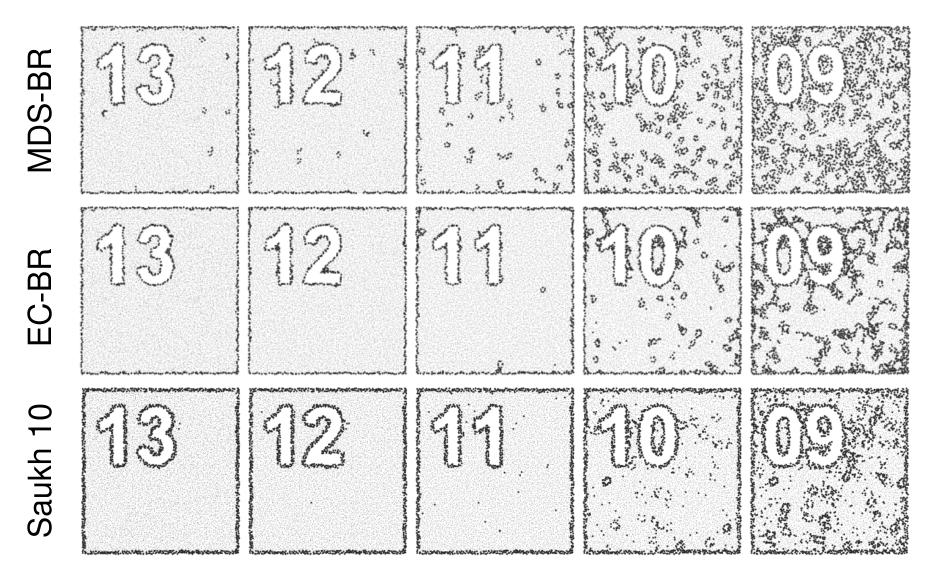


Saukh 10

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(avg. node degree 12)

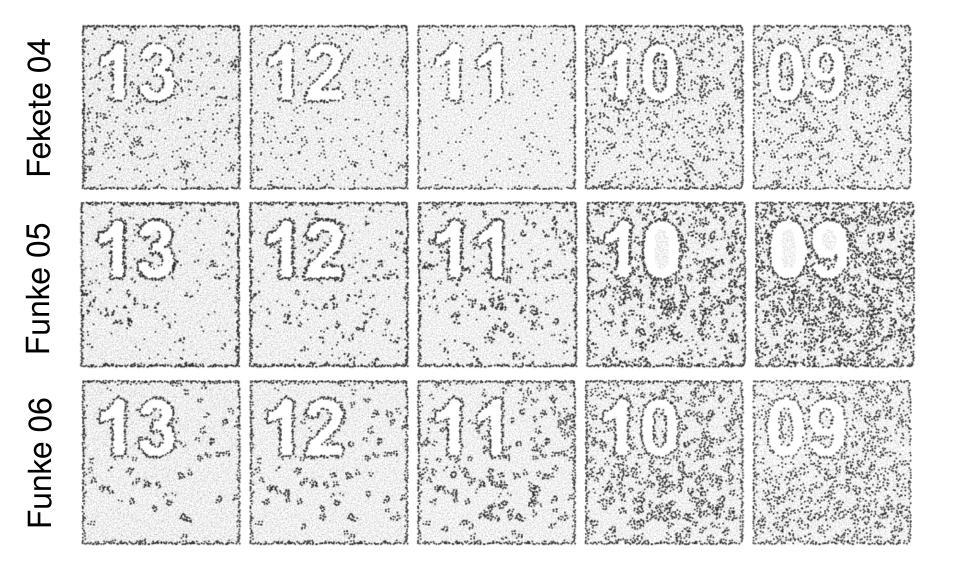
### **Boundary Detection** Effect of node degree







### **Boundary Detection** Effect of node degree





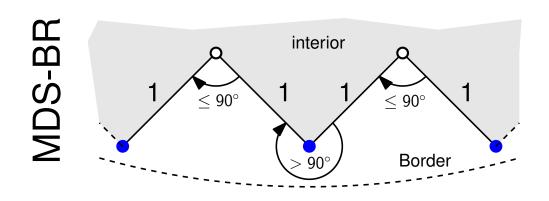


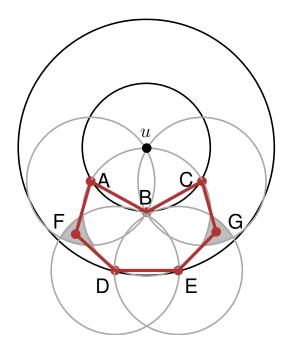
## **Boundary Detection**



#### **Classification Guarantees**

- no guarantees for correct classification
- would require adjusted hole definition or larger comm. radius
- but one can proove that it can go wrong ;-)





#### Happens only rarely for random networks

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EC-BR



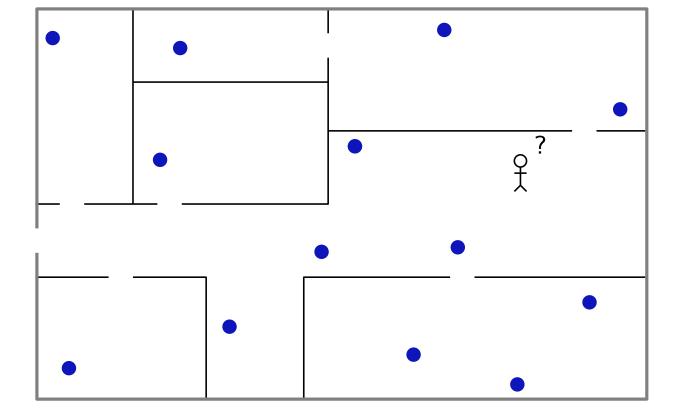
#### **RSS Based Localization**

#### (work in progress, only intermediate results)



#### **RSS Based Localization** Basic Idea

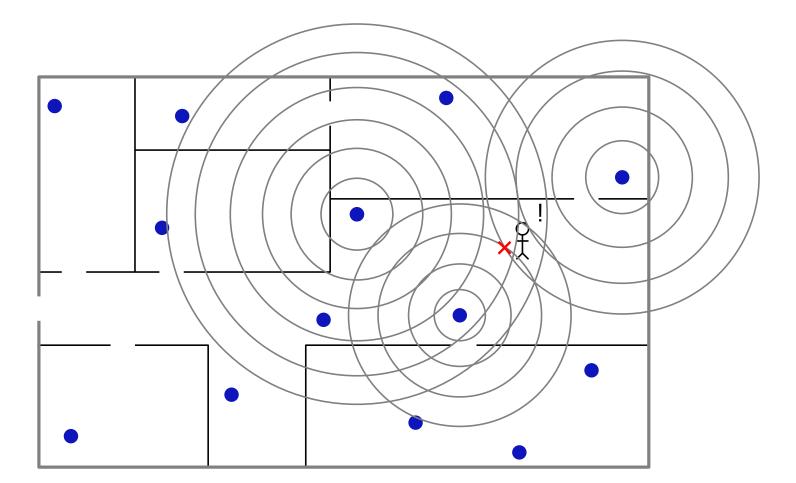






### **RSS Based Localization** Basic Idea

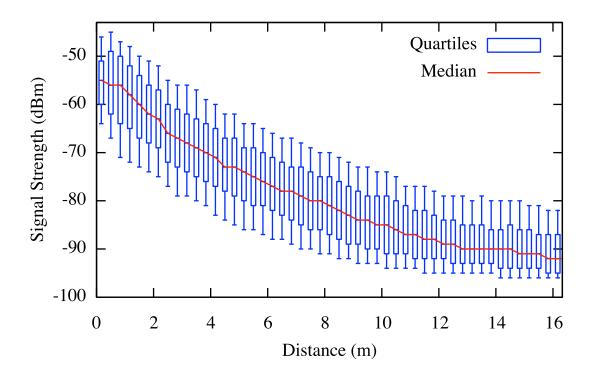






# **RSS Based Localization** Background





#### very noisy, but possible

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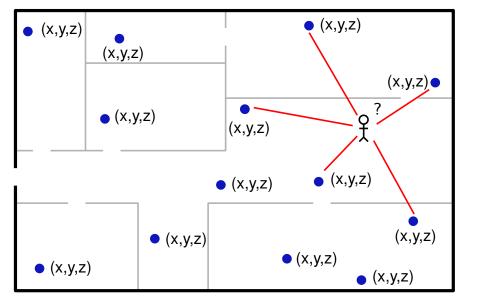


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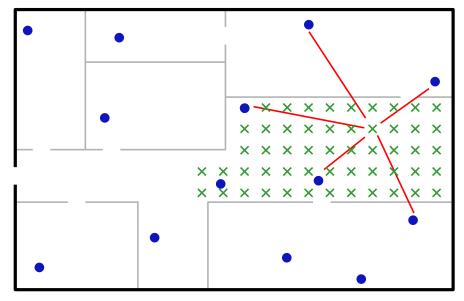
## **RSS Based Localization**



#### **Usual Approaches**



1st variant: Trilateration, Kalman Filter



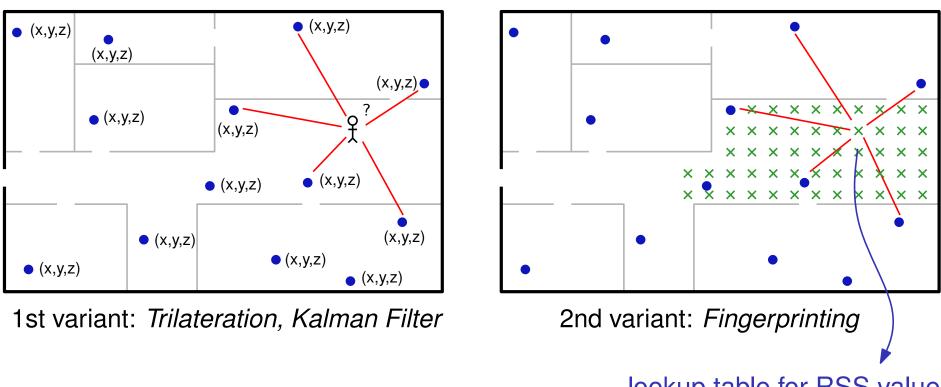
2nd variant: Fingerprinting



## **RSS Based Localization**

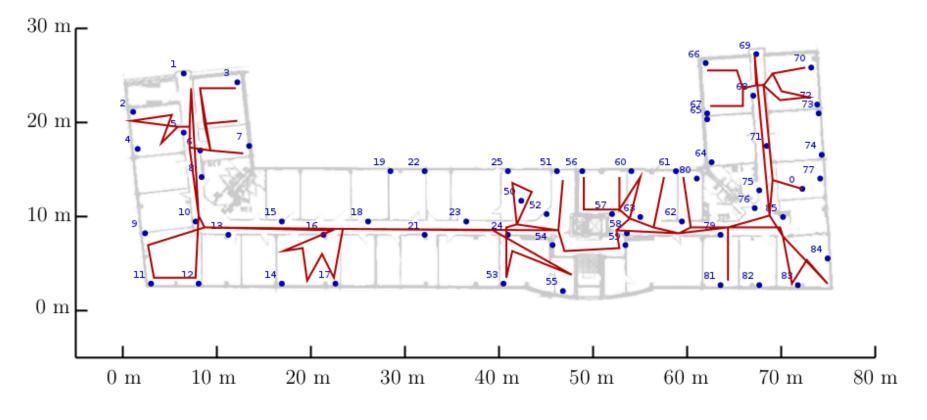


#### **Usual Approaches**



#### lookup table for RSS values



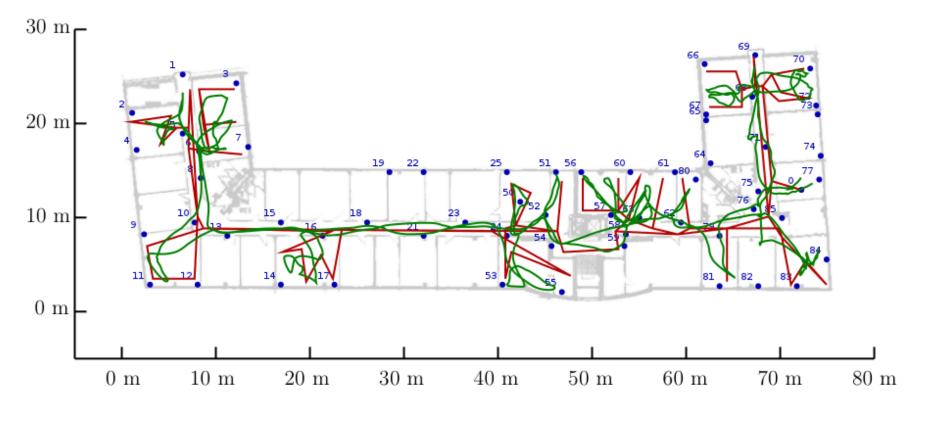


(network with 60 sensor nodes)

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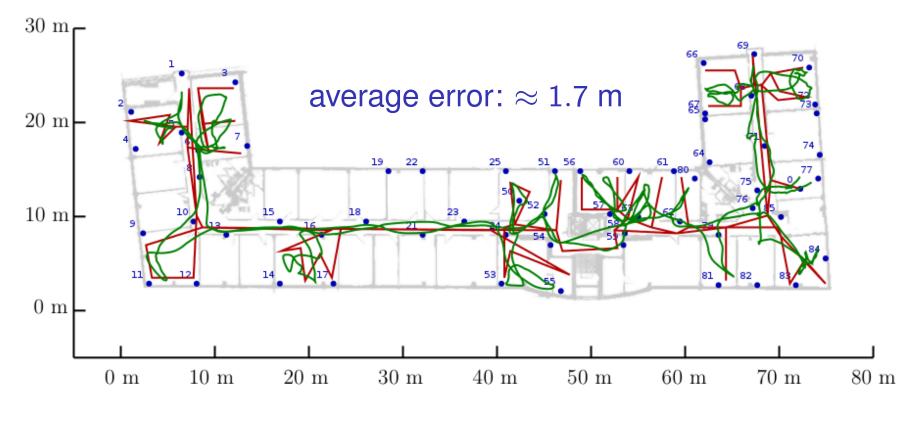


(network with 60 sensor nodes)

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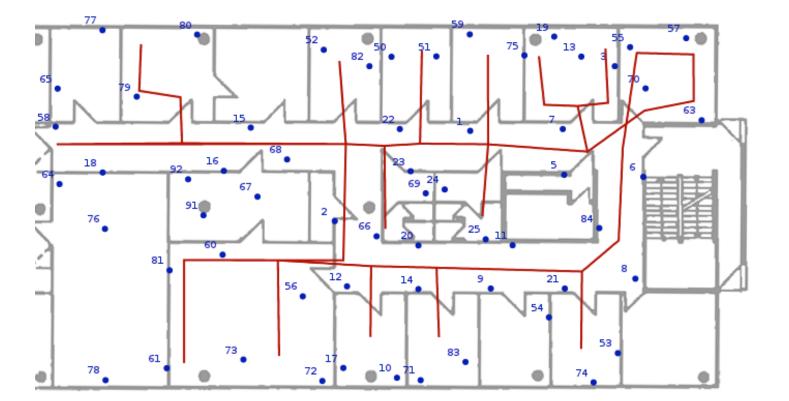


(network with 60 sensor nodes)

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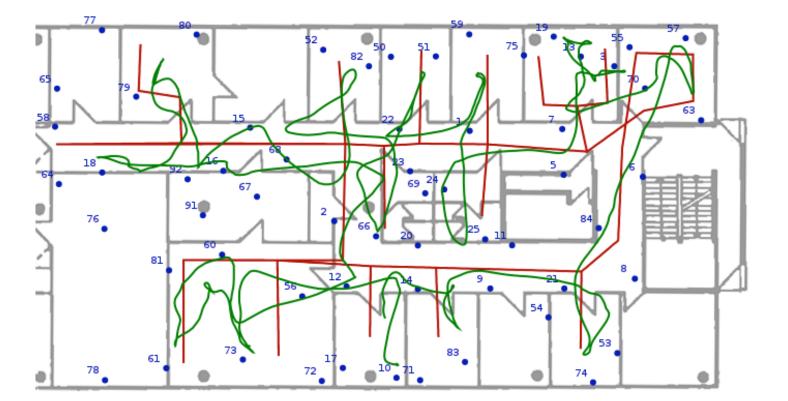


(network with 60 sensor nodes)

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(network with 60 sensor nodes)

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### **RSS Based Localization**



**Real-World Examples** 

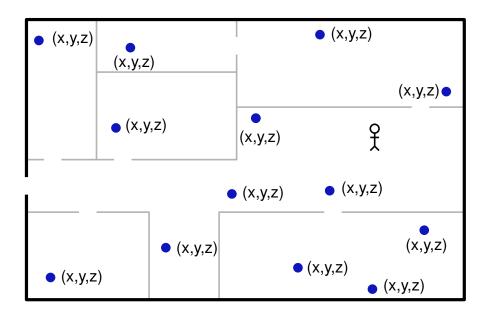
Used sensor nodes

- 65 sensor nodes (build by Johannes Schmid)
- Texas Instruments MSP430 low power MCU
- 2.4 GHz IEEE 802.15.4 compliant CC2520 radio chip
- 5.5 x 2.0 x 2.5 cm<sup>3</sup> casing





### Sensor Network Localization Considered Problem



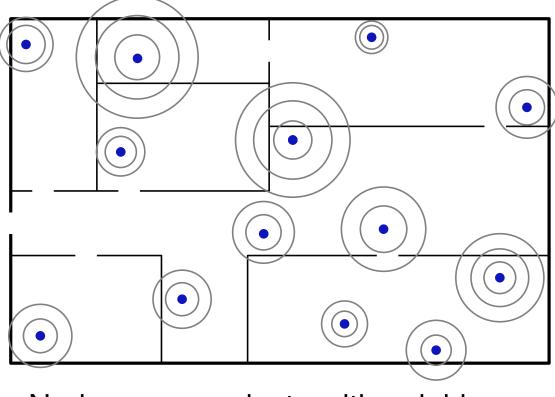
Automatic Localization of Sensor Network?



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### Sensor Network Localization Existing Approach

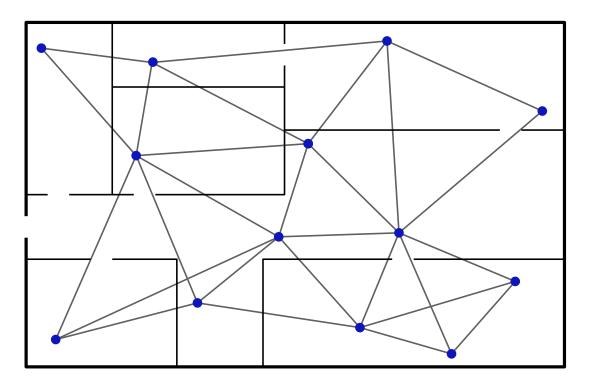




Nodes communicate with neighbors



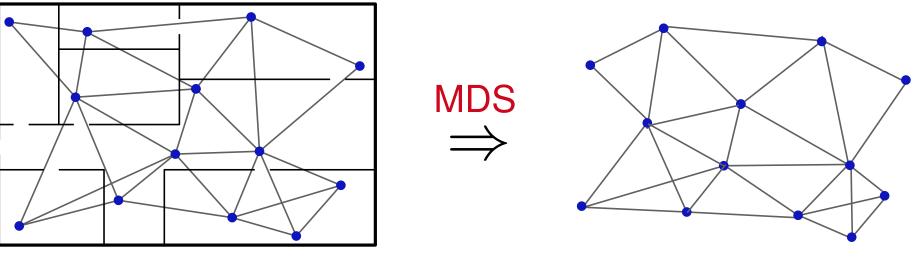
### Sensor Network Localization Existing Approach



Distance estimation from signal strength



### Sensor Network Localization Existing Approach



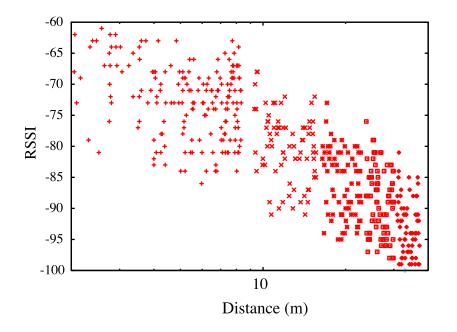
**Real Network** 

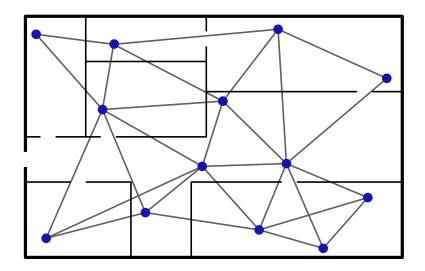
Computed Embedding

Compute embedding for est. distances with Multidimensional Scaling (MDS-MAP, 2004)

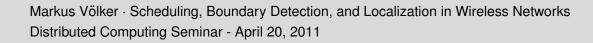


### Sensor Network Localization Existing Approach - Problems



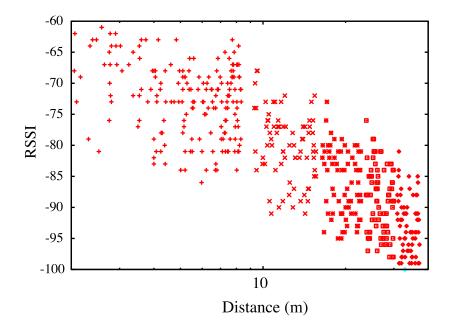


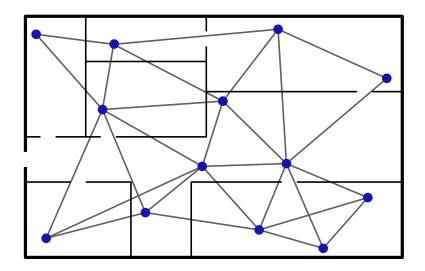
- signal strength fluctuates significantlysmall movements cause large change
- *but:* for fixed position almost constant
- obstacles, walls





### Sensor Network Localization Existing Approach - Problems





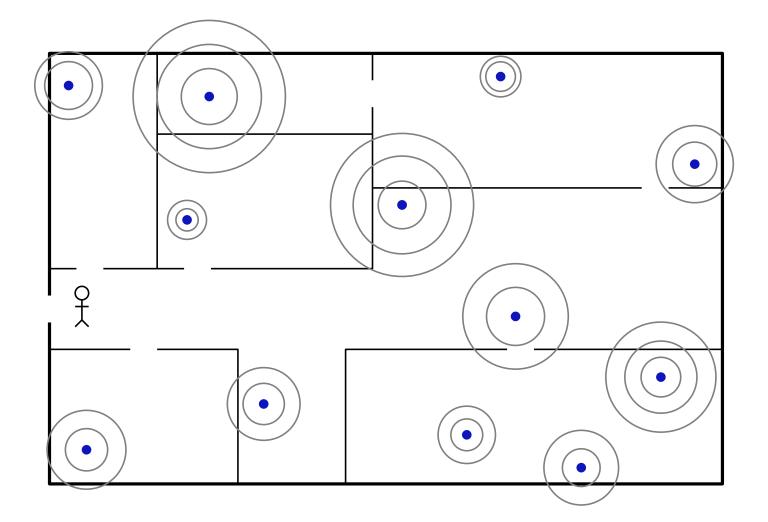
- signal strength fluctuates significantly
- small movements cause large change
- *but:* for fixed position almost constant
- obstacles, walls

#### Plan: use mobility to deal with this problems





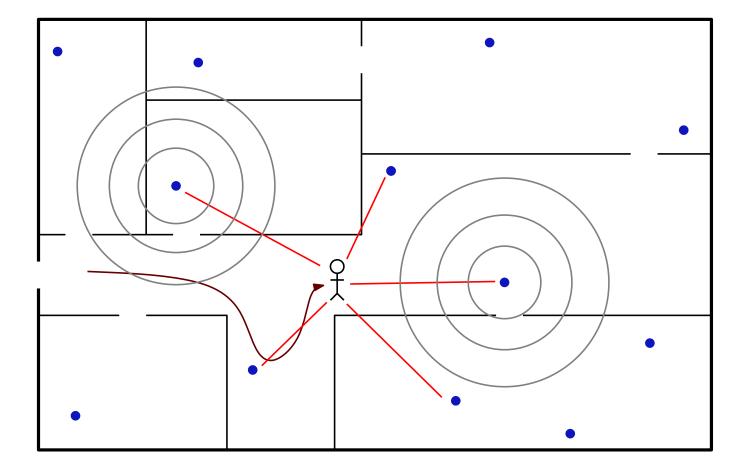
#### Indirect Network Localization







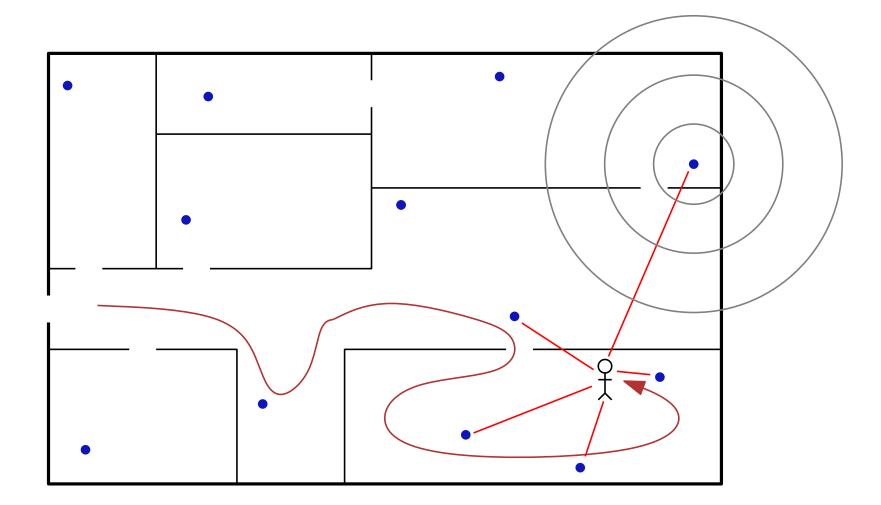
#### Indirect Network Localization







#### Indirect Network Localization



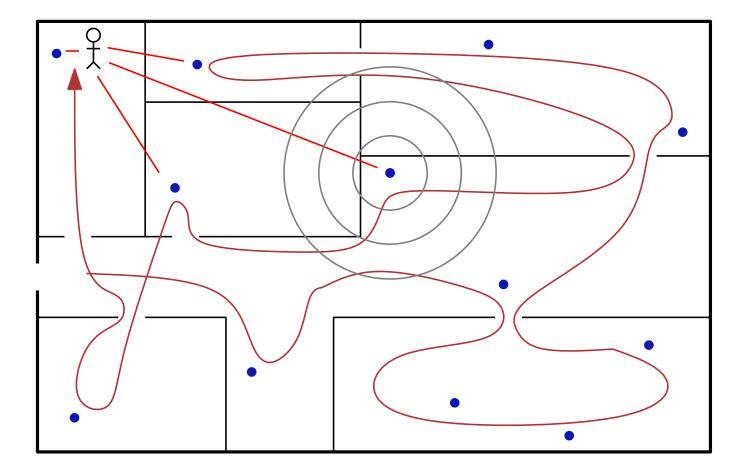
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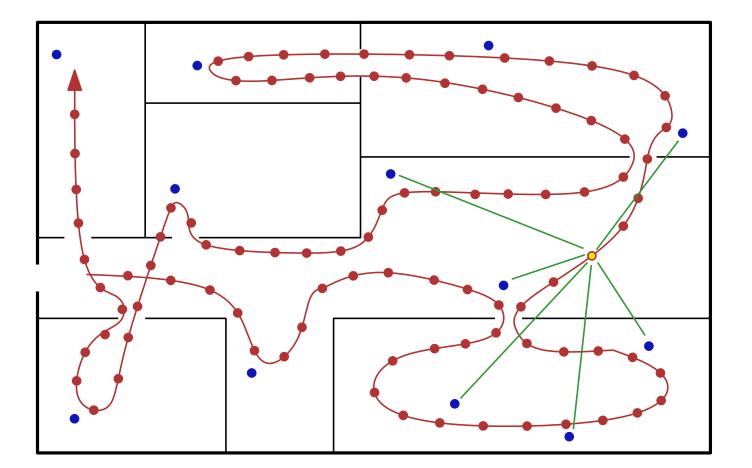
#### Indirect Network Localization







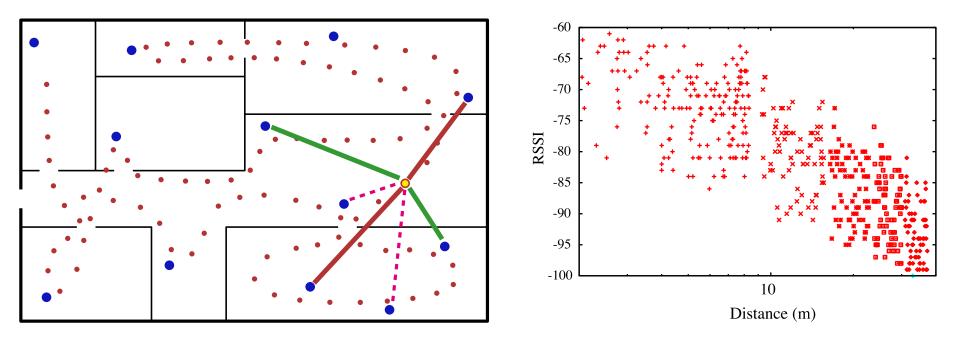
#### Indirect Network Localization







#### Indirect Network Localization - Advantages

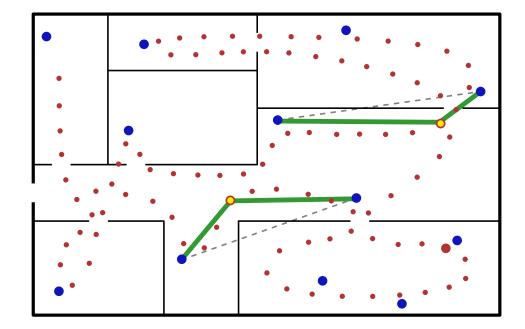


# Measurements at different positions $\Rightarrow$ averaging reduces errors





#### Indirect Network Localization - Advantages

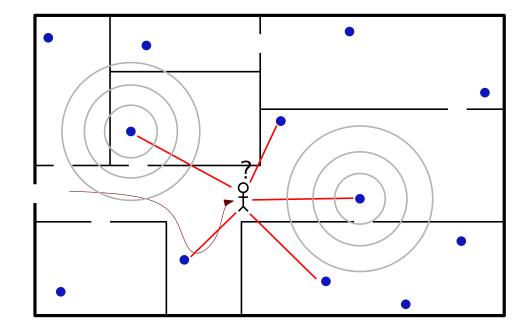


#### Sometimes walls can be avoided





#### Indirect Network Localization - Advantages



#### Stationary nodes only have to transmit $\Rightarrow$ smaller, cheaper $\Rightarrow$ many nodes possible

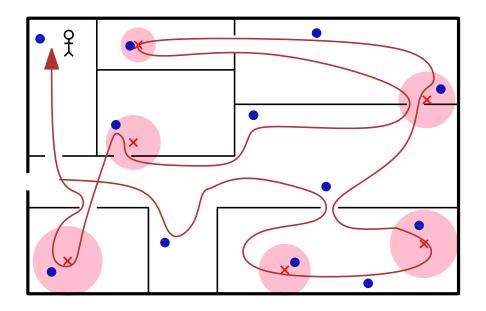


### Sensor Network Localization Existing approach



Information about (some) node positions or walked trajectory available

⇒ Use SLAM methods such as Kalman filter (simultaneous localization and mapping)



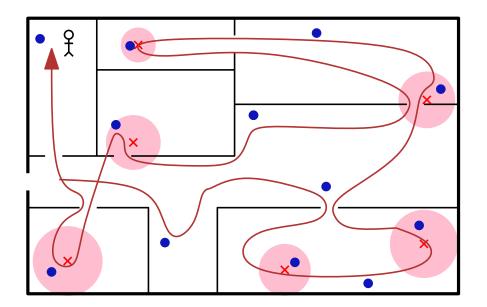


# Sensor Network Localization Existing approach



Information about (some) node positions or walked trajectory available

⇒ Use SLAM methods such as Kalman filter (simultaneous localization and mapping)

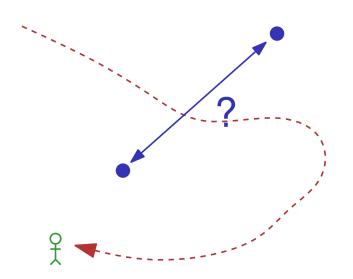


#### We assume that this kind of information is not available.





## Planned Approach

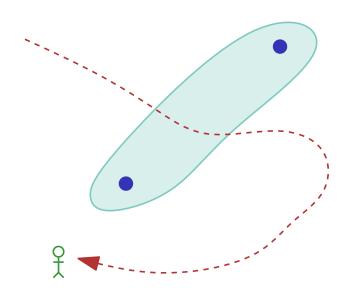






## Planned Approach

#### 1<sup>st</sup> step: try to determine pairwise node distances

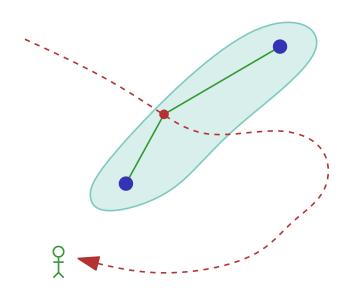






## Planned Approach

#### 1<sup>st</sup> step: try to determine pairwise node distances

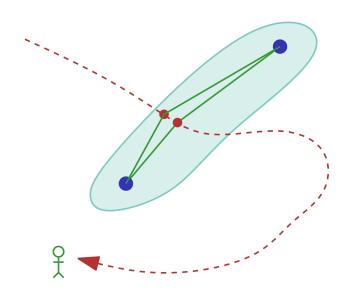






## Planned Approach

#### 1<sup>st</sup> step: try to determine pairwise node distances

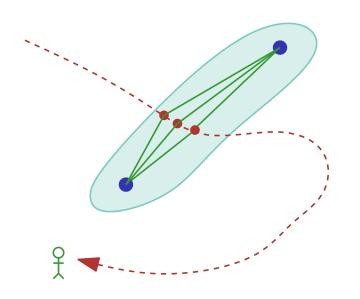






## Planned Approach

#### 1<sup>st</sup> step: try to determine pairwise node distances

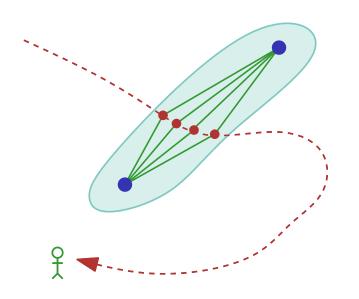






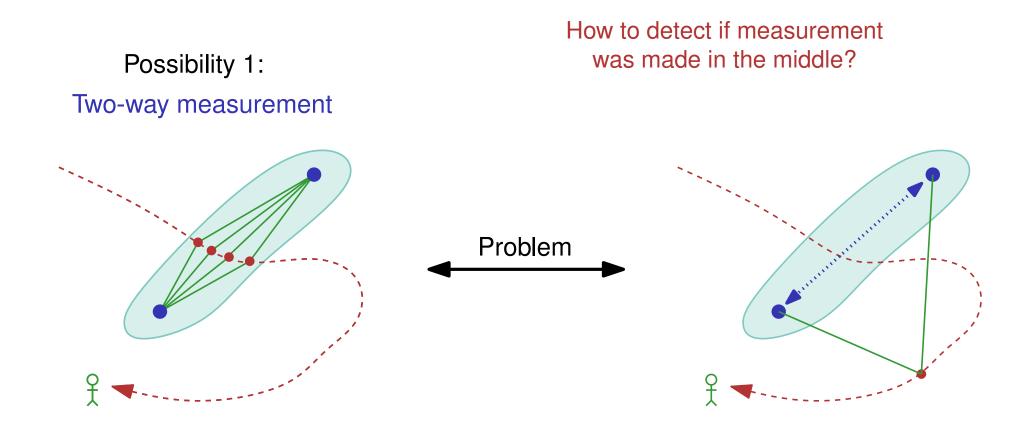
## Planned Approach

#### 1<sup>st</sup> step: try to determine pairwise node distances

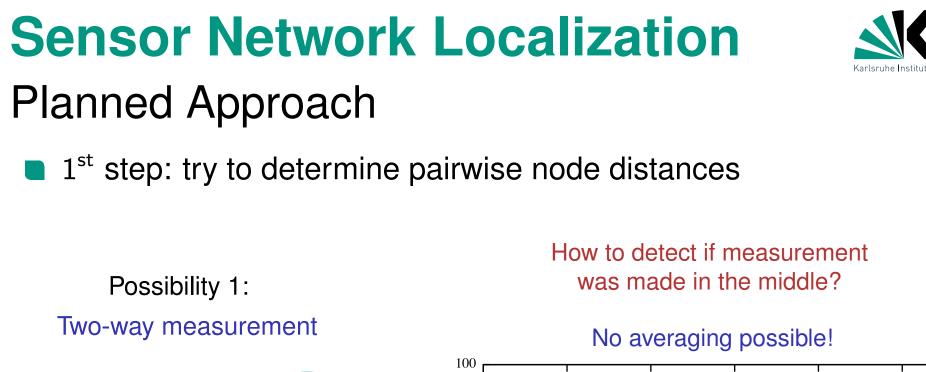


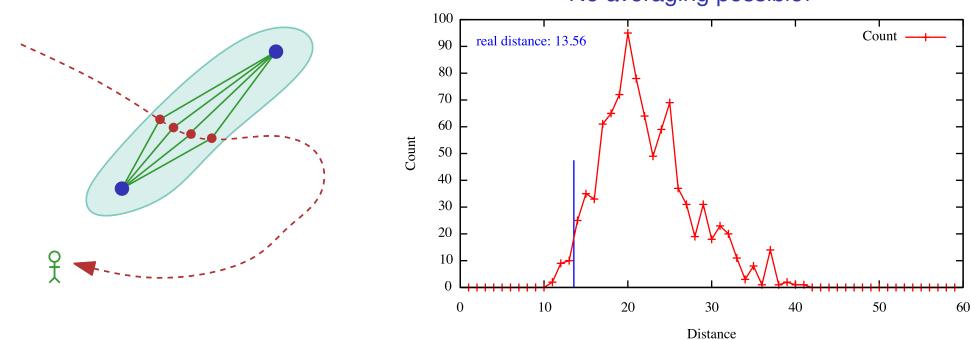






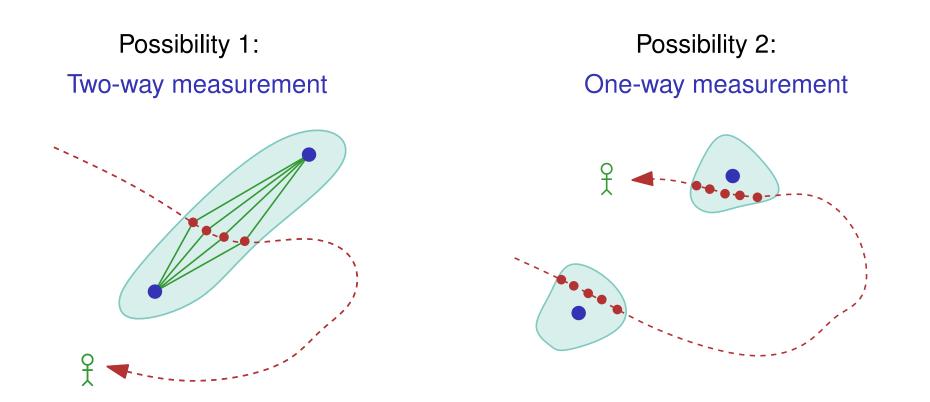






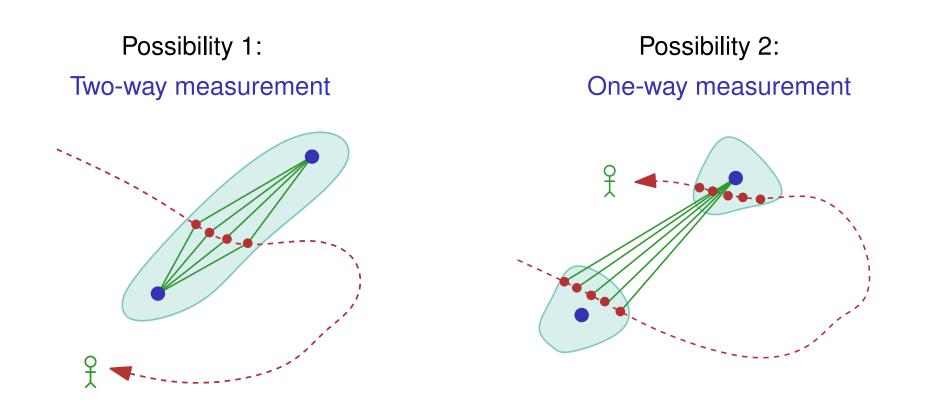






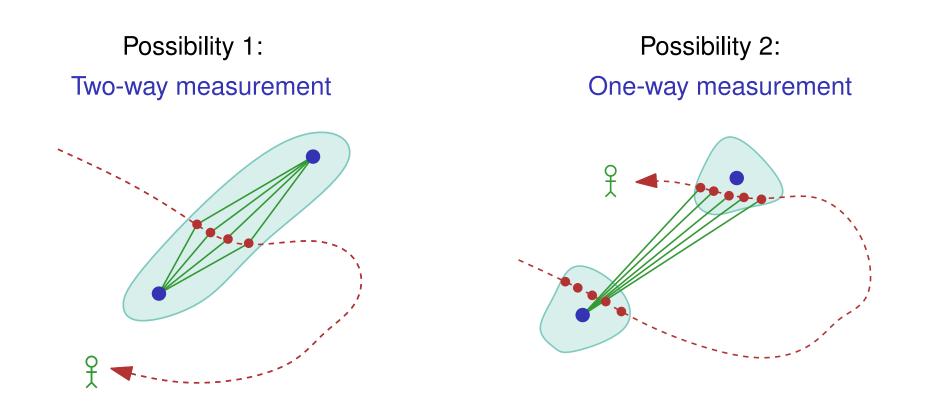








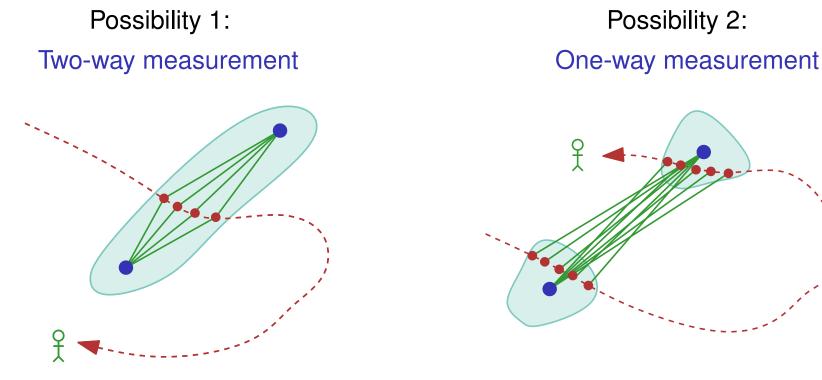








1<sup>st</sup> step: try to determine pairwise node distances



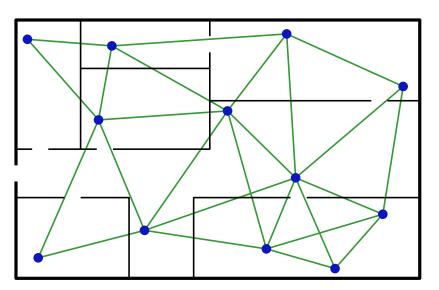
All measurements are equal! Averaging possible!





## Planned Approach

2<sup>nd</sup> step: completing the distance matrix

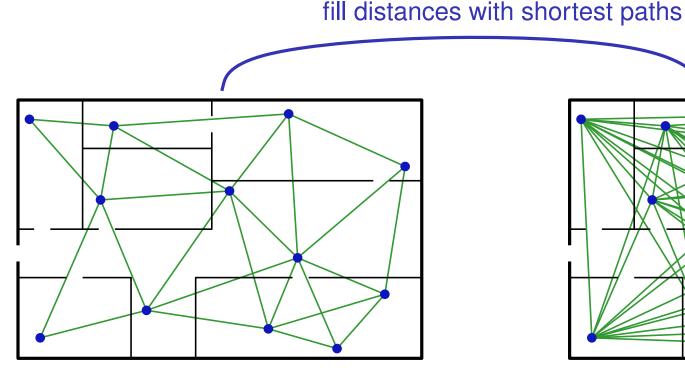


Pairwise distance estimate between some nodes

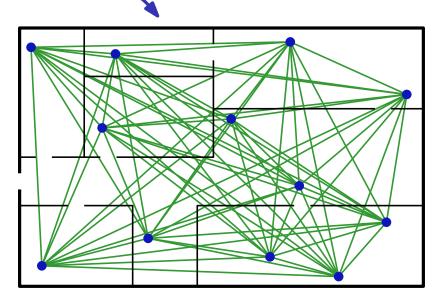




#### 2<sup>nd</sup> step: completing the distance matrix



Pairwise distance estimate between some nodes



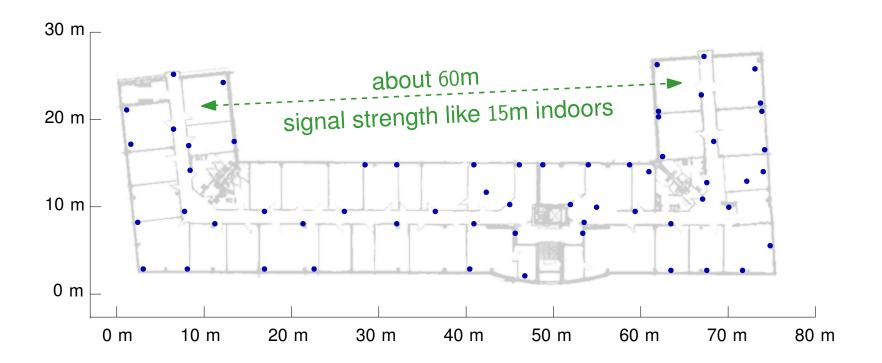
Pairwise distance estimate between all nodes





2<sup>nd</sup> step: completing the distance matrix

Problem 1: some distances are extremely underestimated



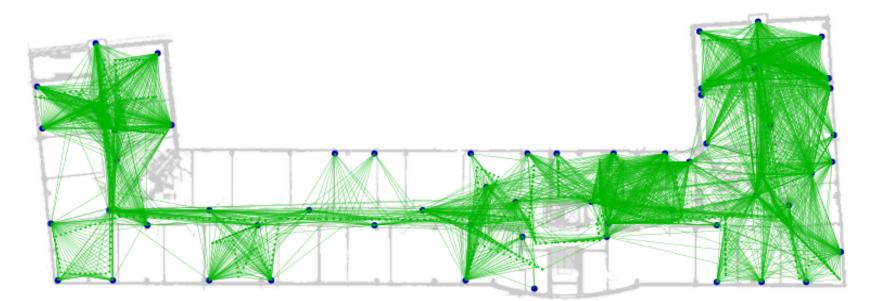




## Planned Approach

2<sup>nd</sup> step: completing the distance matrix

Possible solution: use only strong signals



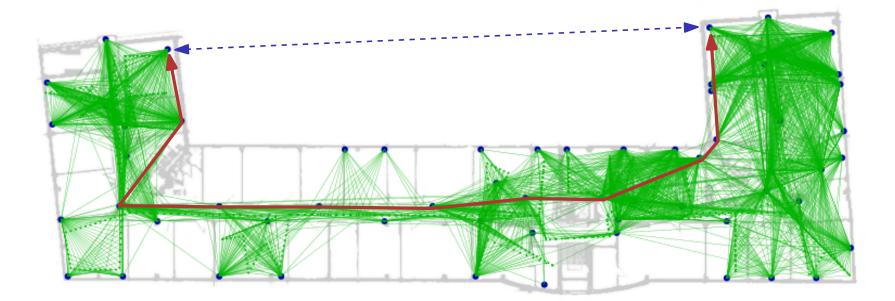
(measurements with RSS < -75 dBm are filtered)





2<sup>nd</sup> step: completing the distance matrix

Problem 2: real distance often overestimated by shortest paths



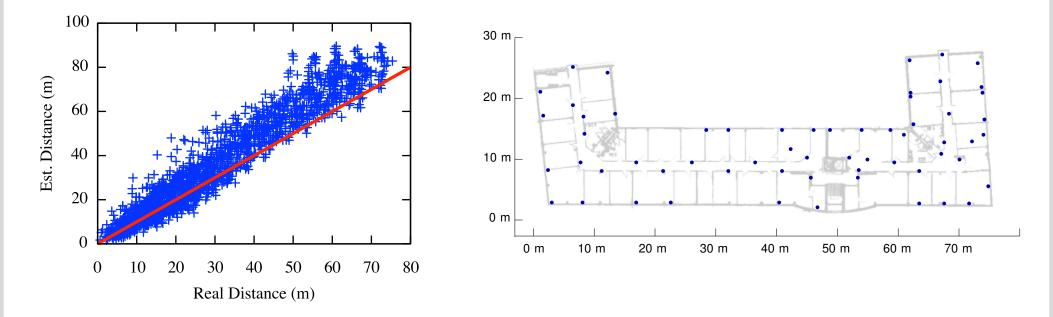




### **Planned Approach**



#### Possible result







■ 3<sup>rd</sup> step: computing an embedding

Naive approach: Standard Multidimensional Scaling







3<sup>rd</sup> step: computing an embedding

Naive approach: Standard Multidimensional Scaling





40

50

60

70

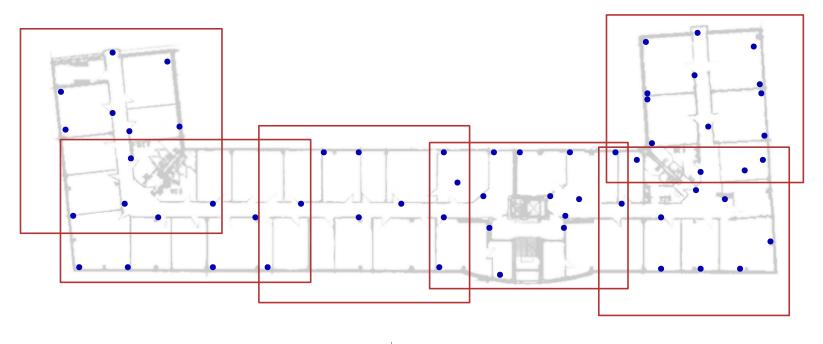
80



## Planned Approach

3<sup>rd</sup> step: computing an embedding

Possible solution: Local MDS



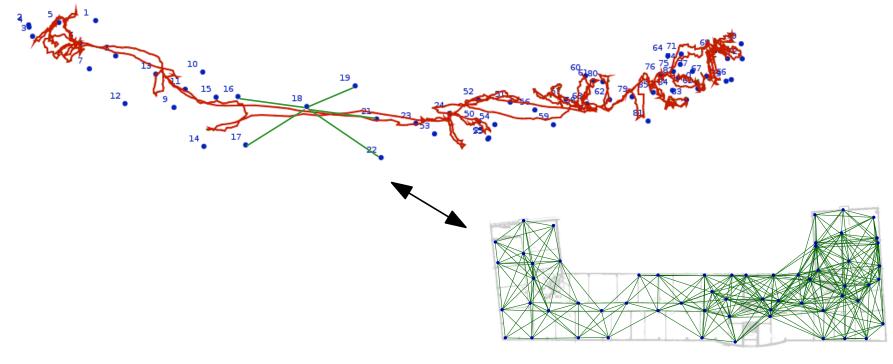
### TODO





#### 3<sup>rd</sup> step: computing an embedding

Possible solution: Force-based methods (like spring embedder)



#### TODO

#### original pairwise distances

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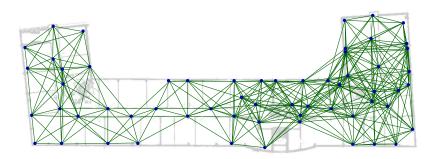


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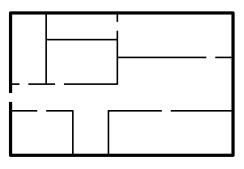
## Comparison with simulations

Why do simulations of MDS-MAP usually look so good?

- usually 5%-10% avg. distance estimation error assumed  $\Rightarrow$  RSS based in reality rather 20% to 50%
- usually smooth distribution of obstacles assumed  $\Rightarrow$  in reality inhomogeneous (walls)
- usually rectangular area assumed
  in reality more complicated shapes possible





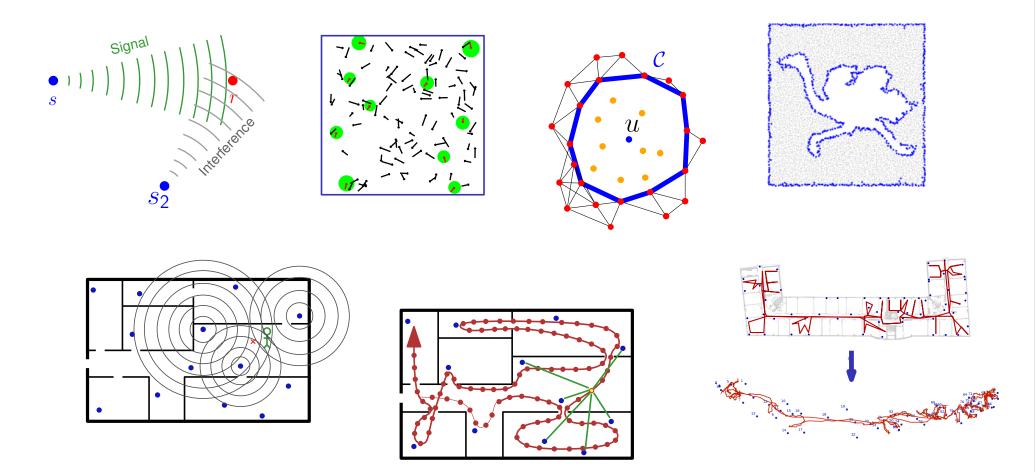






## Thank you for your attention!





### Do you have any questions?

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