Collaborative transmission in wireless sensor networks

A protocol for distributed adaptive beamforming

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Overview and Structure

- Introduction to context aware computing
- Wireless sensor networks
- Wireless communications
- Basics of probability theory
- Randomised search approaches
- Cooperative transmission schemes
- Distributed adaptive beamforming
    - Feedback based approaches
    - Asymptotic bounds on the synchronisation time
    - Alternative algorithmic approaches
- A protocol for distributed adaptive beamforming

Overview and Structure

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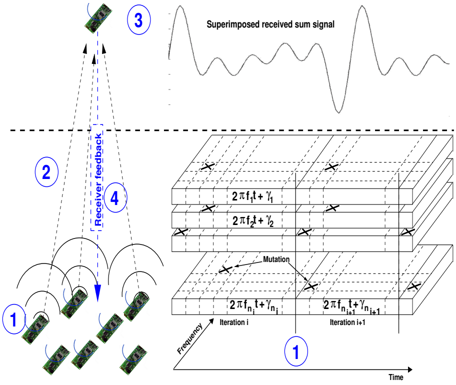
  - Asymptotic bounds on the synchronisation time
  - Alternative algorithmic approaches
- **A protocol for distributed adaptive beamforming**

Outline

A protocol for distributed adaptive beamforming

A protocol for distributed adaptive beamforming

Introduction



- Until now, we have discussed a method for carrier synchronisation
- No data transmission was considered so far
- We will introduce and discuss a simple protocol for distributed adaptive beamforming

Outline

A protocol for distributed adaptive beamforming

1. A protocol for distributed adaptive beamforming
2. Performance of the protocol
3. Impact of environmental effects
4. Learning classifier systems

A protocol for distributed adaptive beamforming

A simple protocol

Devices utilise the iterative distributed carrier synchronisation. In order to adapt to different environments, devices maintain and adapt the following parameters.

$P_{mut,i}$ Probability to alter the phase offset of an individual device i ($P_{mut,i} \in [0, 1]$)

$P_{dist,i}$ Probability distribution for the random process of device i ($P_{dist,i} \in \{\text{normal, uniform}\}$)

var_i Variance for the random process ($var_i \in [0, \pi]$)

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A simple protocol

The transmission protocol consists of the following steps

1. An individual device broadcasts a data sequence s_d to devices in its proximity.
2. Devices decide whether to participate in the transmission. Possible decision parameters are, for instance, the energy level, a required count of participating devices or current computational load.
3. Closed-loop one bit feedback based carrier synchronisation is achieved. Devices utilise $P_{mut,i}$, $P_{dist,i}$, var_i.
4. Upon sufficient synchronisation the receiver broadcasts an acknowledgement.
5. Optimisation parameters $P_{mut,i}$, $P_{dist,i}$ and var_i are adapted.
6. Devices collaboratively transmit s_d.

Outline

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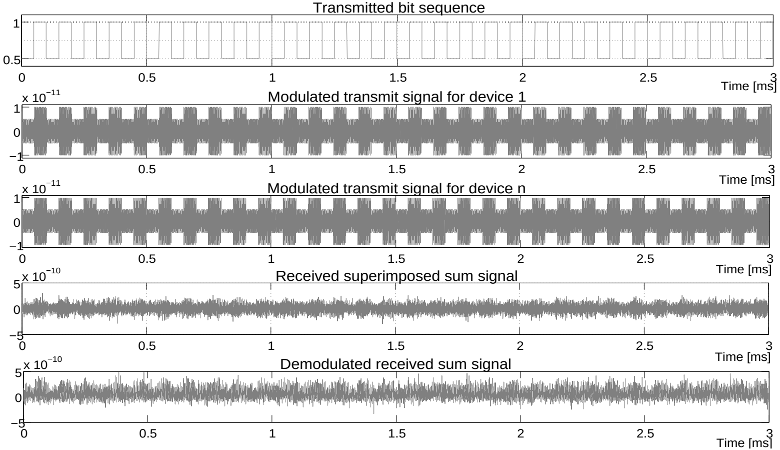
Performance of the protocol



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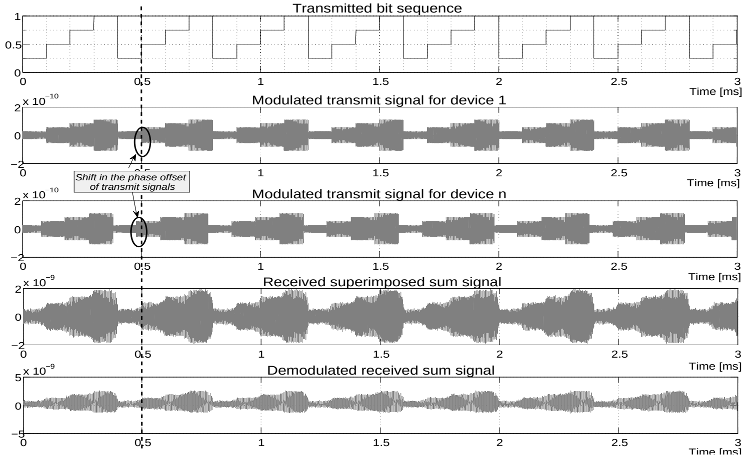
Performance of the protocol



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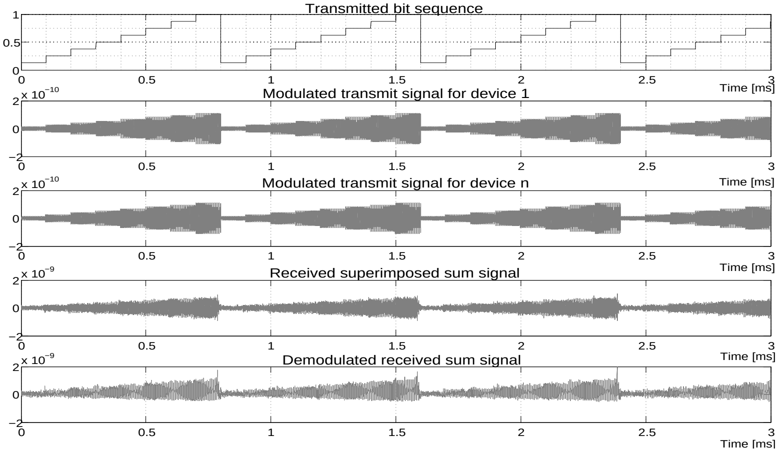
Performance of the protocol



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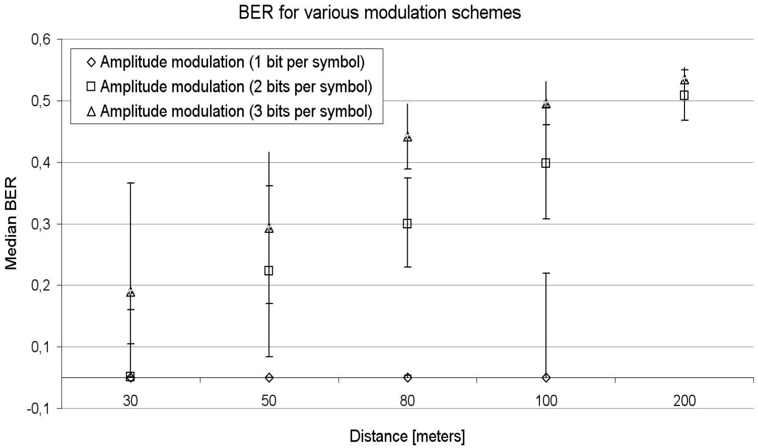
Performance of the protocol



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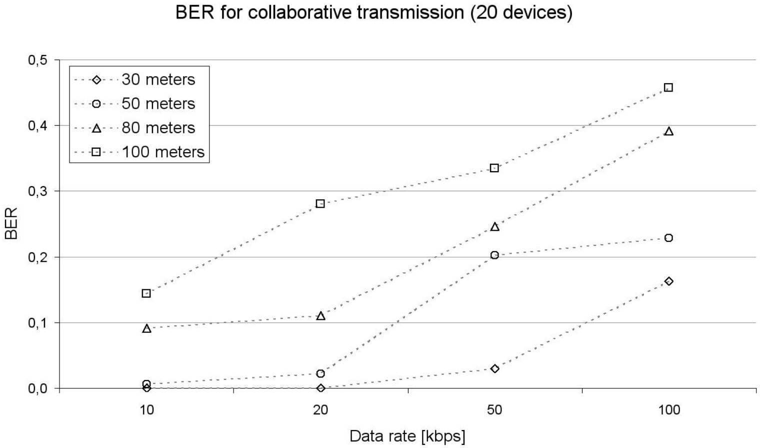
Performance of the protocol



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Impact of environmental effects

However, the performance of the protocol can be impacted by environmental effects.

- Possible environmental impacts
  - Movement
  - Network size
  - Noise figure

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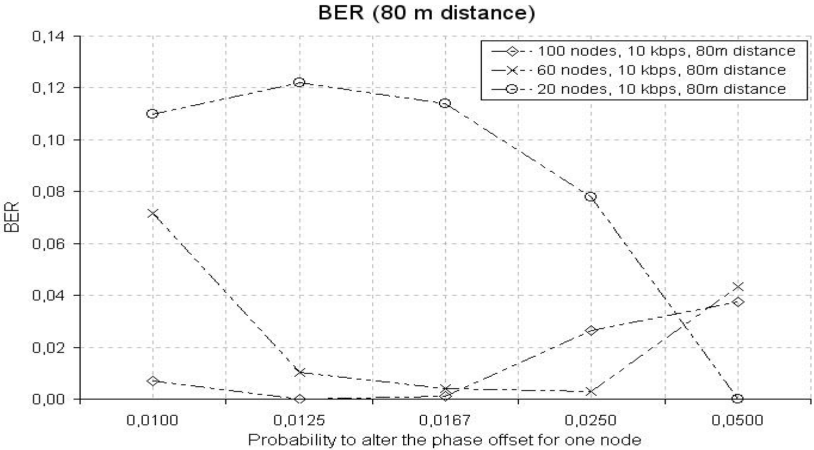
Impact of environmental effects

Impact of the network size



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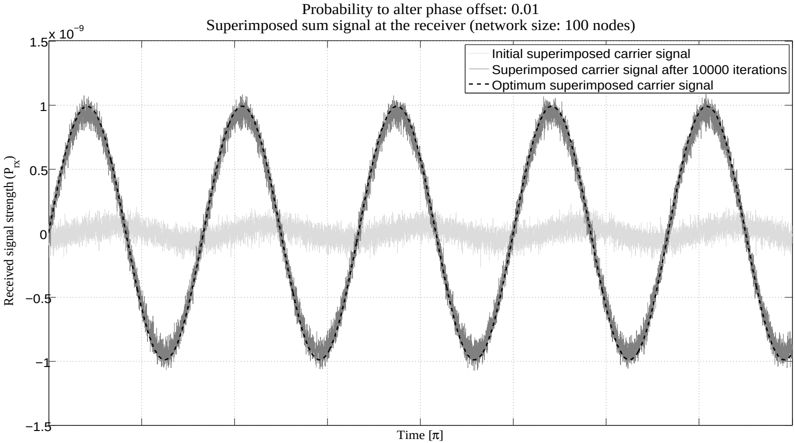
Impact of environmental effects

Impact of the transmission distance



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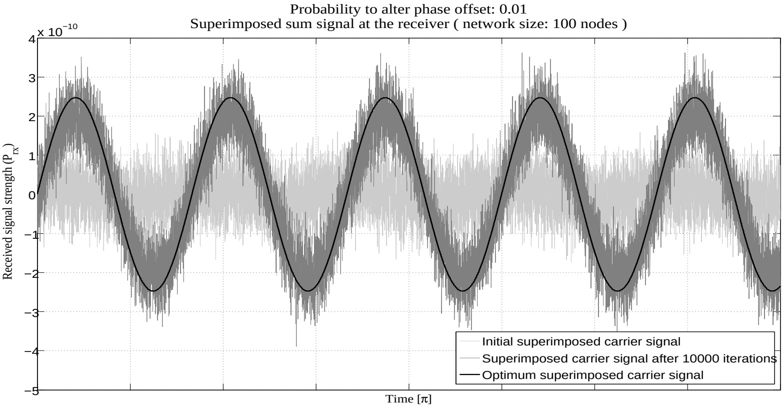
Impact of environmental effects

Impact of the transmission distance



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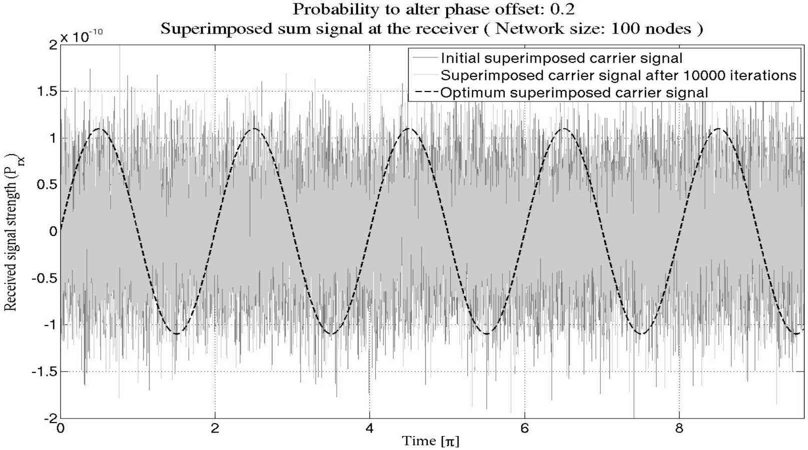
Impact of environmental effects

Impact of the transmission distance



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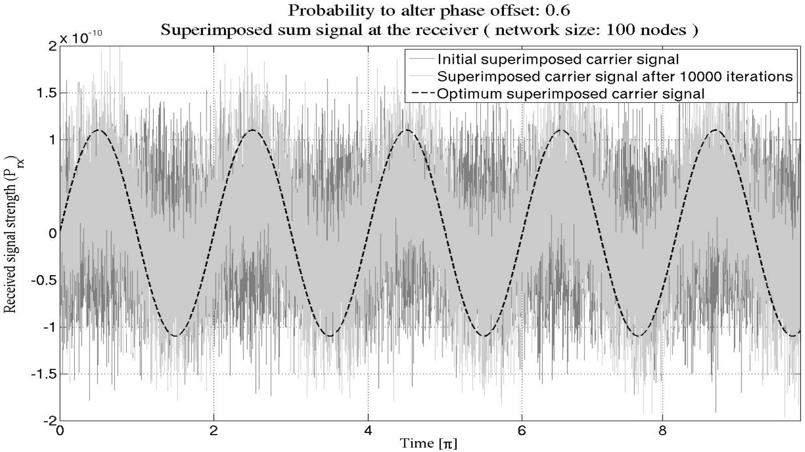
Impact of environmental effects

Impact of the transmission distance



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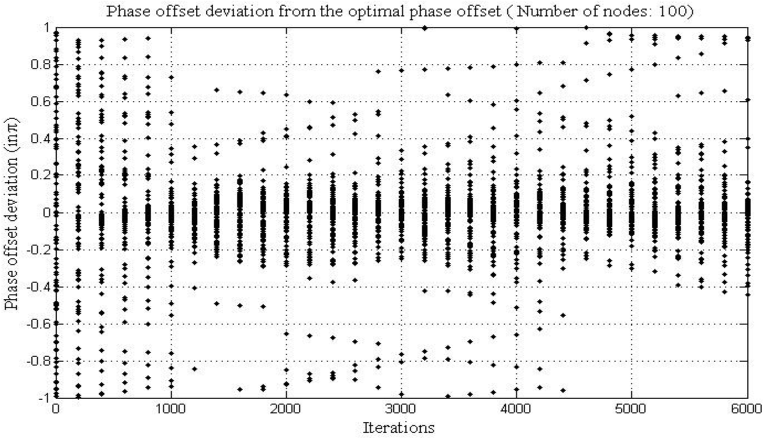
Impact of mobility

Impact of the transmission distance



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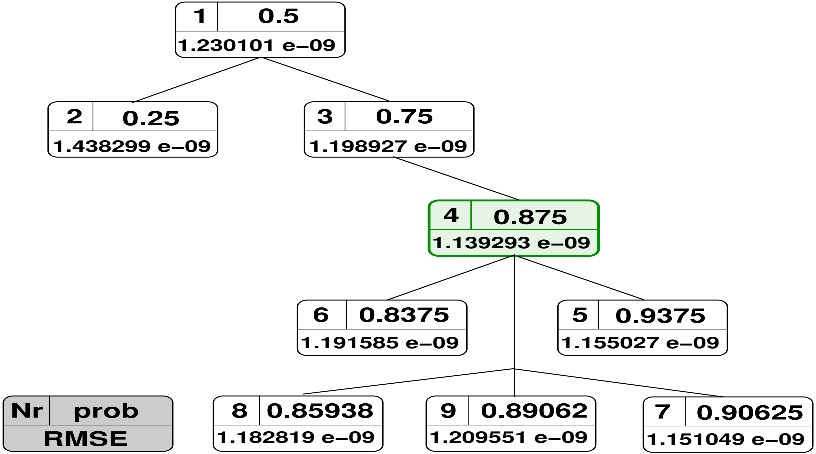
Impact of environmental effects

A simple binary learning approach



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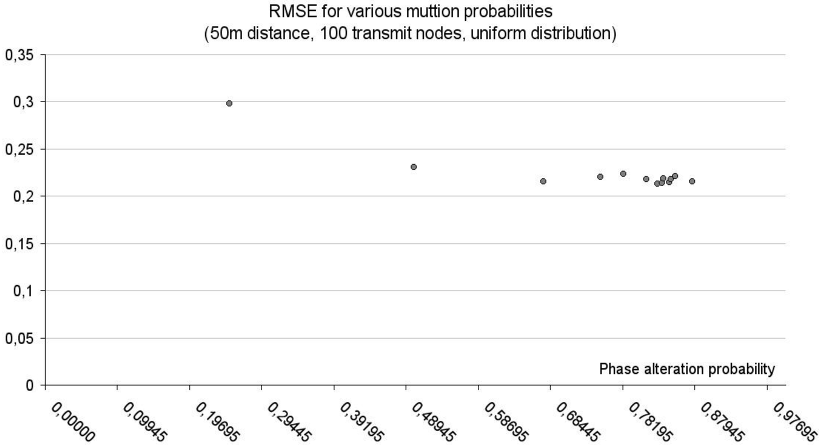
Impact of environmental effects



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A protocol for distributed adaptive beamforming

Learning classifier systems

- With such a protocol, adaptation to static scenarios is possible
- However, when a scenario is frequently altered, we might want to remember past optimum parameter values when a given situation reoccurs.
- This can be solved by learning classifier systems

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Learning classifier systems

- Learning classifier systems are machine learning systems
- Related to reinforcement learning and evolutionary algorithms
- First described by John Holland [1]
  - Population of binary rules
  - Evolutionary algorithm altered these and selected the best rules

[1] J. H. Holland, Adaptive algorithms for discovering and using general patterns in growing knowledge-bases, International Journal of Policy Analysis and Information Systems, vol. 4, pp. 217-240, 1980

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Learning classifier systems

- Learning classifier systems can be split into two distinct types
  - Pittsburgh type
  - Michigan type

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Learning classifier systems

Pittsburgh-type LCS :

- Population of separate rule sets
- Evolutionary algorithm recombines the best of these rule sets

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Learning classifier systems

Michigan-type LCS :

- Only a single rule set
- Algorithm selects the best classifiers within the rule set
- Distinction between fitness definitions:
  - Strength-based (ZCS)
  - Accuracy-based (XCS)

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Learning classifier systems

- Originally, classifiers or rules were binary
- Now: real-valued, neural network, and functional conditions
- As evolutionary algorithms in general, Learning classifier systems are not fully understood mathematically

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Learning classifier systems

- The LCS consists of a high number of condition-action rules (the classifiers)
- When a particular input occurs, the LCS forms a so-called match set of classifiers whose conditions are satisfied by that input
  - Example: $t(x) = 1$ (true) for $-110dBm \leq x \leq -100dBm$, where x represents e.g. the noise figure in a given setting.
- If the classifiers condition is satisfied it is further considered by the LCS and influences the systems action decision

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Learning classifier systems

- Each classifier Υ maintains
  - A fitness value F_Υ
  - A prediction $\mathcal{P}_\Upsilon$ about the expected fitness it will achieve
  - An estimate ε of the error of its predictions
- These values are used to decide on the best alternative among all classifiers
- The actual fitness $\mathcal{F}$ achieved by applying the parameters described by the classifiers to the search problem is used to alter these values:
  - p is moved slightly closer to $\mathcal{F}$
  - ε is moved closer to the current absolute error $|p - \mathcal{F}|$
  - The classifiers is fitness is moved slightly closer to ε^{-1}

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Learning classifier systems

- Additionally, the classifiers are modified by mutation and crossover operators
- Therefore, also the population of classifiers changes over time

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Learning classifier systems

Conclusion:

- A LCS system is a broadly applicable learning approach
- The system is capable of identifying rule sets well suited for distinct situations
- However, due to its great complexity and multiple stages of operation, it is mathematically not fully understood

Questions ?

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