Advanced Topics in Digital Communications
Spezielle Methoden der digitalen Datenübertragung

Dr.-Ing. Carsten Bockelmann
Institute for Telecommunications and High-Frequency Techniques
Department of Communications Engineering
Room: SPT C3160, Phone: 0421/218-62386
bockelmann@ant.uni-bremen.de

Lecture
Thursday, 10:00 – 12:00 in N3130
Exercise
Wednesday, 14:00 – 16:00 in N1250
Dates for exercises will be announced during lectures.

Tutor
Tobias Monsees
Room: SPT C3220
Phone 218-62407
tmonsees@ant.uni-bremen.de

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Outline

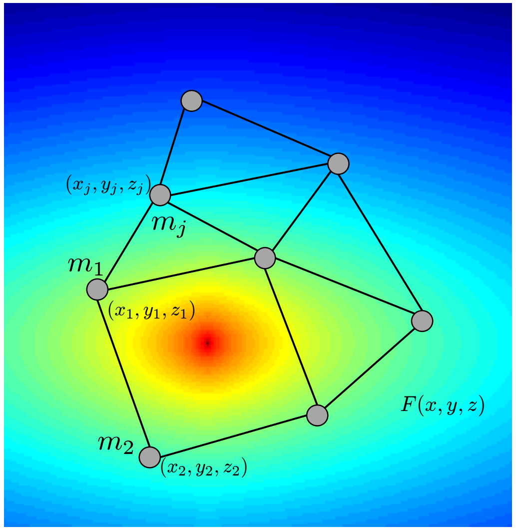
- Part 1: Linear Algebra
  - Eigenvalues and eigenvectors, pseudo inverse
  - Decompositions (QR, unitary matrices, singular value, Cholesky)
- Part 2: Basics and Preliminaries
  - Motivating systems with **M**ultiple **I**nputs and **M**ultiple **O**utputs (multiple access techniques)
  - General classification and description of MIMO systems (SIMO, MISO, MIMO)
  - Mobile Radio Channel
- Part 3: Information Theory for MIMO Systems
  - Repetition of IT basics, channel capacity for SISO AWGN channel
  - Extension to SISO fading channels
  - Generalization for the MIMO case
- Part 4: Multiple Antenna Systems
  - SIMO: diversity gain, beamforming at receiver
  - MISO: space-time coding, beamforming at transmitter
  - MIMO: BLAST with detection strategies
  - Influence of channel (correlation)
- Part 5: Relaying Systems
  - Basic relaying structures
  - Relaying protocols and exemplary configurations

Outline

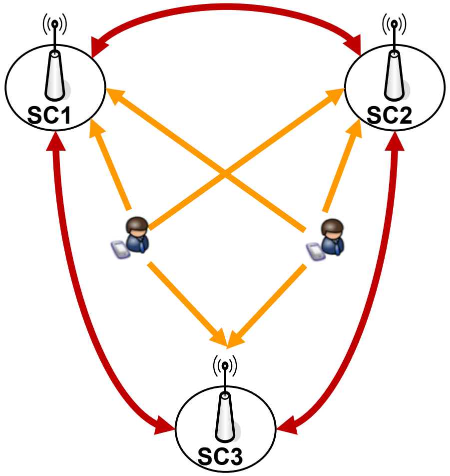
- Part 6: In Network Processing
  - Basic of distributed processing
  - INP approach
- Part 7: Compressive Sensing
  - Motivating Sampling below Nyquist
  - Reconstruction principles and algorithms
  - Applications

Problem Statement

- Network of nodes perform different measurements of same quantity
- Measurements need to be combined to estimate unknown „source“
- Examples:



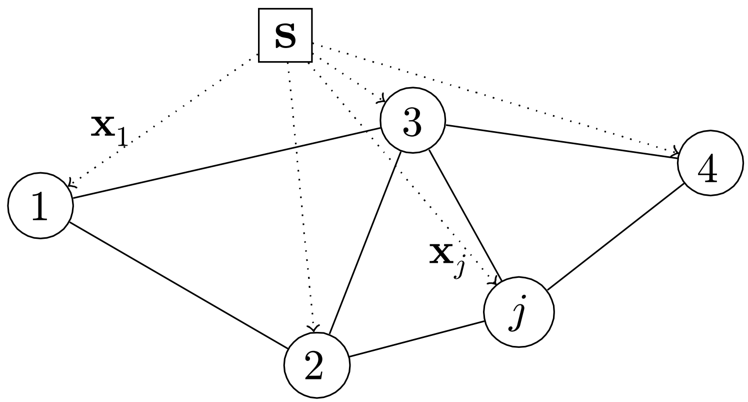
Wireless sensor network measuring temperature, humidity, salinity, etc of a medium → estimate field distribution



Network of base stations („small cells“) receiving different replicas of radio signals → recover data transmitted by users

Example: Linear Estimation

- **Assume**:
  - network of J nodes connected by inter-node-links
  - every node j makes different observation $\mathbf{x}_j$ of the same quantity $\mathbf{s}$
  - observations are linearly distorted with additional noise term



$$\mathbf{x}_j = \mathbf{H}_j \mathbf{s} + \mathbf{n}_j$$

- **Objective**: Estimate $\mathbf{s}$ by fully utilizing all information available at J observations
- Note: $\mathbf{H}_j$ can be any matrix, e.g. underdetermined system

Non-cooperative approach

- Every node performs an individual estimation
- **For example**: Least-Square estimation

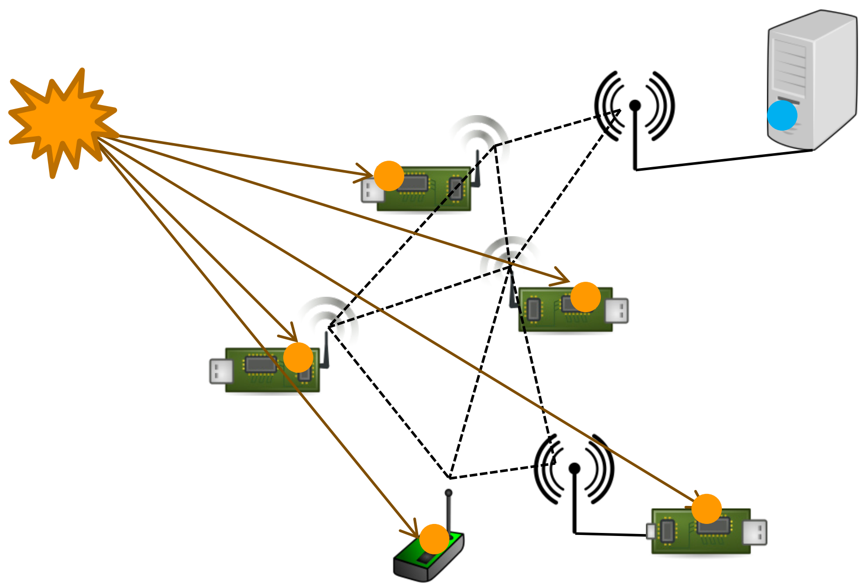
$$\hat{\mathbf{s}}_j = \arg\min_{\mathbf{s}_j} ||\mathbf{x}_j - \mathbf{H}_j \mathbf{s}_j||^2 \quad \forall j \in \mathcal{J}$$

$\mathcal{J}$: set of nodes

- **Pros**: No inter-node cooperation required
- **Cons:**
  - Per node the equation system might be **underdetermined** ($\mathbf{H}_j$ is rank deficient), e.g Multi-User MIMO
  - Estimations differ from node to node → no consensus between nodes → further processing required to reconstruct (the single) s

Centralized processing

- Every node passes on observations and channel $\mathbf{H}_j$ to „fusion center“
- Fusion center performs centralized estimation using all observations



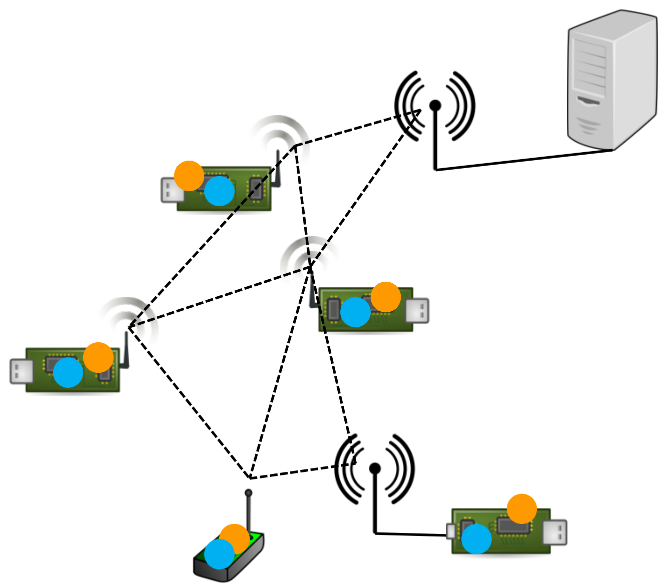
$$\hat{\mathbf{s}} = \arg\min_{\mathbf{s}} ||\tilde{\mathbf{x}} - \tilde{\mathbf{H}}\mathbf{s}||^2$$

$$\tilde{\mathbf{x}} = \begin{bmatrix} \mathbf{x}_1 \\ \vdots \\ \mathbf{x}_J \end{bmatrix} \quad \text{and} \quad \tilde{\mathbf{H}} = \begin{bmatrix} \mathbf{H}_1 \\ \vdots \\ \mathbf{H}_J \end{bmatrix}$$

- **Pros:** SotA algorithms yield optimum solution
- **Cons:** Communication effort → routing protocols needed / single point of failure

In-Network-Processing

- **Idea:** Calculate a function within a network, e.g. average, MMSE/LS estimation
- **Consensus based:** Identical solution at all nodes



- **Challenge:** Desing of algorithms yielding optimum solution, but being signalling efficient and robust
- **Our approach:** Start from a mathematical optimization framework

In-Network-Processing

- Rewrite centralized optimization problem as

$$\hat{\mathbf{s}} = \arg\min_{\mathbf{s}} ||\tilde{\mathbf{x}} - \tilde{\mathbf{H}}\mathbf{s}||^2 = \arg\min_{\mathbf{s}} \sum_{j=1}^{J} ||\mathbf{x}_j - \mathbf{H}_j \mathbf{s}||^2$$

- **Question**: How to solve it by In-Network-Processing?
- **Solution**: It can be shown that

$$\hat{\mathbf{s}} = \arg\min_{\mathbf{s}} \sum_{j=1}^{J} ||\mathbf{x}_j - \mathbf{H}_j \mathbf{s}||^2 \equiv \boxed{\begin{array}{l} \left\{\hat{\mathbf{s}}_j | j \in \mathcal{J}\right\} = \arg \min\limits_{\{\mathbf{s}_j | j \in \mathcal{J}\}} \sum\limits_{j=1}^{J} ||\mathbf{x}_j - \mathbf{H}_j \mathbf{s}_j||^2 \\ \text{s.t.} \quad \mathbf{s}_j = \mathbf{s}_i \quad \forall \quad j \in \mathcal{J}, \quad i \in \mathcal{N}_j \end{array}}$$

$\mathcal{J}$: set of nodes

$\mathcal{N}_j$: set of neighbor nodes of node j

- **Algorithmic approach:** Augmented Lagrangian method / Method of Multipliers [Nocedal&Wright] → Iterative algorithm with cooperation between neighbor nodes only → For l_2-norm: decomposition into local, but coupled problems

Distributed Consensus-Based Estimation (DiCE)

- **Idea:**
  - Introduce node specific auxiliary variables $\mathbf{z}_j$ and decouple variables $\mathbf{s}_j$
  - Variables $\mathbf{s}_j$, $\mathbf{z}_j$: iteratively calculated and broadcast
  - Lagrangian multipliers $\boldsymbol{\lambda}_{ji}$: iteratively calculated and unicast
- **Algorithm:**

$$
\begin{aligned}
\mathbf{z}_j(k+1) &= f(\boldsymbol{\lambda}_{j,i}(k), \mathbf{s}_i(k)), \quad i \in \mathcal{N}_j \cup j \\
\mathbf{s}_j(k+1) &= f(\boldsymbol{\lambda}_{i,j}(k), \mathbf{z}_i(k+1), \mathbf{x}_j, \mathbf{H}_j) \\
\boldsymbol{\lambda}_{i,j}(k+1) &= f(\boldsymbol{\lambda}_{i,j}(k), \mathbf{s}_j(k+1), \mathbf{z}_i(k+1))
\end{aligned}
$$

k: iteration index

- **Convergence:**
  - Perfect links: DICE converges to optimum solution
  - Noisy links: DICE converges in mean sense to optimum solution
  - Link failures: DICE converges to optimum solution
- **Main issue:** Reduction of inter-node signaling

DICE with reduced inter-node signaling

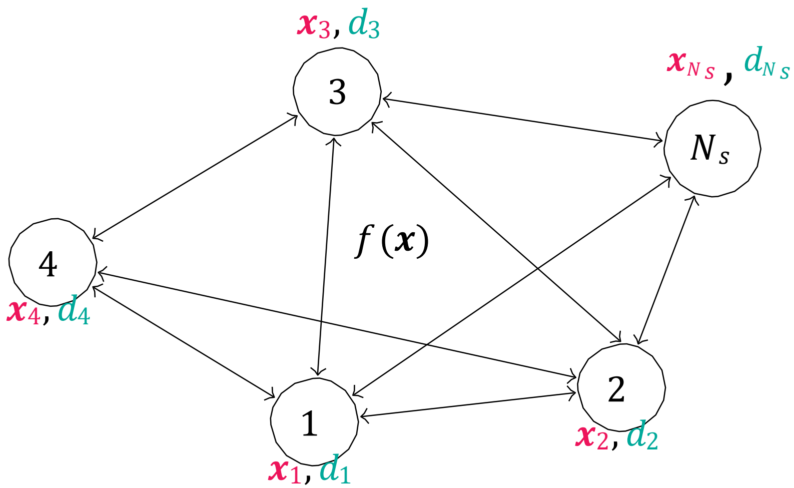
- Reduced Overhead DiCE (**RO-DiCE**) [Shin'13]
  - Avoid exchange of edge specific Lagrange multipliers $\boldsymbol{\lambda}_{ji} \rightarrow$ avoid unicast transmissions, broadcast transmissions only

- **Fast-DiCE** [Xu'14]
  - Acceleration of DICE by using Nesterov's optimal gradient descend method
  - Less #of iterations required for same estimation quality → reduced inter-node communication

[Shin'13] B.-S. Shin, H. Paul, D. Wübben, A. Dekorsy, "Reduced Overhead Distributed Consensus-Based Estimation Algorithm", IWCPM 2013, Atlanta, GA, USA, December 2013.

[Xu'14] G. Xu, H. Paul, D. Wübben, A. Dekorsy, "Fast Distributed Consensus-based Estimation for Cooperative Wireless Sensor Networks", WSA 2014, Erlangen, Germany, March 2014.

Kernel-based distributed estimation



- Sensor network with N_S nodes observes **nonlinear function** $f(\boldsymbol{x})$
- SN measures noisy value of function output d_j at specific positions $\boldsymbol{x}_j$:

$$d_j = f(\boldsymbol{x}_j) + n_j$$

- N_s training samples $\{(\boldsymbol{x}_j, d_j)\}$

Objective: Estimate $f(\boldsymbol{x})$ at arbitrary positions $\boldsymbol{x}$ **by INP** within sensor network
→ Distributed nonlinear regression on training samples $\{(\boldsymbol{x}_j, d_j)\}$
→ Use kernel methods for nonlinear regression:

$$f^* = \arg\min_{\hat{f}\in\mathcal{H}} \sum_{j=1}^{N_S} d_j - \hat{f}(\boldsymbol{x}_j)$$

Kernel DiCE

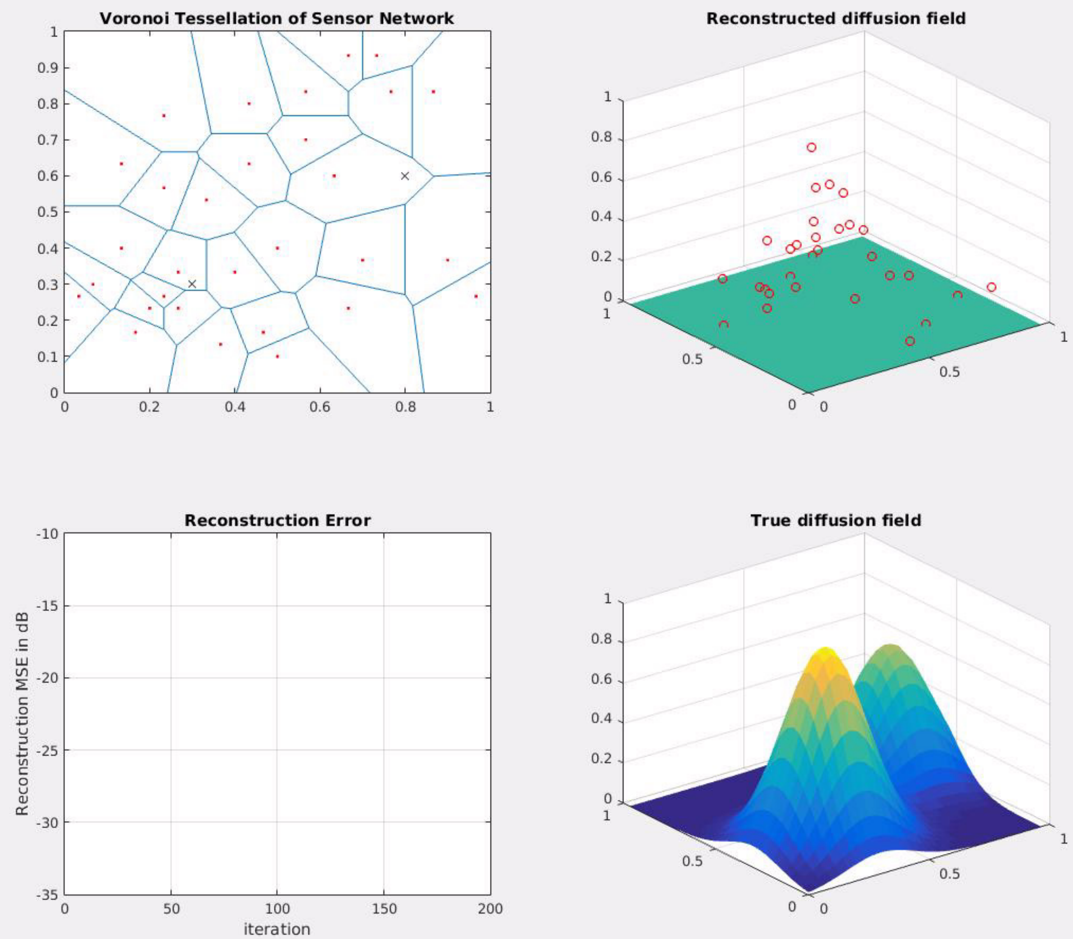
- Representer theorem states that optimal solution f^*, i.e., the function estimate $\hat{f}$ can be represented by linear superposition of positive semidefinite kernels $\kappa(\cdot,\cdot)$:

$$f^*(\cdot) = \sum_{l=1}^{N} w_l \, \kappa(\mathbf{x}_l, \cdot) \qquad \mathbf{x}_l\text{: dictionary (size } N\text{)}$$

- Kernel represents inner product between argument vectors in some higher dimensional (possibly infinite-dimensional) kernel Hilbert space
- Objective: Find weights w_l for given kernel (e.g., Gaussian) and dictionary (e.g., sensor locations) $\rightarrow$ estimation problem
- Approach: Calculate per-node weights using DiCE, enforcing consensus among nodes
- Reconstruction of field possible *at every node* using above equation

Example: Estimate diffusion by moving sensors

- $f(\boldsymbol{x})$ describes a diffusion process with 2 sources
- sensors can move $\rightarrow$ optimize sensor movement to improve estimation quality



B.-S. Shin, H. Paul, A. Dekorsy: Spatial Field Reconstruction with Distributed Kernel Least Squares in Mobile Sensor Networks. Accepted for publication at SCC 2017