

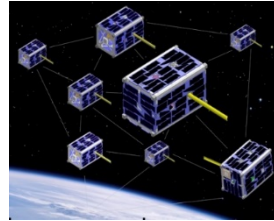
23. VDE/ITG Fachtagung Mobilkommunikation
Hochschule Osnabrück

NEW DIRECTIONS IN WIRELESS COMMUNICATION RESEARCH AND WHAT THEY WILL ENABLE

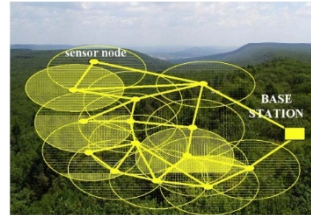
Prof. Dr. Armin Dekorsy
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University of Bremen



- Ubiquitous communication among people and devices to serve huge amount of very divers future applications



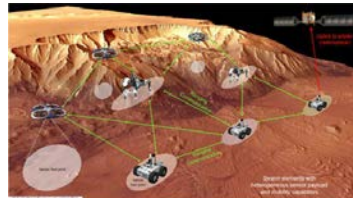
source: University of Bremen



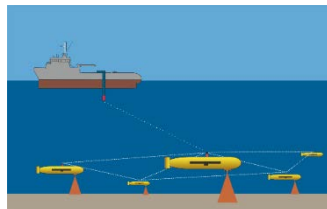
source: Universita Padova



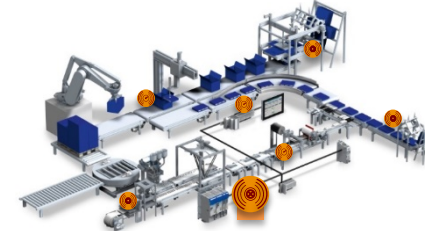
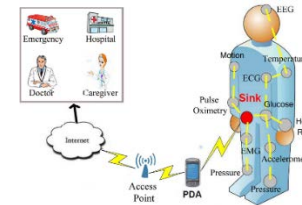
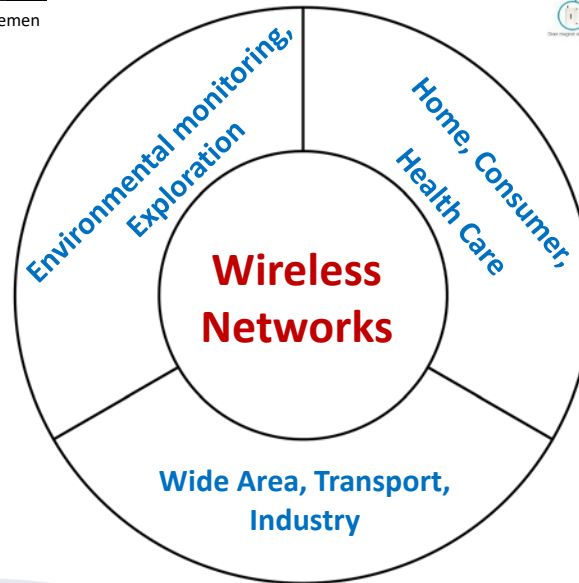
source: EBIZBY Design



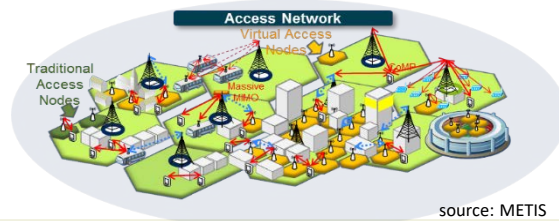
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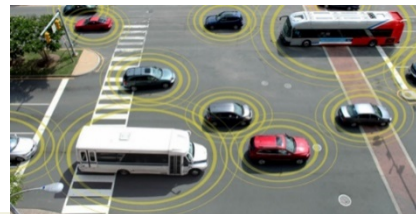
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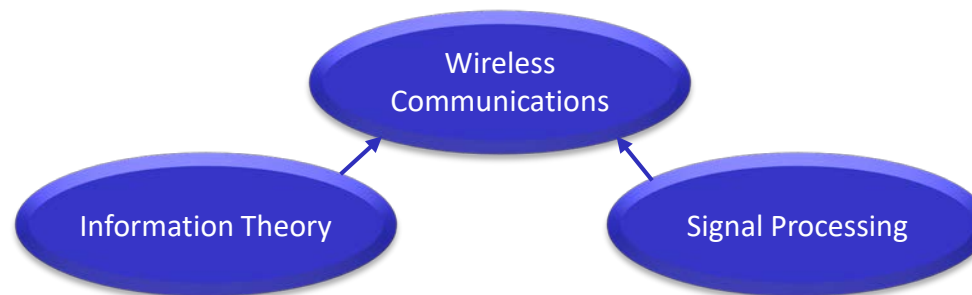


source: METIS



source: UBI telematics

- **Key challenges:**
 - ◆ Massive amount of connections
 - ◆ Massive amount of data
 - ◆ Huge variety of data rates and latencies
 - ◆ Huge variety of reliable requirements
 - ◆ ...
- **Key enabling/driving technologies**
 - ◆ Wireless communication technologies (e.g. massive MIMO, mmWave, cooperative communications, relaying)
 - ◆ Signal and data processing approaches (e.g. compressive sensing, in-network processing, relevant information processing, graph-based processing, machine learning)
 - ◆ Information theoretical approaches (e.g. Information Bottleneck Framework)



COMPRESSIVE SENSING

- Signal Structure Processing-

C. Bockelmann, F. Monsees, H. Schepker, E. Beck, T. Schnier, A. Dekorsy
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- Donoho/Candes 2006: Signal $\mathbf{z} \in \mathbb{R}^{1 \times N}$ is compressible in some basis $\Phi \in \mathbb{R}^{N \times N}$

$$\mathbf{z} = \Phi \mathbf{x} \quad \text{with} \quad \mathbf{x} \in \mathbb{R}^{1 \times N}$$

- Compressible:

\mathbf{x} is k -sparse

$$\begin{pmatrix} 0 \\ 0 \\ 1.4 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 2 \end{pmatrix}$$

only a few non-zeros
2-sparse vector



Positions and values of non-zeros
represent signal!

- Observe \mathbf{z} by measurement matrix $\Psi \in \mathbb{R}^{M \times N}$ with $M < N$ noisy observations

$$\begin{aligned} \mathbf{y} &= \Psi \mathbf{z} + \mathbf{n} \\ &= \Psi \Phi \mathbf{x} + \mathbf{n} = \mathbf{A} \mathbf{x} + \mathbf{n} \end{aligned}$$

(underdetermined linear system)

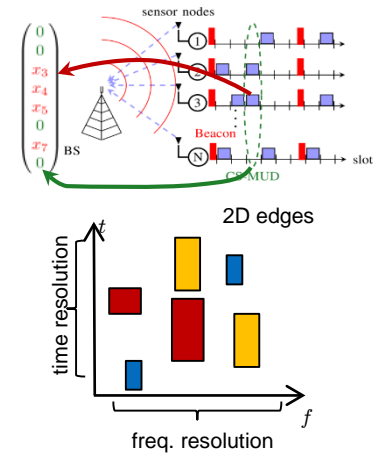
with noise $\mathbf{n} \in \mathbb{R}^M$ and $\mathbf{A} = \Phi \Psi \in \mathbb{R}^{M \times N}$

- Task:** Recover $\mathbf{x} \in \mathbb{R}^N$ using $M < N$ measurements in vector \mathbf{y} by exploiting the signal structure that \mathbf{x} is sparse → l_1/l_2 -optimization problems

$$\hat{\mathbf{x}} = \underset{\mathbf{x} \in \mathbb{R}^N}{\operatorname{argmin}} \|\mathbf{x}\|_1 \quad \text{s.t.} \quad \|\mathbf{y} - \mathbf{A} \mathbf{x}\|_2^2 < \epsilon$$

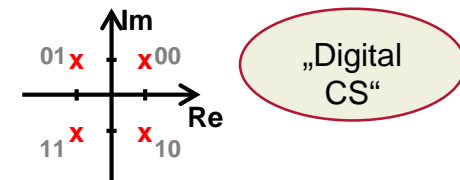
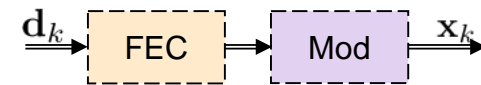
Applications

- Channel Estimation
 - Most impulse responses of wireless channels are sparse in sample clock
- Sporadic Communication
 - Machine type traffic leads to sparse detection problems
- Spectrum Sensing
 - Cognitive radio idea: Spectrum or edges of spectrum are sparse

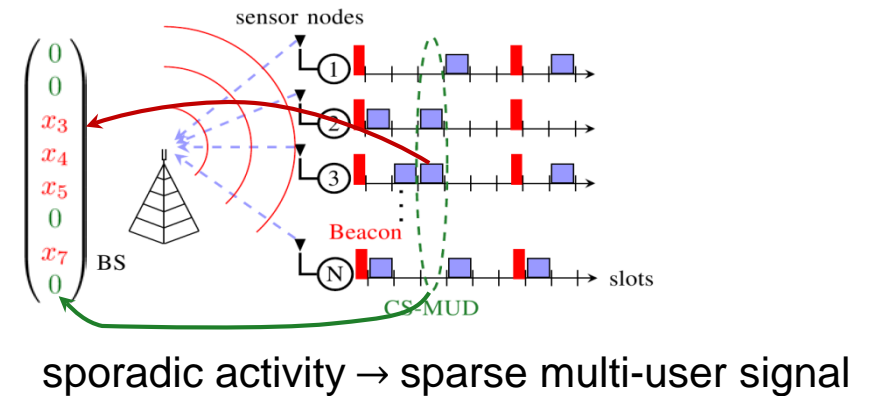
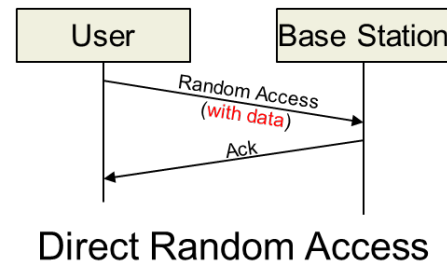
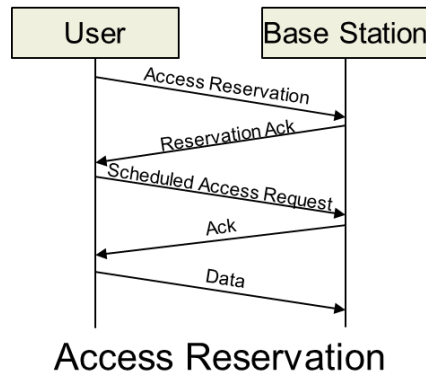


Key differences to standard CS problems

- Forward Error Correction: non-zero elements in \mathbf{x} are part of a codeword
 - Additional structure that can be exploited, e.g. by iterative decoding
- Modulation: non-zero elements in \mathbf{x} are not continuous
 - Discrete symbol alphabets \rightarrow requires adapted CS-algorithms
 - \rightarrow Digital CS

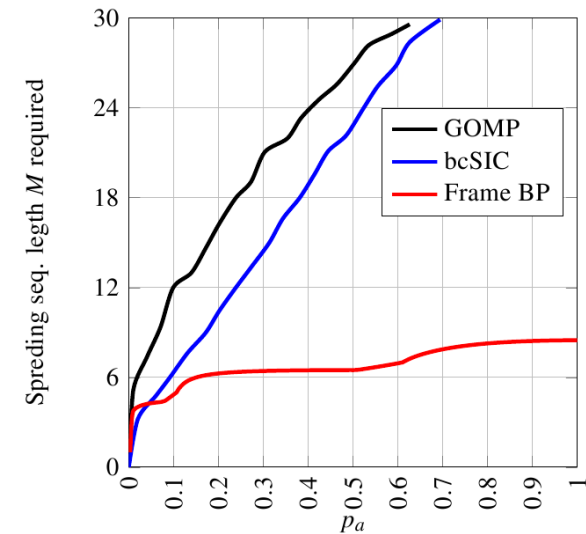
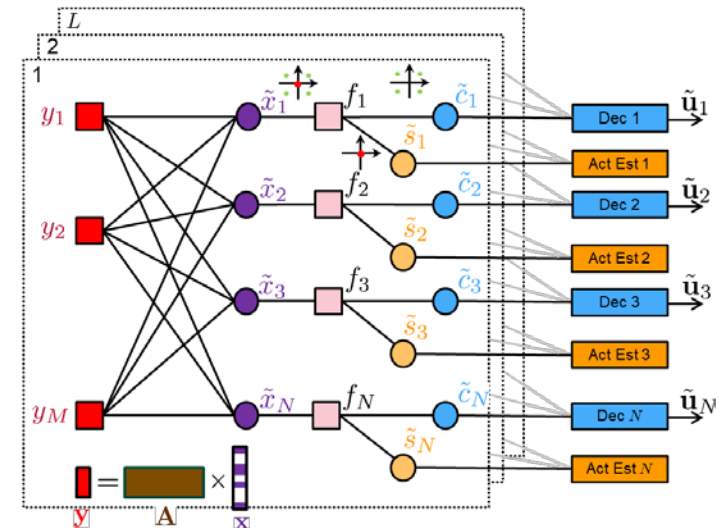


- IoT/5G challenge: Massive Machine type Communication (MMC)
 - MMC is usually of low power, low rate and intermittent activity
 - New PHY/MAC are needed to handle massive access with **very low control signaling overhead**



- Task:** Design **sparsity exploiting multi-user receivers** (linear and non-linear) for activity, data and channel estimation

- Research task: Message Passing for CS-MUD
 - Graph-based CS-MUD detector
 - Exchange of soft information (PDFs)
 - Spreading based transmission
- Key challenge:
 - Joint soft activity and data detection
- Key results:
 - Plot: spreading sequence length M required for a $\text{FER} < 10^{-3}$
 - $M < N \rightarrow$ overloaded system
 - Frame Belief Propagation (Frame BP): slight increase in M for high p_a
 - Frame BP outperforms state-of-the-art algorithms such as GOMP and bcSIC



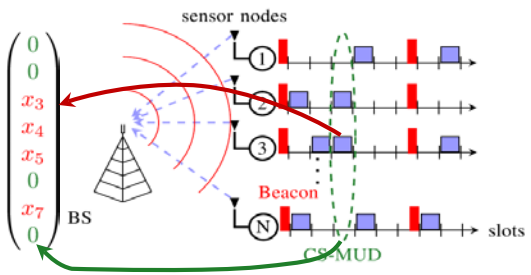
$N=30$ Nodes, Frame Length $L=30$ code-symbols

Repetition code $R=5$

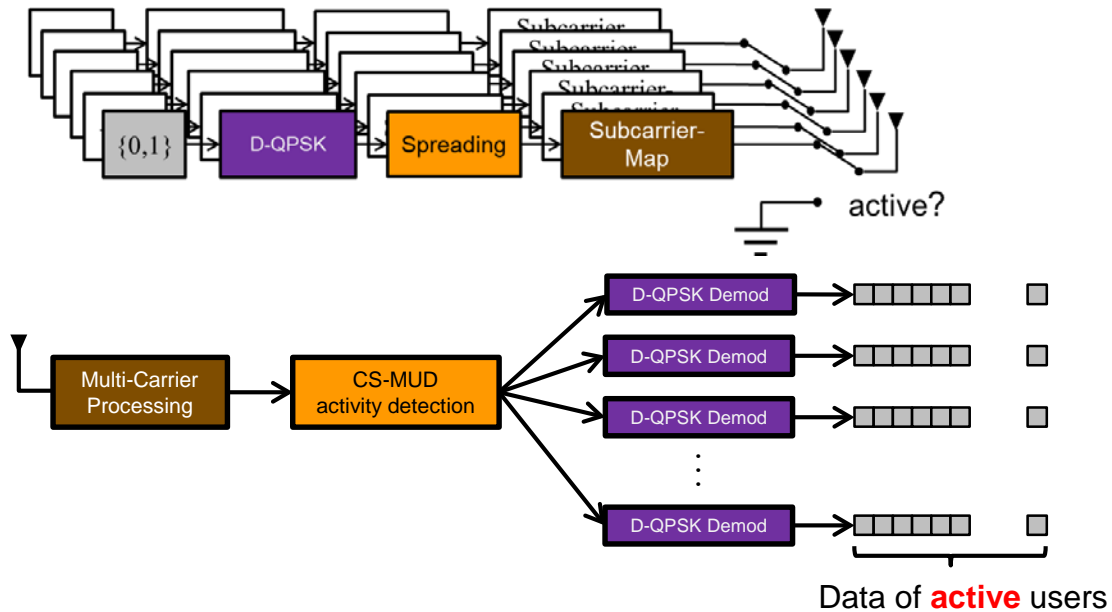
Multi-Carrier Compressive Sensing Multi-User Detection (MCSM)

MMC: Massive Machine type Communications

CS-Theory



MCSM concept



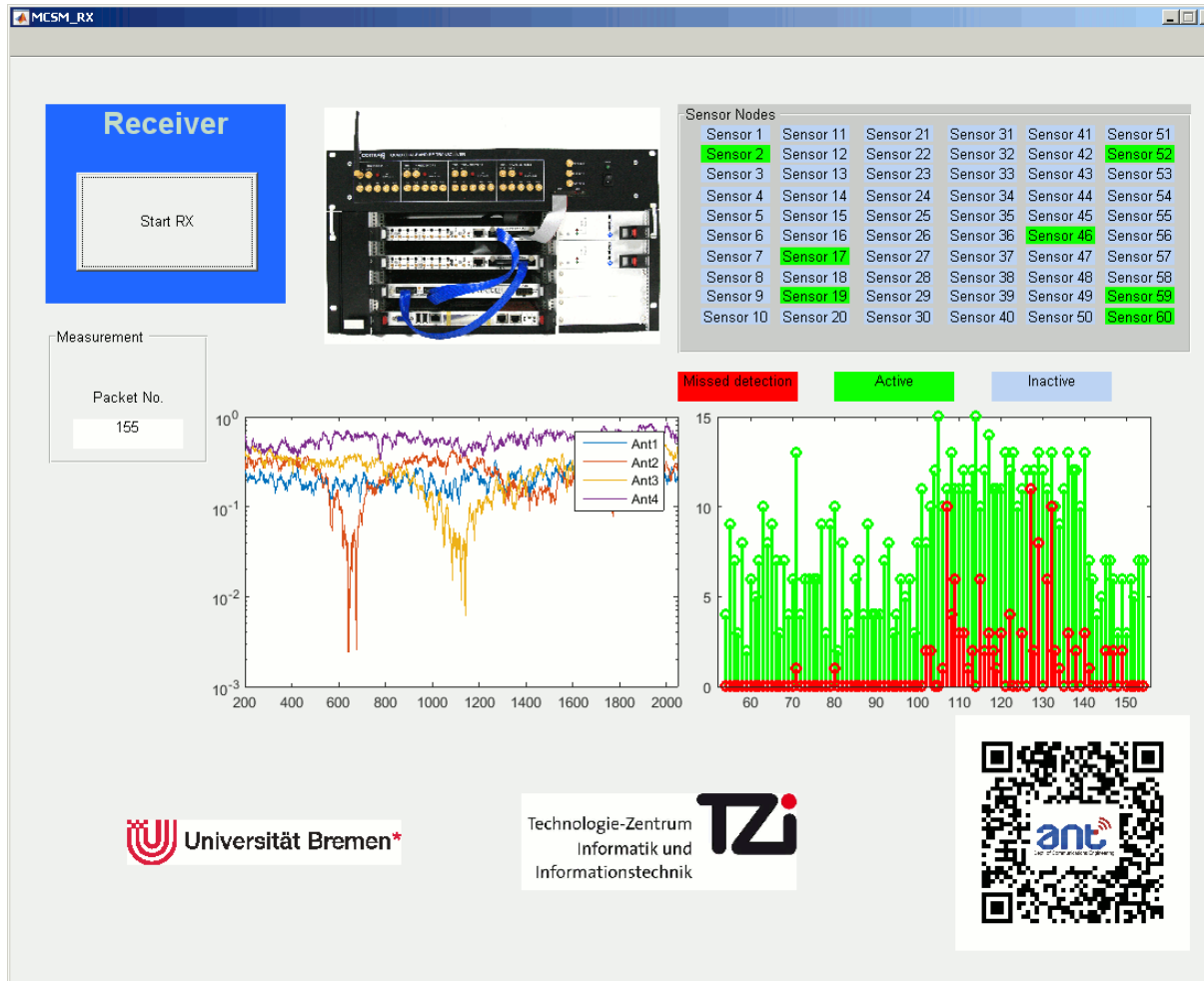
design process

industry, standards

proof of concept

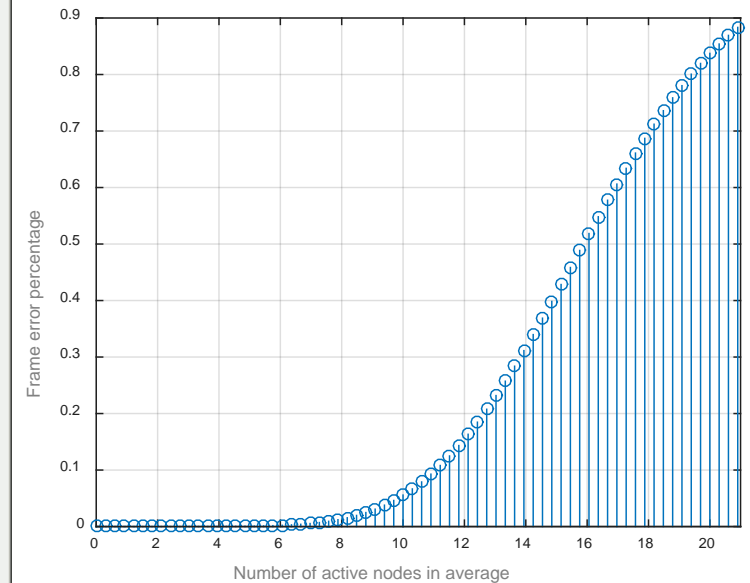


Demos:
SCC17, Wireless
Automation 2017

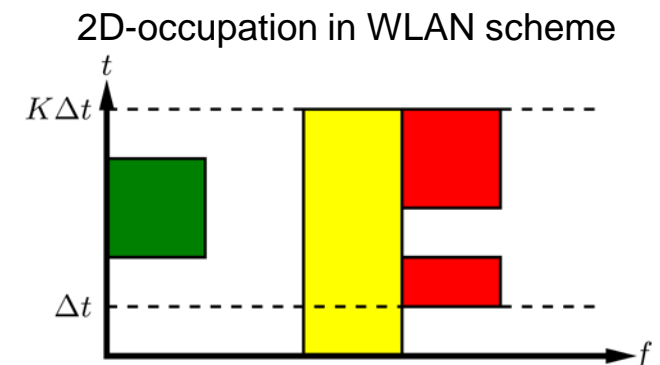
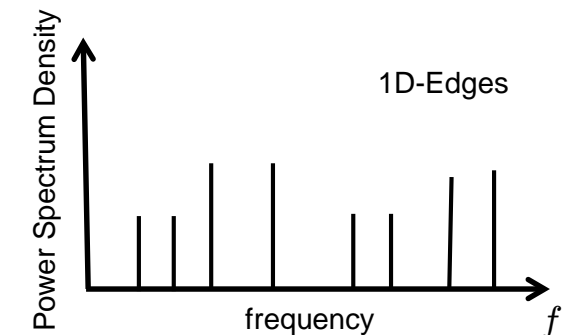
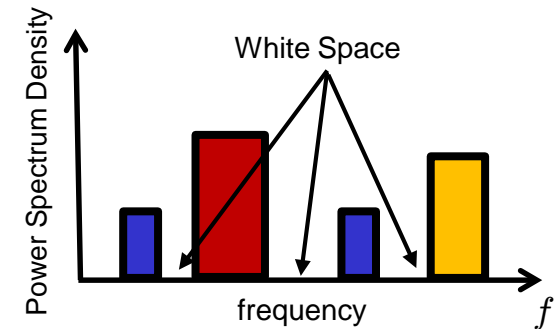


■ MCSM Receiver GUI

- ◆ Live recording of sporadic transmission of 60 nodes
- ◆ Packet 1-100 with $p_a = 0.1$
- ◆ Packet 101-140 with $p_a = 0.25$
- ◆ FER performance: Graceful degradation with higher activity



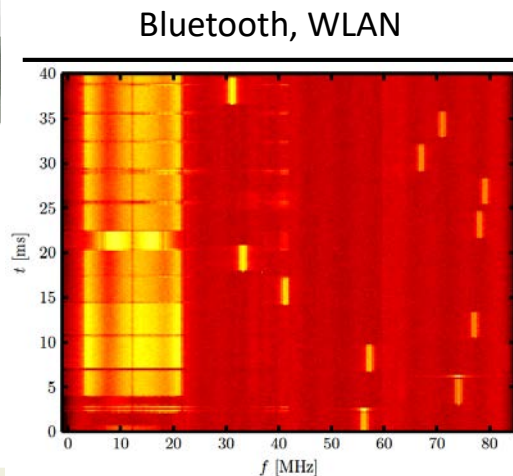
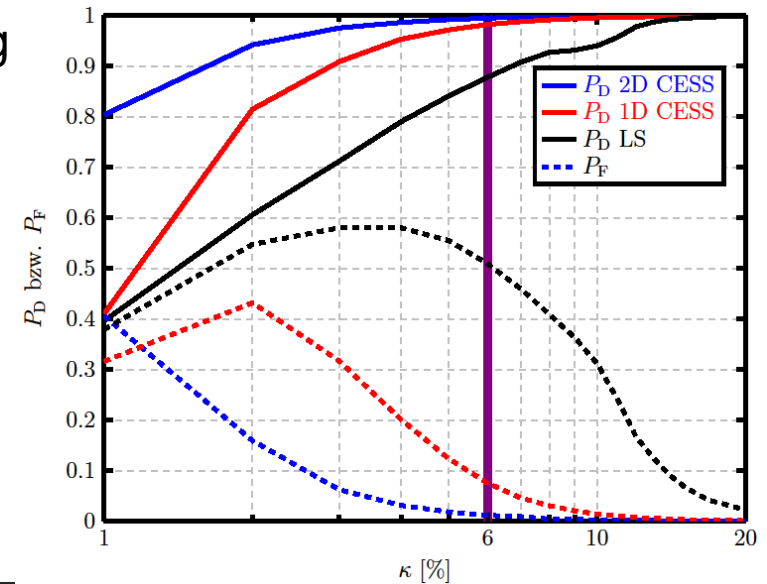
- **Research task:** Design of CS-spectrum sensing algorithms (input for coexistence management)
- **SotA:** Sensing approaches using Nyquist sampled signals → wide-band sensing → high sampling rate → costly hardware
- **Approach:**
 - ◆ Exploit sparsity in spectral domain → go for undersampling with CS using autocorrelation properties
 - ◆ Edge detection → even more sparse signals
 - ◆ Sporadic activity → 2D edge sensing (f and t) by minimizing total variation
- **Key challenges:**
 - ◆ Reconstruct edges in 1D or 2D



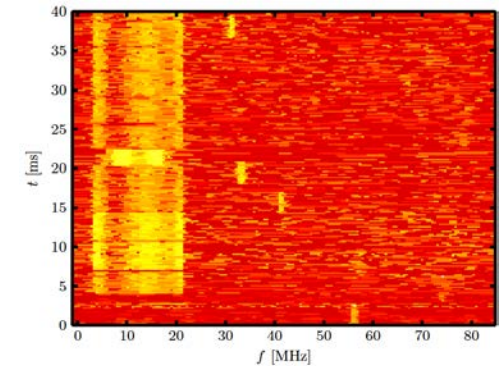
- Key results:
 - 1D and 2D outperforms classical LS sensing
 - 100% detection at 6% of Nyquist rate

- Proof-of-Concept: WLAN and Bluetooth
 - WLAN: 15% of Nyquist rate works
 - Bluetooth (narrow band) more sensitive

Sporadic access with 40% mean occupation
bandwidth 100 MHz, blocks of 20 MHz, 1D: OMP, 2D: I1/I2-optimization



Wideband Sensing
80 MHz band, 2.4 GHz ISM-Band
1D, OMP reconstruction



8% of Nyquist rate

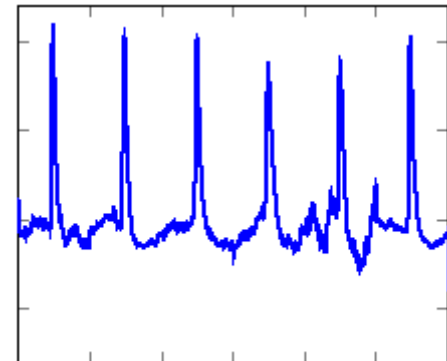
CS-Signal Acquisition and Reconstruction of Neuronal Signals

- Research task: Reduction of data rate for neural data acquisition

- Utilize sporadic nature of spikes
- Design of reconstruction algorithms



source: www.extremetech.com/extreme



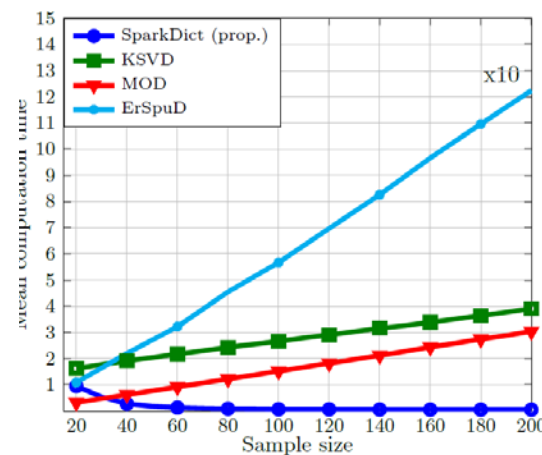
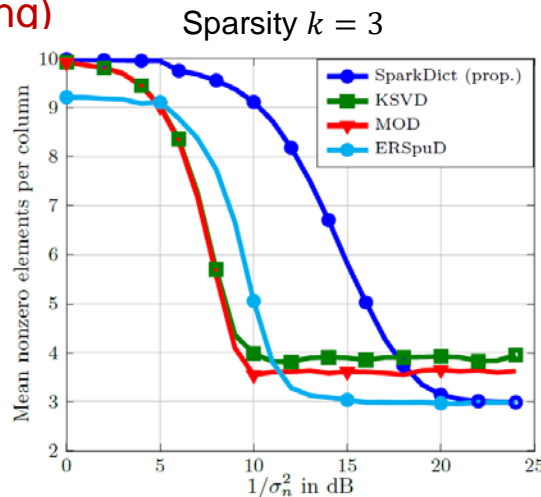
Typical neural spike shape

- Key challenges:

- Strict circuit area and power constraint
- Multiple correlated electrodes
→ joint reconstruction of correlated signals
- Sparsity domain unknown
→ dictionary learning (machine learning)

- Key results:

- SparkDict: CS reconstruction algorithm for joint reconstruction w/ dictionary learning



[KSVD] M. Aharon, M. Elad, and A. Bruckstein, k-SVD: An Algorithm for Designing Overcomplete Dictionaries for Sparse Representation", IEEE Transactions on Signal Processing

[MOD] K. Engan, S. O. Aase, and J. H. Husoy (Editors), Method of optimal directions for frame design, 1999, ISBN 0780350413

[ERSpuD] D. A. Spielman, H. Wang, and J. Wright, Exact recovery of sparsely used dictionaries", arXiv preprint arXiv:1206.5882, 2012.

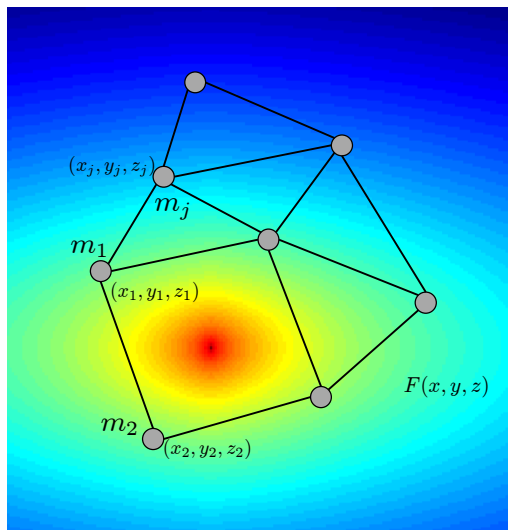
IN-NETWORK-PROCESSING

Distributed Signal Processing

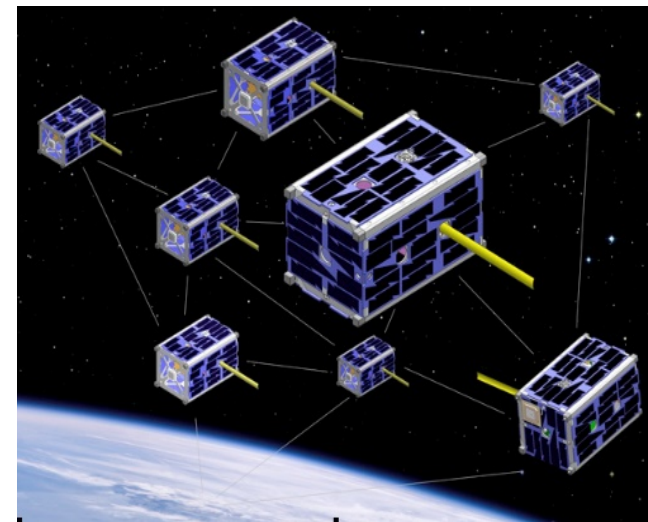
H. Paul, G. Xu, S. Wang, M. Röper, B. Shin, A. Dekorsy
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University of Bremen



- Network of nodes perform noisy measurements of same physical quantity, e.g. temperature
- Measurements are processed within multi-agent system/network (In-Network Processing) to perform distributed estimation of physical entity
- Examples:

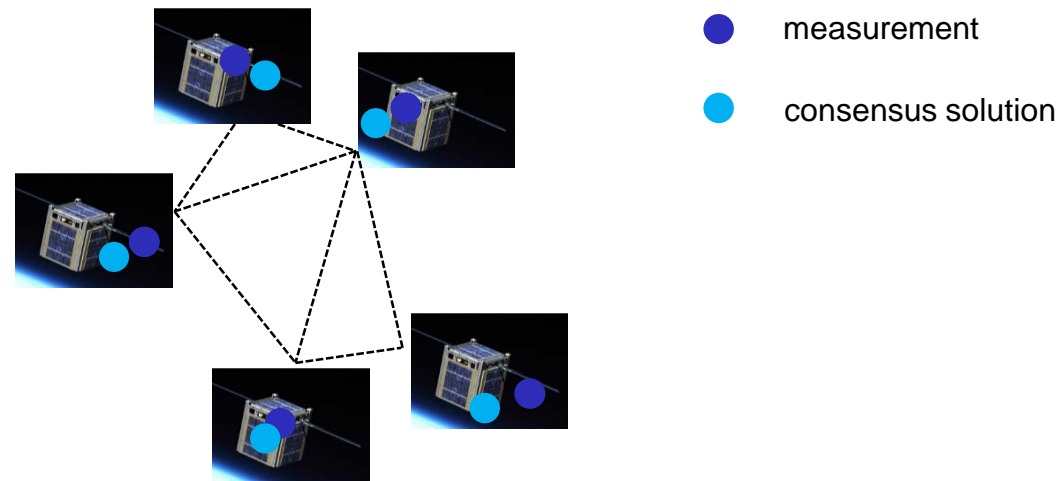


Environmental monitoring



CubeSat swarms e.g. for earth observations

- **Idea:** Calculate a function within a network, e.g. averaging, MMSE/LS, Kalman filtering
- **Consensus based:** Algorithm converges to identical solution at all nodes, e.g. central solution



- **Advantages:** No single point of failure/trust, data processing in local network (no cloud), communication robustness, more secure (e.g. attacks)
- **Challenges:** Design of algorithms converging to central (optimum solution) with less communication overhead, facilitating tight integration of wireless communication

- Research task: **Distributed nonlinear regression of any function $f(x)$**
- Application: Predict diffusion field $f(x)$ at positions x using sensor measurements d
- Key challenges:

- Nonlinear $f(x)$, convergence, communication overhead**

- Mathematical approach:

- Transform all sensor positions x_i by nonlinear kernel function $k(\cdot, x_i)$ into reproducing kernel Hilbert space (RKHS)
 - Unknown nonlinear function f is modeled in **linear form**

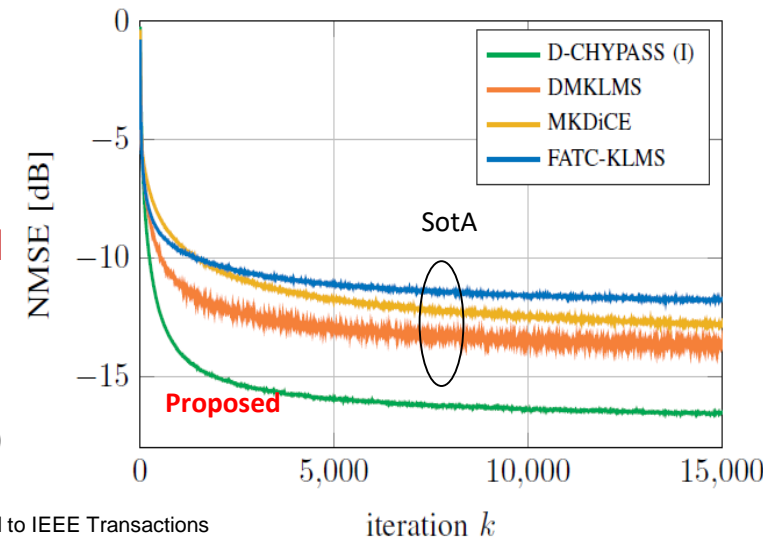
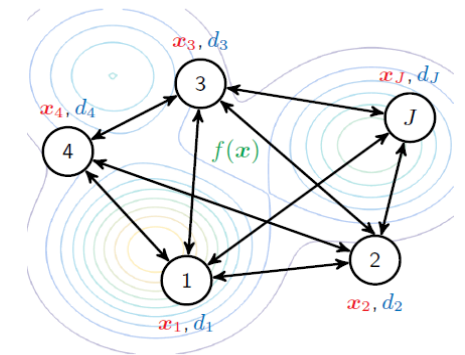
$$f(\cdot) = \sum_i w_i k(\cdot, x_i)$$

as element of RKHS

- Estimate coefficients w_i by expanding **set-theoretic learning to a distributed setting** → **faster convergence and improved estimation accuracy (NMSE)**

- Key results:

- Distributed kernel-based adaptive learning (**D-CHYPASS**)

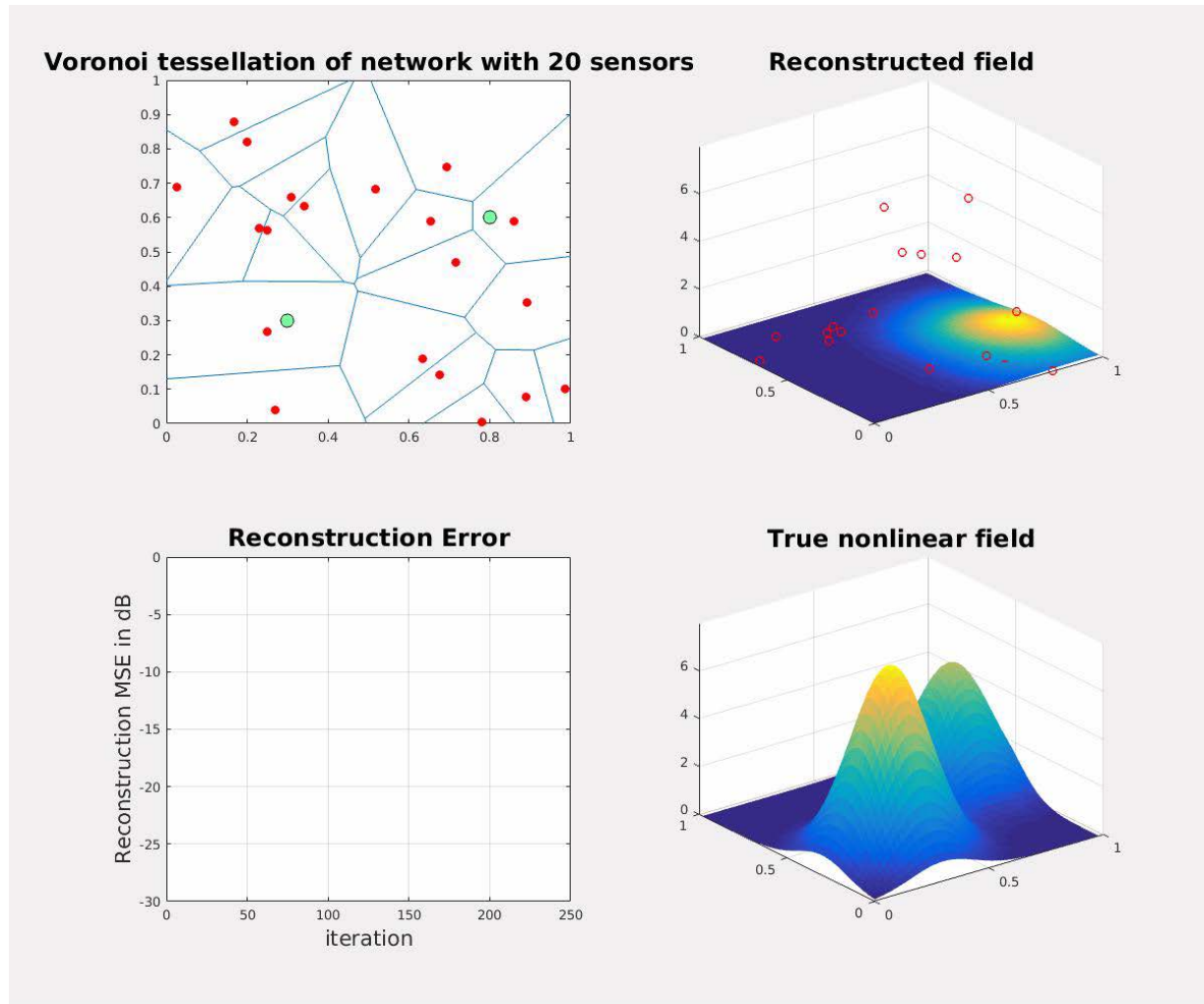


[DMKLMS] Shin, Yukawa, Cavalcante, Dekorsy, "Distributed adaptive learning with multiple kernels in diffusion networks", submitted to IEEE Transactions on Signal Processing, 2018

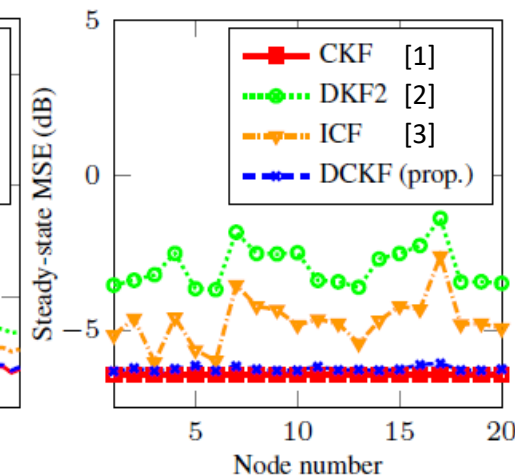
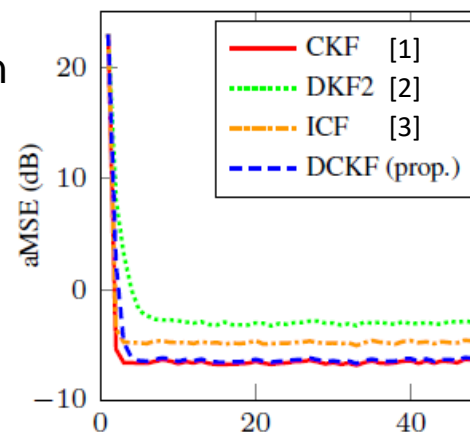
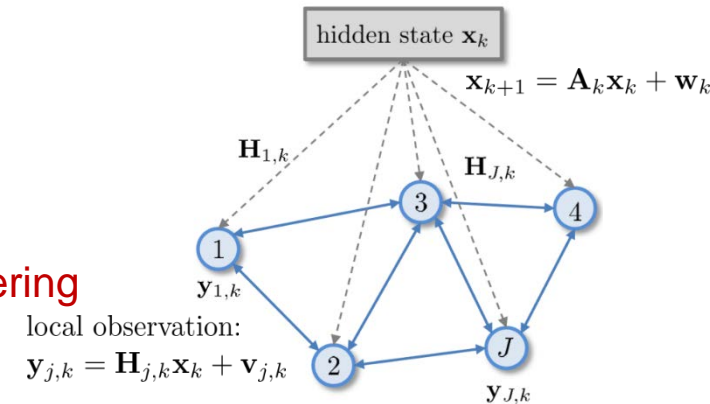
[MKDiCE] Shin, Paul, Yukawa, Dekorsy, "Distributed nonlinear regression using in-network processing with multiple Gaussian kernels", IEEE SPAWC 2017

[FATC-KLMS] Gao, Chen, Richard, Huang, "Diffusion adaptation over networks with kernel least-mean-square", IEEE CAMSAP 2015

- Demo of **mobile sensor network** with distributed kernel least squares (KDiCE) algorithm
 - ♦ Mobile sensor network with 20 nodes (**red**)
 - ♦ Nonlinear field $f(x)$ with two diffusive sources (**green**)
 - ♦ Sensor moves to centroid of Voronoi cell of reconstructed field



- **Research task:** Distributed state estimation for dynamic systems
- **Application:** Distributed control, e.g. control of a swarm of unmaned autonomous vehicles (UAVs)
- **Key challenge:** Joint design of control and communication
 - ◆ Distributely estimate hidden states of system to be controlled by using local observation of states → Distributed Kalman Filtering
- **Mathematical approach:**
 - ◆ Exploit equivalence of KF and MAP estimation in Gaussian setting
- **Key results:** DCKF algorithm
 - ◆ Convergence to central solution proofed
 - ◆ DCKF ensures consensus on estimates



[1]. R. E. Kalman, "A new approach to linear filtering and prediction problems," Journal of Basic Engineering.

[2]. R. Olfati-Saber, "Distributed Kalman filtering for sensor networks," in Proc. of the 46th IEEE Conf. on Decision and Control, 2007.

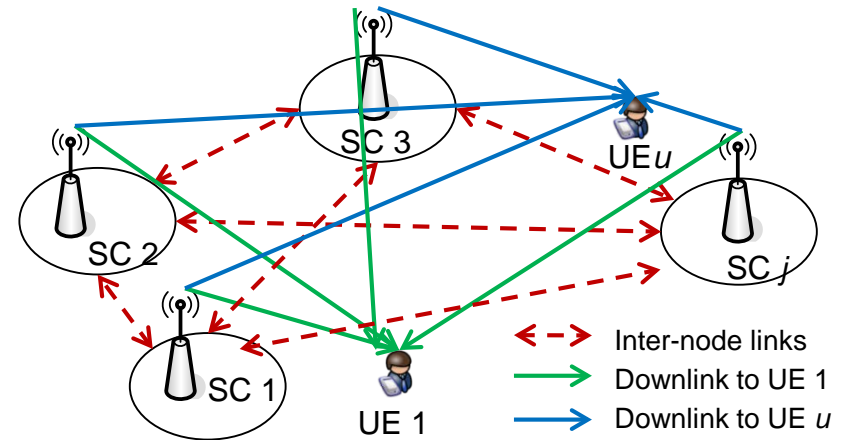
[3]. A. T. Kamal, J. A. Farrell, and A. K. Roy-Chowdhury, "Information weighted consensus," in Proc. of the 51st IEEE Conf. on Decision and Control, 2012.

- **Research task:** Investigations on algorithms for **distributed precoder/beamformer design**
- **Application:** Distributed RAN (5G) - Downlink
- **Key challenges:**
 - ◆ Computational efficient / low latency
 - ◆ Low communication overhead

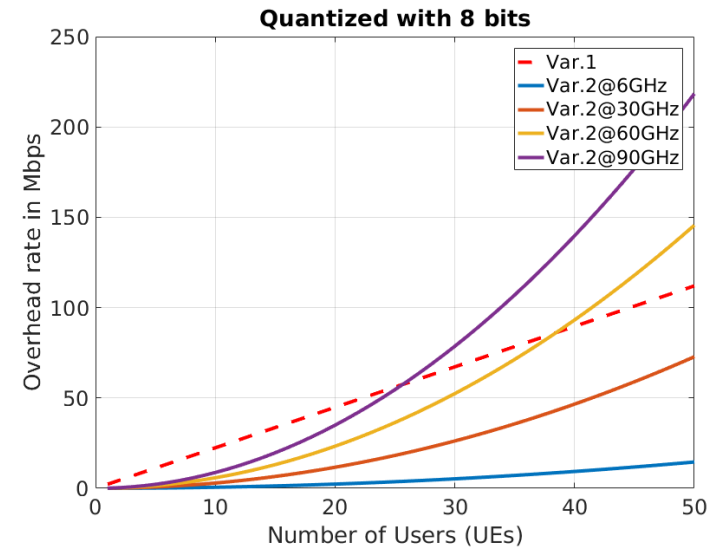
$$\mathbf{x}_j = \mathbf{G}_j \mathbf{s}; \quad \dim(\mathbf{G}_j) = \# \text{ transmit antennas} \times \# \text{ UEs}$$

data: \mathbf{s} multiuser vector

receive signal: $\mathbf{y}_u = \sum_{j=1}^{N_{SC}} \mathbf{x}_j + \mathbf{n}$; superposition of all SCs



- **Key results:**
 - ◆ **Distributed MMSE (e.g., Richardson (PR) iteration)**
 - ◆ Var.1: Communicate transmitted signals $\propto \# \text{ UEs}$
 - ◆ Var.2: Communicate precoding matrices $\propto (\# \text{ UEs})^2$
 - ◆ Var.2: The faster the channel the more often we have to update the matrix \rightarrow overhead increases
 - ◆ **Trade-off between Var1 and Var2**



- **Research task:** Design an analysis of **distributed estimation algorithms**
- **Application:** Distributed RAN (5G) – Uplink → Small Cells share information to jointly estimate received user signals → **distributed multi-user detection**

Distributed consensus-based LS problem

central LS problem

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

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

s.t. $\mathbf{s}_j = \mathbf{s}_i \quad \forall j \in \mathcal{J}, i \in \mathcal{N}_j$

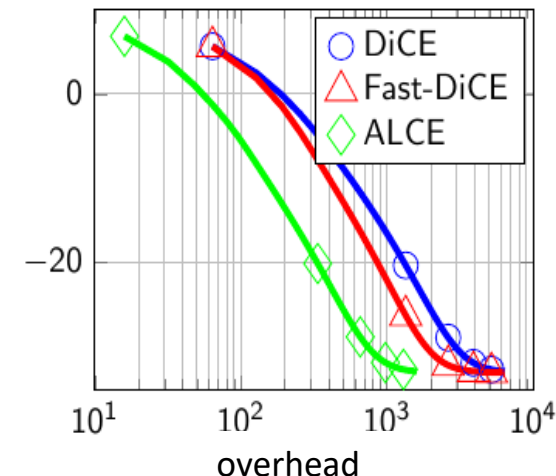
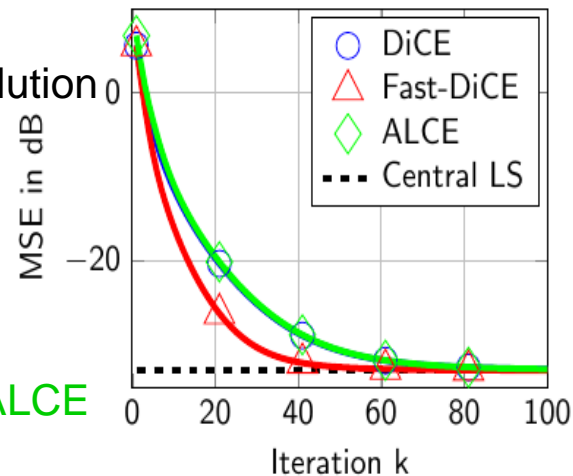
\mathcal{J} : set of nodes
 \mathcal{N}_j : set of neighbor nodes of node j

Key challenges:

- ◆ Guarantee convergence to central solution
- ◆ Ensure high convergence rate and/or low communication overhead

Key results:

- ◆ Several algorithms **DiCE**/**Fast-DiCE**/**ALCE**

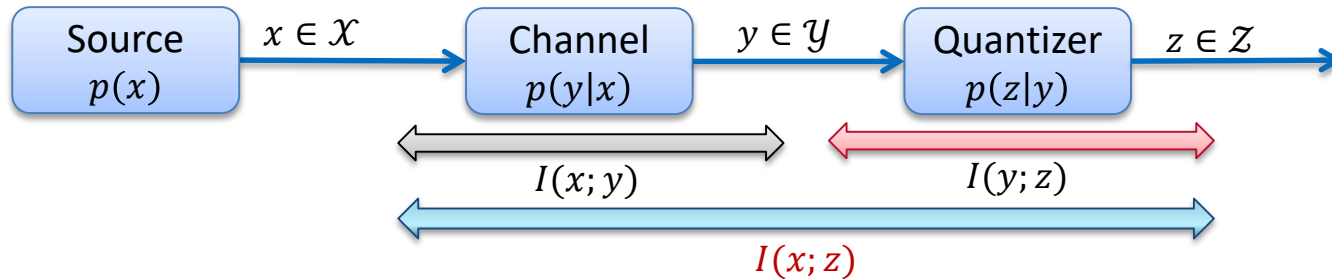


INFORMATION BOTTLENECK

Relevant Information Processing

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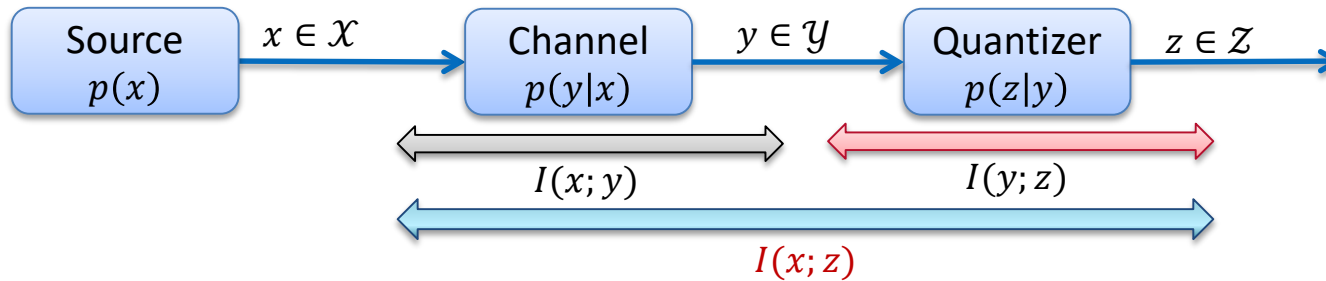




Markov chain: $x \rightarrow y \rightarrow z$
 $p(x, z|y) = p(x|y) \cdot p(z|y)$

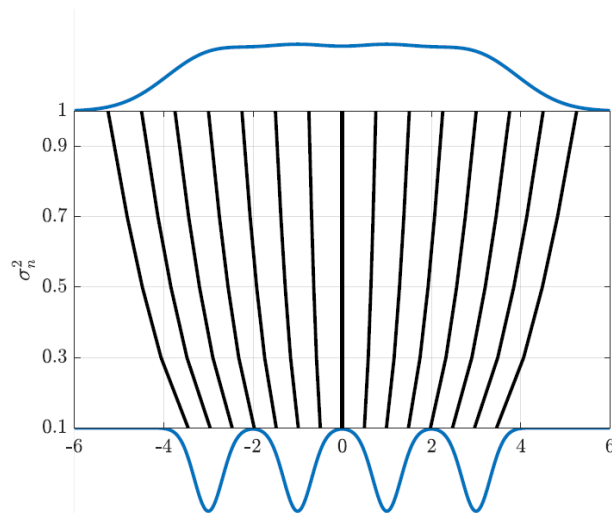
- Mutual Information $I(x; y)$: amount of information one random variable contains about the other
- Conventional quantization – information in signal x is not specifically considered, just by means of received signal y
 - ♦ Minimization of MSE $d(y, z) = \mathbb{E}\{|y - z|^2\}$ → Lloyd-Max/LBG algorithm
 - ♦ Rate-Distortion Theory: Minimization of **compression rate** $I(y; z)$, **i.e. number of bits**, for given maximum distortion $d(r, q) \leq D$ → Blahut-Arimoto algorithm
- Information Bottleneck Method (IBM)
 - ♦ **Relevant information processing**: interest is on information of source signal x
 - ♦ Trade-off between compression rate and **relevant information**

$$p^*(z|y) = \arg \min_{p(z|y)} (I(y; z) - \beta I(x; z)) \text{ with } |Z| \leq N$$



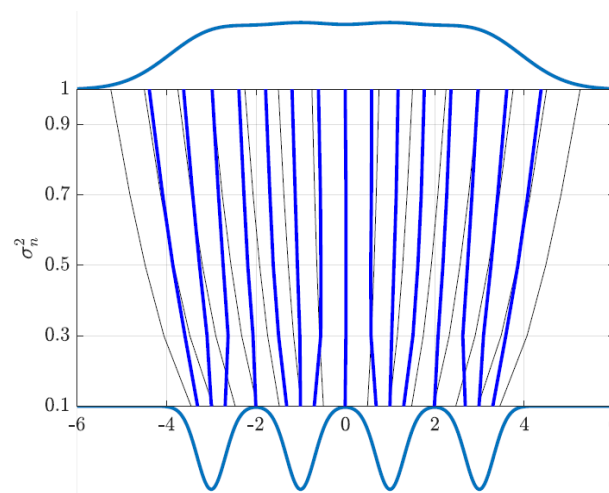
Quantization boundaries: 4-ASK over AWGN, noise variance σ_n^2 , quantized to $N_z = 16$

Uniform Quantizer (UQ)



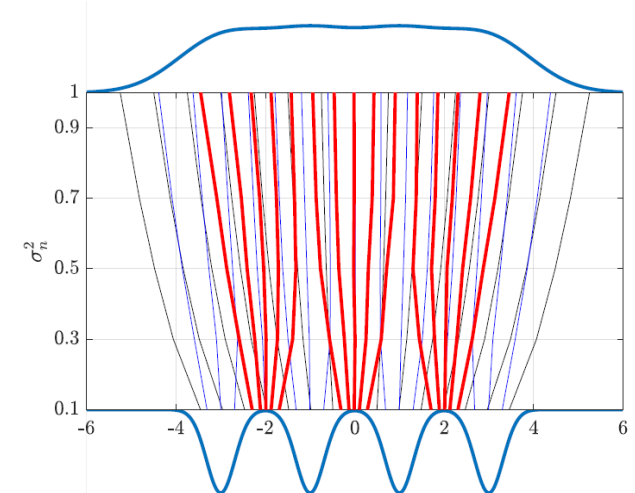
equidistant quantization

Lloyd-Max Quantizer (LM)



concentrates quantization levels around expected signals ($\pm 1, \pm 3$)

KL-Means-IB Algorithm



considers quantization levels around the middle values ($\pm 2, 0$)

- Research task: Design and analyze IBM algorithms

$$p^*(z|y) = \arg \min_{p(z|y)} (I(y; z) - \beta I(x; z)) \text{ with } |Z| \leq N \quad 0 < \beta < \infty$$

neither convex nor concave
stochastic quantizer $0 \leq p(z|y) \leq 1$

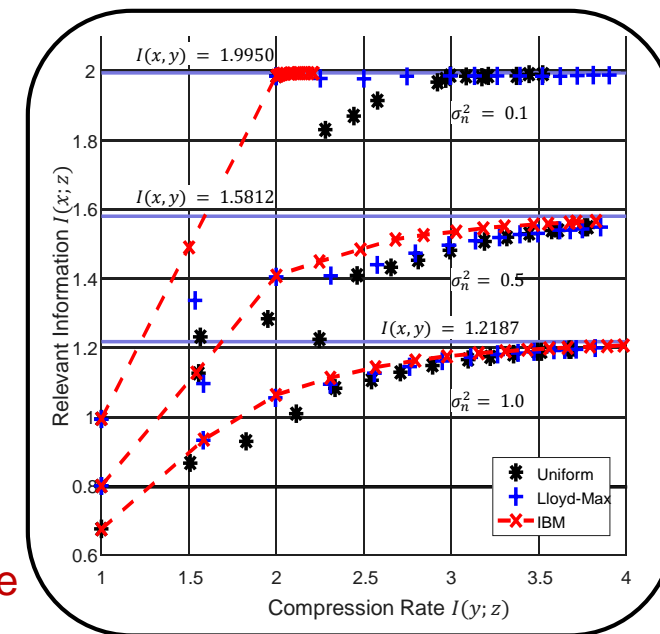
$\beta \rightarrow \infty$ concave optimization with optimal deterministic solution $p(z|y) \in \{0,1\}$

- Key challenges:

- Quantizer design is a non-convex optimization problem

- Key results:

- Proving equivalence among bunch of algorithmic approaches
- SotA IBM algorithms:
output z is a random variable, i.e. its values are indices
→ new pre-processing is required, e.g. new APP estimator
- Affinity propagation based IBM quantizer ($\beta \rightarrow \infty$)
output z represents a signal value → we can keep conventional pre-processing
- Keeping more relevant information with lower compression rate



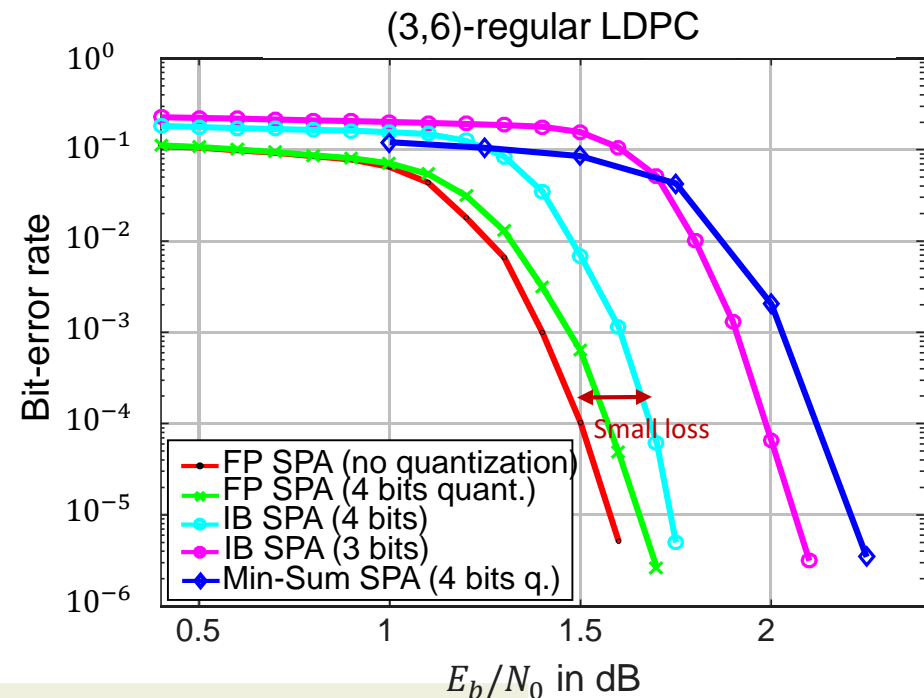
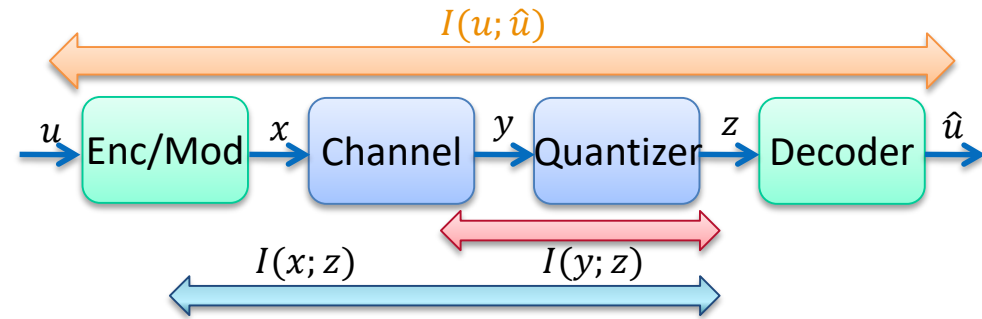
- Research task: Analysis of **Information Bottleneck based receivers**
 - LDPC decoder:** Information Bottleneck → **discrete sum-product algorithm (IBM-SPA)**

Key challenges:

- Trade-off between compression rate $I(y; z)$ and end-to-end information $I(u; \hat{u})$
- Information Bottleneck based SPA (IBM-SPA)** → instead of complex floating point operations discrete implementation by using **LUTs**

Key results:

- Trade-off between complexity and performance
- IBM-SPA with 4-bit shows **small loss** compared to floating point SPA w/ quantization



[1] F.J.C. Romero and B. Kurkoski, LDPC Decoding Mappings That Maximize Mutual Information, IEEE Journal on Selected Areas in Communications

[2] J. Lewandowsky, M. Stark, G. Bauch, Optimum Message Mapping LDPC Decoders derived from the Sum-Product Algorithm, IEEE ICC 2016

LOW LATENCY, SHORT PACKAGES

HiFlecs

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Department of Communications Engineering
University of Bremen





Hochperformante, sichere Funktechnologien
und deren Systemintegration in zukünftige industrielle
Closed-Loop Automatisierungslösungen

Coordination: Prof. Dr. Armin Dekorsy, University of Bremen



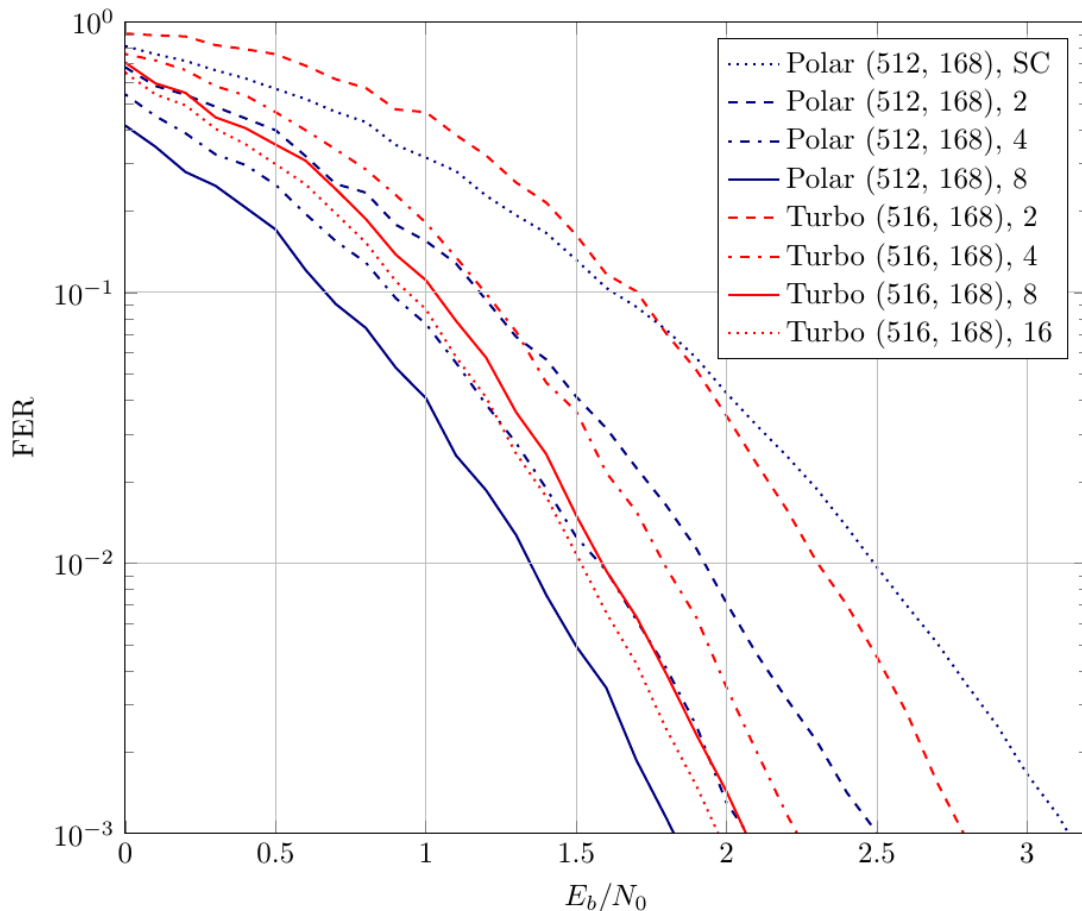
GEFÖRDERT VOM



Design of an industrial radio system

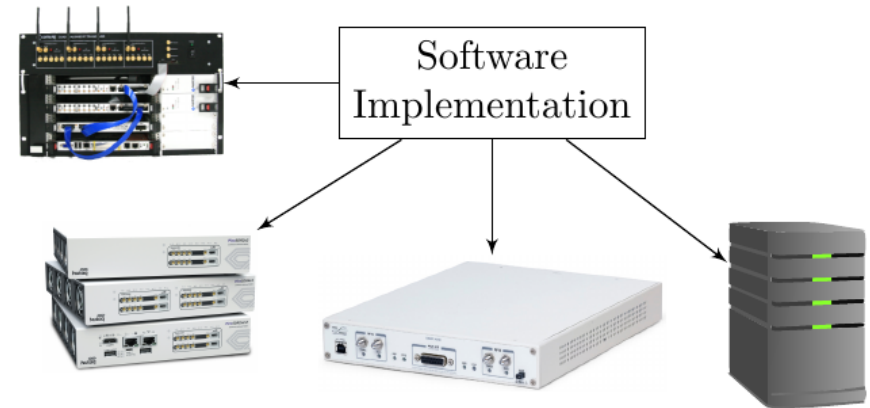
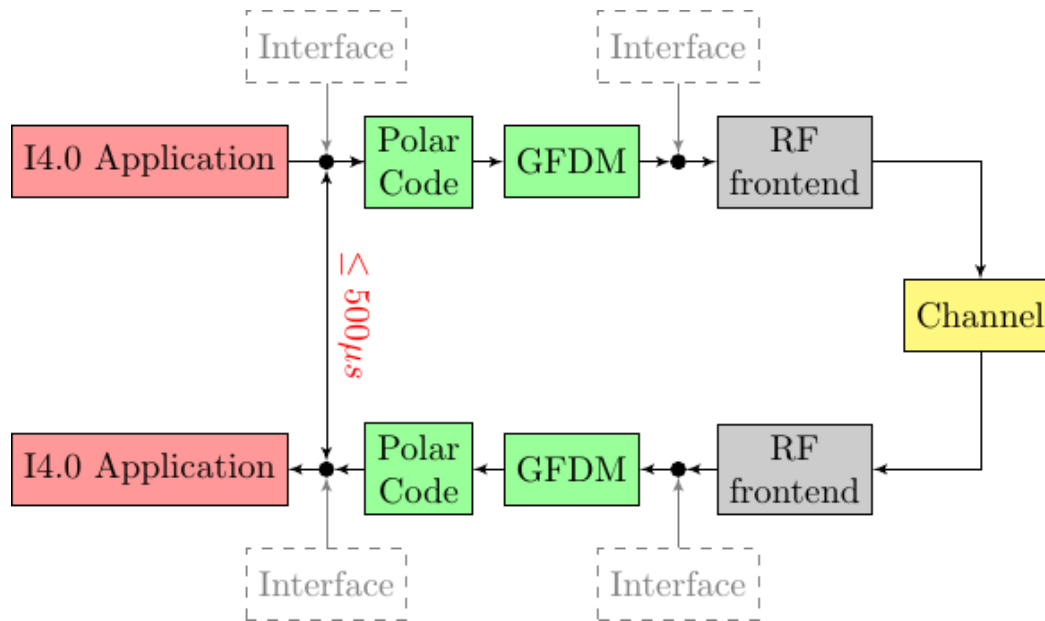
- Extremely low latency ($< 1\text{ms}$)
- Extremely high availability and reliability ($\text{PER} < 10^{-9}$)

- Polar Codes with CRC vs. Turbo-Codes (e.g. used in LTE)
- Decoder: List-Decoder for Polar Codes
- Example: Packet length of **168 info bits**



**Polar Codes outperform
Turbo Codes**

PHY - Latency optimized SDR Baseband Implementation

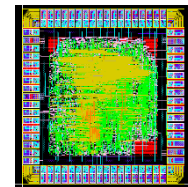
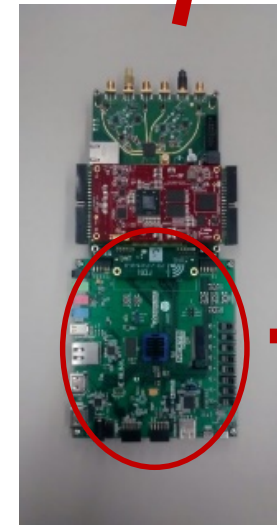
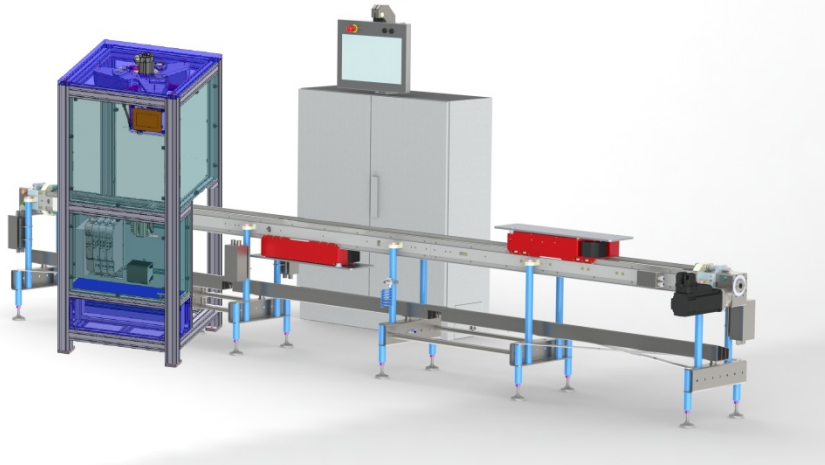
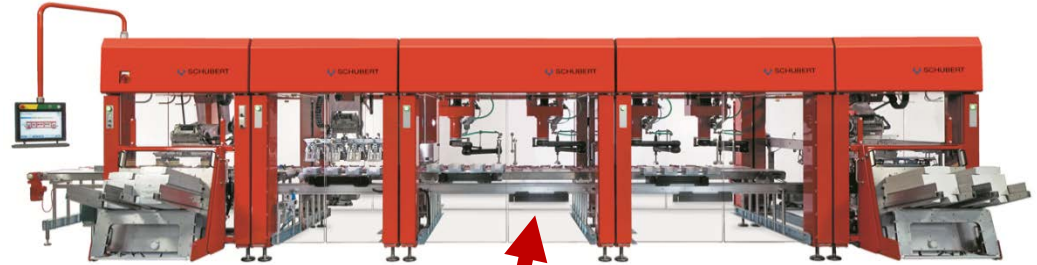


- **GFDM scheme:** low latency implementation
- **Polar Codes:** State-of-the-Art high throughput implementation
- **Phy processing latency less than 1ms** per link for typical block sizes used in control loop applications

Demonstrator: Transmodul line of a packing machine



- Wireless data transmission between control module (SPS) and transport modules by **HiFlecs**
- Synchronization with delta-robot and linear measurement system via **HiFlecs** (cycle time 1ms)



Grafiken: Gerhard Schubert GmbH

- **Compressive Sensing**
 - ♦ Exploiting channel coding in CS-MUD [ETT13, TCom15], Missed Detections / False alarms control [SCC15] Joint channel, activity and data estimation [ISWCS13], PHY/MAC integration [Globe14, ICC17]
 - ♦ PhD-Theses: Dr. Henning Schepker (2016), Dr. Fabian Monsees (2017)
 - ♦ C. Bockelmann, E. Beck, A. Dekorsy, One- and Two-dimensional Compressive Edge Spectrum Sensing, KommA 2017
 - ♦ E. Beck, C. Bockelmann, A. Dekorsy, Compressed Edge Spectrum Sensing for Wideband Cognitive Radios, submitted to EUSIPCO 2018
 - ♦ E. Beck, C. Bockelmann, A. Dekorsy, CESS: Extensions and Practical Considerations, submitted to at-Automatisierungstechnik (special issue)
 - ♦ E. Beck, Compressed Spectrum Sensing for Cognitive Radio in Time and Space, Master-Thesis University of Bremen, 2017
 - ♦ T. Schnier, C. Bockelmann, A. Dekorsy, RSCS: Minimum Measurement MMV Deterministic Compressed Sensing based on Reed Solomon Coding, Asilomar 2015
 - ♦ T. Schnier, C. Bockelmann, A. Dekorsy, SparkDict: A Fast Dictionary Learning Algorithm, 25th European Signal Processing Conference (EUSIPCO 2017)
- **In-Network Processing**
 - ♦ H. Paul, J. Fliege, A. Dekorsy, "In-Network-Processing: Distributed Consensus-Based Linear Estimation," IEEE Communications Letters, vol.17, no.1, Jan. 2013.
 - ♦ G. Xu, H. Paul, D. Wübben, A. Dekorsy, "Distributed Augmented Lagrangian Method for Cooperative Estimation in Small Cell Networks" SCC 2015
 - ♦ G. Xu, H. Paul, T. Schier, P. Svedman, A. Dekorsy, "Distributed precoding by in-network processing," European Wireless 2017 (EW17), May 2017.
 - ♦ M. Röper, P. Svedman, A. Dekorsy, "Distributed precoder design under per-small cell power constraint," IEEE VTC2018-Fall , August 2018. (planned)
 - ♦ S. Wang, H. Paul, A. Dekorsy, „Distributed Optimal Consensus-Based Kalman Filtering and Its Relation to MAP“, IEEE ICASSP 2018
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 - ♦ Shin, Yukawa, Cavalcante, Dekorsy: A Hybrid Dictionary Approach for Distributed Kernel Adaptive Filtering in Diffusion Networks, IEEE ICASSP 201
 - ♦ Shin, Paul, Yukawa, Dekorsy: Distributed Nonlinear Regression Using In-Network Processing With Multiple Gaussian Kernels, SPAWC 2017
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 - ♦ Shin, Paul, Dekorsy: Spatial Field Reconstruction with Distributed Kernel Least Squares in Mobile Sensor Networks, SCC17
- **Information Bottleneck**
 - ♦ S. Hassanpour, D. Wübben, A. Dekorsy, A Graph-Based Message Passing Approach for Noisy Source Coding via Information Bottleneck Principle, submitted to GLOBECOM 2018
 - ♦ S. Hassanpour, D. Wübben, A. Dekorsy, On the Equivalence of Double Maxima and KL-Means for Information Bottleneck-Based Source Coding, WCNC 2018
 - ♦ S. Hassanpour, D. Wübben, A. Dekorsy, On the Equivalence of Two Information Bottleneck-Based Routines Devised for Joint Source-Channel Coding, ICT 2018
 - ♦ S. Hassanpour, D. Wübben, A. Dekorsy, B. Kurkoski: On the Relation Between the Asymptotic Performance of Different Algorithms for Information Bottleneck Framework, ICC 2017
 - ♦ S. Hassanpour, D. Wübben, A. Dekorsy: Overview and Investigation of Algorithms for the Information Bottleneck Method, SCC 2017
 - ♦ D. Wübben: The Information Bottleneck Method: Fundamental Idea and Algorithmic Implementations, AEW 2017
 - ♦ T. Monsees, D. Wübben, A. Dekorsy, Information Bottleneck based Implementation of the Sum-Product Algorithm for Binary LDPC Codes, ESIT 2017
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- **Low latency/short packet coding**
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 - ♦ J. Demel, C. Bockelmann, A. Dekorsy, A. Rode, S. Koslowski, F. Jondral, An optimized GFDM software implementation for future Cloud-RAN and field tests, GNU Radio Conference 2017
 - ♦ J. Demel, C. Bockelmann, A. Dekorsy, Evaluation of a Software Defined GFDM Implementation for Industry 4.0 Applications, ICIT 2017

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Thank you for your attention!