Narrowband Interference Parameterization for Sparse Bayesian Recovery

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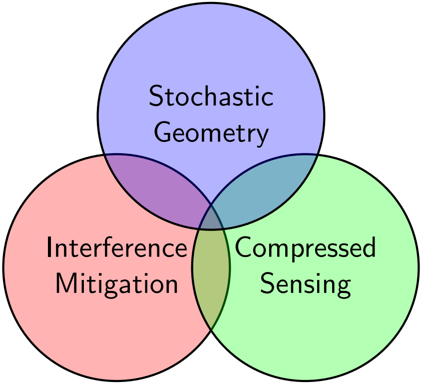
Content



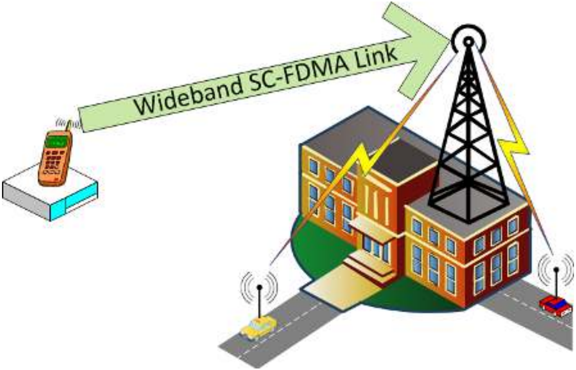
Stochastic Geometry
Interference Mitigation
Compressed Sensing

Introduction

Single Carrier-FDMA (SC-FDMA) is used in LTE uplink [1]

Narrowband Interference (NBI) Sources

- Coexisting systems in unlicensed bands
- Garage door openers
- Cordless phones etc

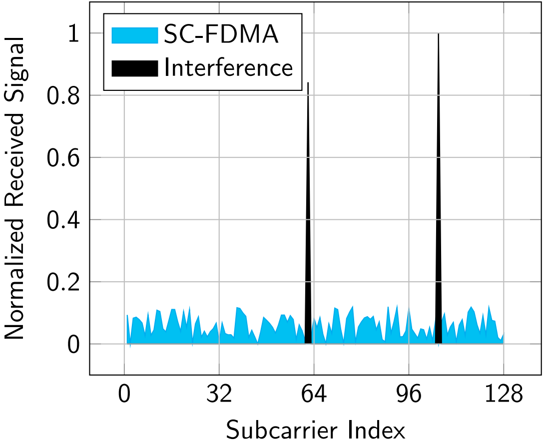


[1] H. G. Myung, J. Lim, and D. Goodman, "Single carrier FDMA for uplink wireless transmission," *IEEE Veh. Technol. Mag.*, vol. 1, no. 3, pp. 30-38, 2006.

Introduction

Interference Impact on SC-FDMA

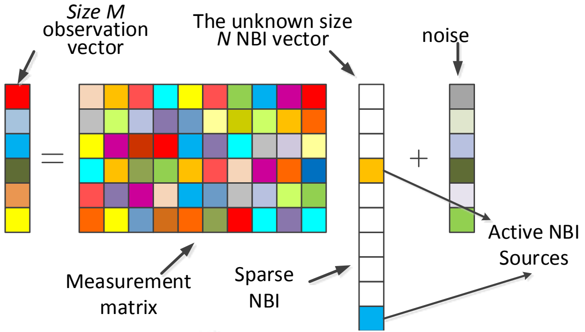
- A single strong interference source can completely destroy the data in single carrier-FDMA



Bayesian Sparse Recovery

How and Why?

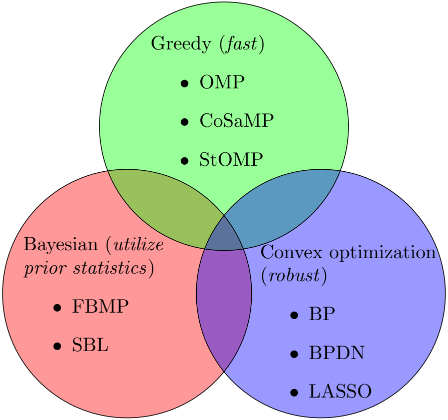
- Active interference on few frequencies $\longrightarrow$ **Compressed Sensing** based recovery is possible
- Randomly chosen data points are kept data free to sense interference at the receiver



$$\mathbf{y} = \mathbf{A}\mathbf{x} + \mathbf{n}$$

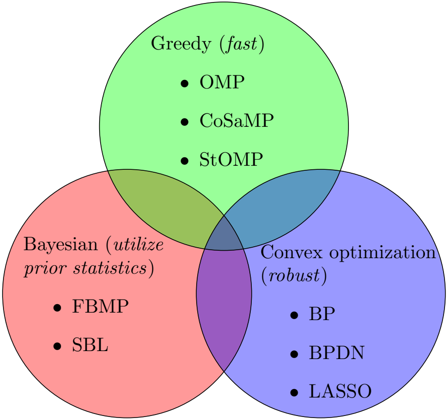
Bayesian Sparse Recovery

Sparse Signal Recovery Approaches



Bayesian Sparse Recovery

Sparse Signal Recovery Approaches

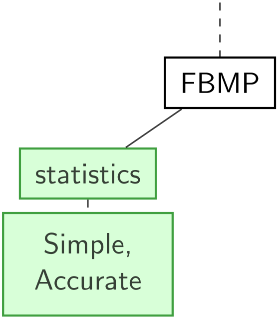


- Use **Bayesian** schemes for sparse recovery
  - Low computational complexity
  - Good reconstruction accuracy
  - Acknowledge Gaussianity of noise

Bayesian Sparse Recovery

Fast Bayesian Matching Pursuit (FBMP) [2]

- Low complexity
- minimum mean squared error (MMSE) estimation
- Gaussian prior



[2] P. Schniter, L. C. Potter, and J. Ziniel, "Fast Bayesian matching pursuit," in *Proc. Inform. Theory & Appl. Workshop*, 2008, pp. 326-333.

Bayesian Sparse Recovery

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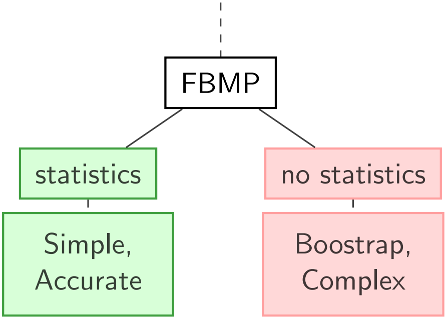

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Bayesian Sparse Recovery

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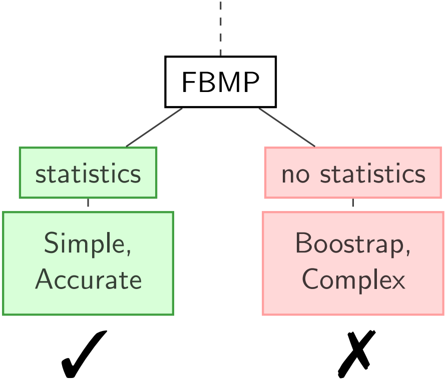

Challenge: → How to estimate mean, *variance*, and sparsity rate.

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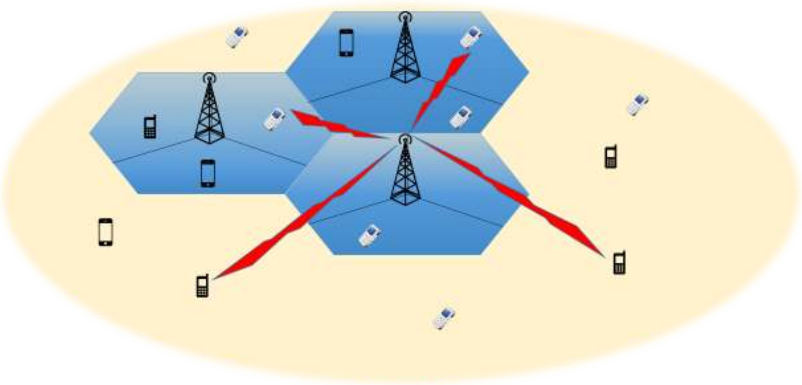
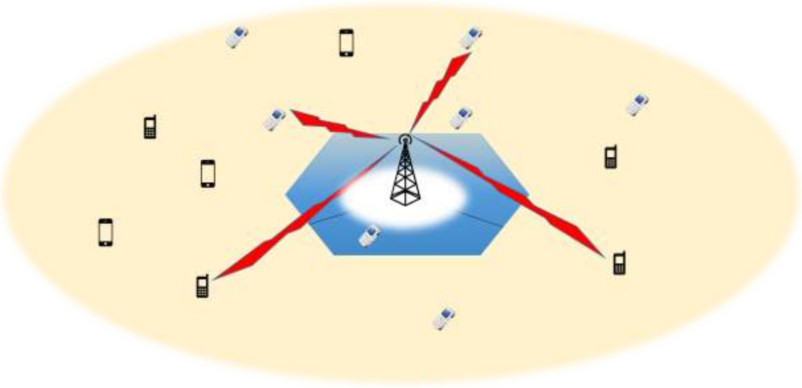
Interference Parameterization



Interference Parameterization

1: Transmiter Power ✓
2: PathLoss Coefficient ✓
3: Location ?



Interference Parameterization

Homogenous Poisson Point Process

- Tractable Analysis [3]
- Accurate expressions
- Widely used
- Applicable to diverse types of networks
  - ad-hoc networks
  - cellular networks

Process→ $\boldsymbol{\Psi}$, Intensity→ λ

Transmitted Symbol

Transmitted Energy

$$\mathcal{I}_{\text{agg}} = \sum_{i \in \Psi} \sqrt{E}\; s_i \; h_i$$

Aggregate Interference

Channel Including Pathloss

[3] H. ElSawy, E. Hossain, and M. Haenggi, "Stochastic geometry for modeling, analysis, and design of multi-tier and cognitive cellular wireless networks: A survey," *IEEE Commun. Surveys and Tutorials*, vol. 15, no. 3, pp. 996-1019, 2013.

Interference Parameterization

For interference $\mathcal{I}_{\text{agg}} = \sum_{i\in\Psi} \sqrt{E} s_i h_i$, Characteristic Function (CF) is

$$\Phi(\omega) = \exp\left\{-\lambda\pi\gamma^2 \sum_{q=1}^{+\infty} \Upsilon_q \mathbb{E}\left[|s|^{2q}\right] \left(\frac{|\omega|^2 E\Omega}{\gamma^{2b}}\right)^q\right\}$$

Obtain mean and variance by differentiating the CF

$$\mu_{\mathcal{I}_{\text{agg}}} = \mathbb{E}\left[\mathcal{I}_{\text{agg}}\right] = \jmath^{-1}\Phi'(0) = 0$$

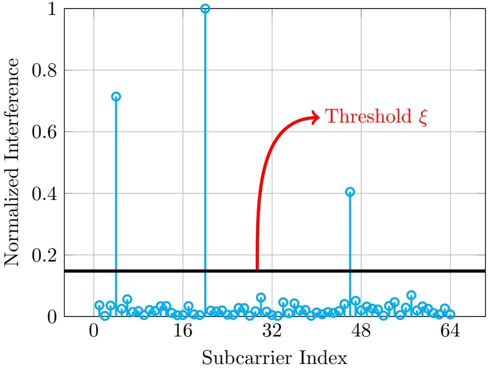
$$\sigma^2_{\mathcal{I}_{\text{agg}}} = \mathbb{E}\left[|\mathcal{I}_{\text{agg}}|^2\right] = \jmath^{-2}\Phi''(0) = 2\pi\lambda\gamma^2\Upsilon_1\mathbb{E}\left[|s|^2\right]\left(\frac{E\Omega}{\gamma^{2b}}\right)$$

Interference Parameterization

Gaussian Assumption

Sparsity Rate

- ρ dominant elements
- $N - \rho$ elements at noise level
- Decide a threshold ξ^a.
- Assume Gaussianity on interference



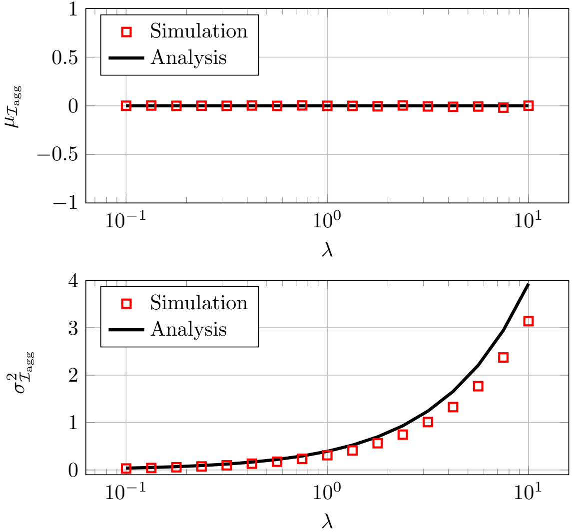
$$\hat{s} = \frac{2\rho}{N} Q(4\sqrt{\mathrm{INR}^{-1}}) + 2\frac{N-\rho}{N} Q(4)$$

INR: Impulse-to-noise ratio, $Q(\cdot)$ is Q function.

a. We use $\xi = 4\sqrt{\sigma_z^2}$.

Results

Mean and Variance as a function of intensity λ

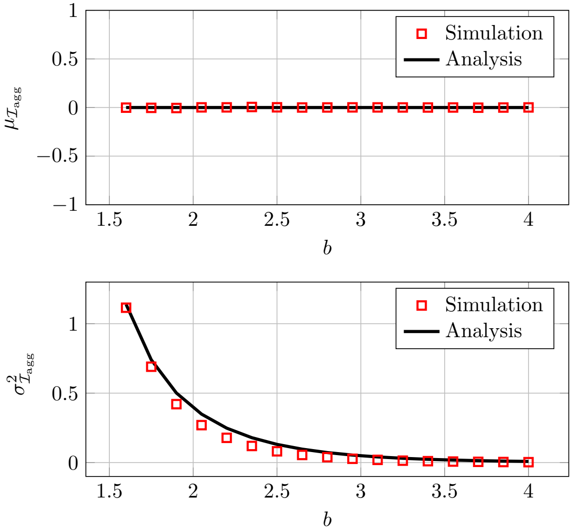


Simulation Parameters:

- b=2
- γ=2m
- R=20m
- Subcarriers=256
- Users=2
- Modulation=64 QAM

Results

Mean and Variance as a function of pathloss coefficient b

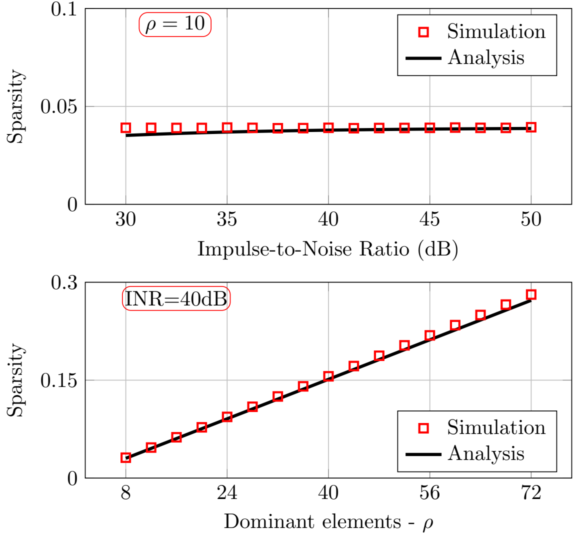


Simulation Parameters:

- λ=1
- γ=2m
- R=20m
- Subcarriers=256
- Users=2
- Modulation=64 QAM

Results

Sparsity rate as a function of INR and dominant elements ρ

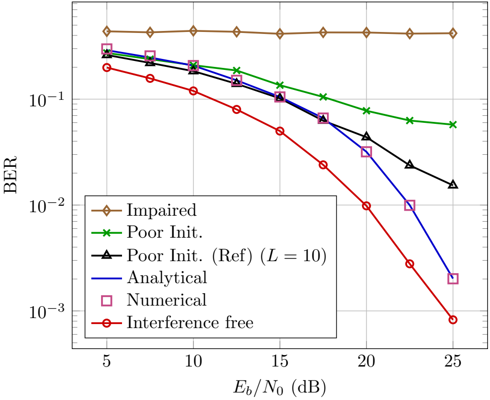


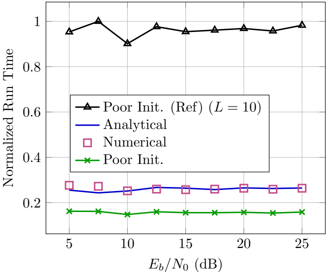
Simulation Parameters:

- $\xi = 4\sqrt{\sigma^2_{\mathcal{Z}}}$
- γ=2m
- R=20m
- Subcarriers=256
- Users=2
- Modulation=64 QAM

Results

BER performance of the proposed scheme





Simulation Parameters:

Measurements= 25%,
SIR=−10dB, ρ=4,
Subcarriers=256, Users=2,
Modulation=64 QAM

Summary

- Interference has a dire impact of SC-FDMA systems
- Compressed sensing can be used to mitigate interference
- Bayesian compressed sensing has good performance and low complexity
- Bayesian schemes require interference parameters
- Parameters can be obtained analytically using stochastic geometry
- Analytical parameter estimation reduces computational complexity significantly

Thank you for your Attention!