Spectral Tweets: A Community Paradigm for Spatio-temporal Cognitive Sensing and Access

Nikos Sidiropoulos, Georgios Giannakis, Jarvis Haupt

NSF EARS PI Workshop, Mon. Oct. 7, 2013, 9:40-10:00 AM

Spectral Tweeters



Nikos Sidiropoulos, Georgios Giannakis, Jarvis Haupt

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Omar
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Emiliano
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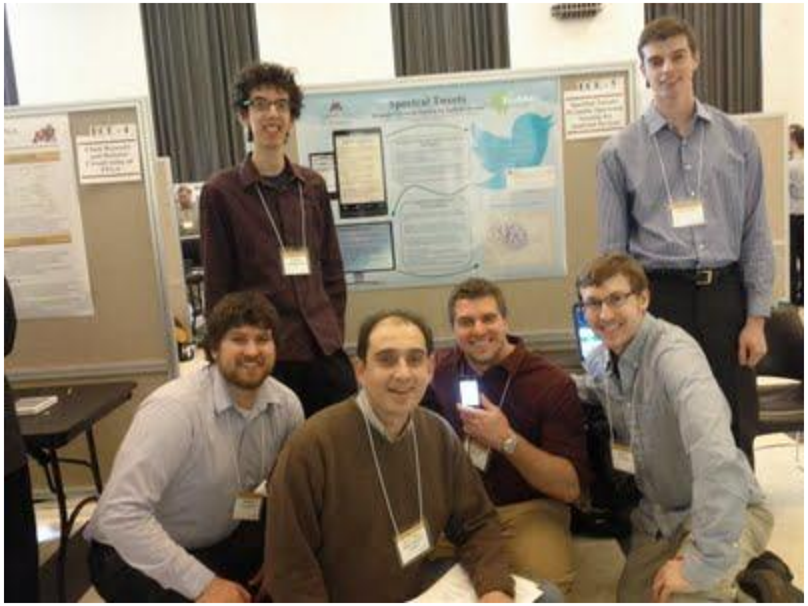

Akshay
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Grayson Malinowski, Michael Owczarek, Michael Fiore, Martin Corbett, Alex Hulke

Spectral Tweets: A Community Paradigm for Spatio-temporal Cognitive Sensing and Access

Research Goals

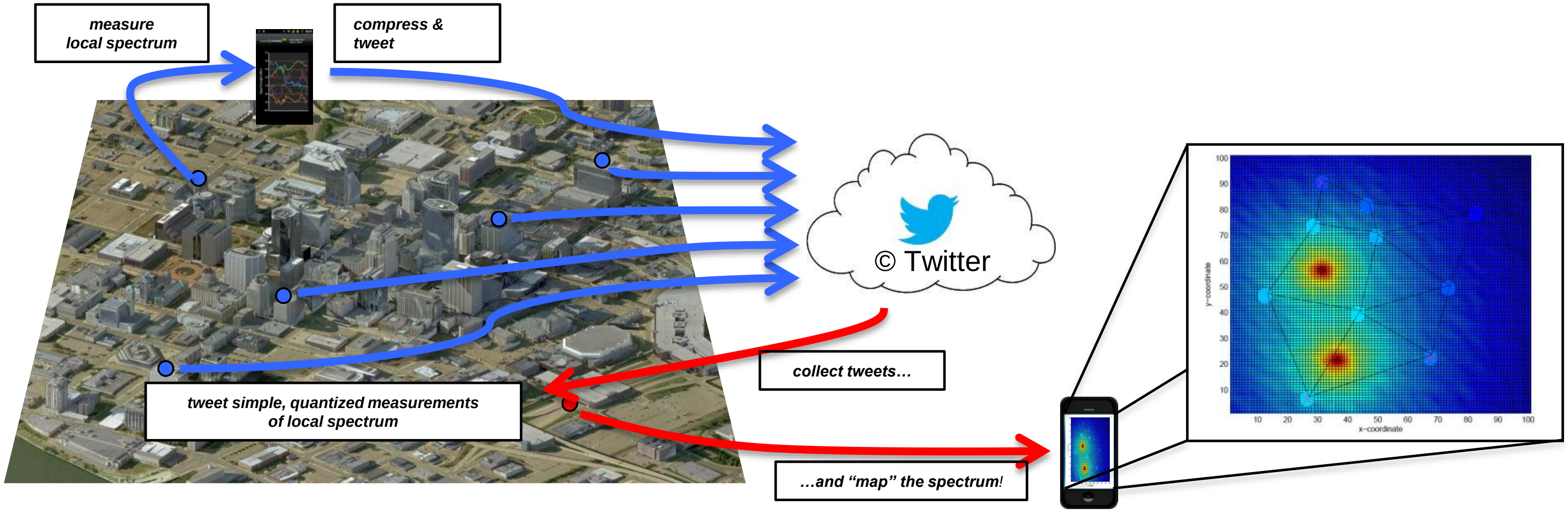
- Crowdsource spectrum sensing → *spectrum sensing web* of mobile devices
- Efficient distributed power spectrum compression
- Dictionary learning (DL) and quantized compressed sensing (CS) – based spectrum sensing, primary user and interference channel estimation and tracking
- Measurement-based spectrum management

Potential Payoff

- Mobile spectrum sensing web can reveal abundant transmission opportunities → enhance access for millions of people
- Distributed spectral analysis, rate-distortion, quantized DL/CS tools

Education

- Sensing/twitting app development & demo senior/honors design. Top talent trained in spectrum sensing, CR, wireless app programming



measure local spectrum

compress & tweet

© Twitter

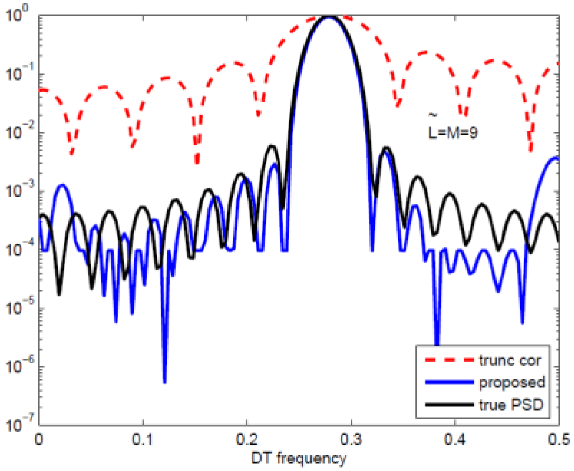
collect tweets…

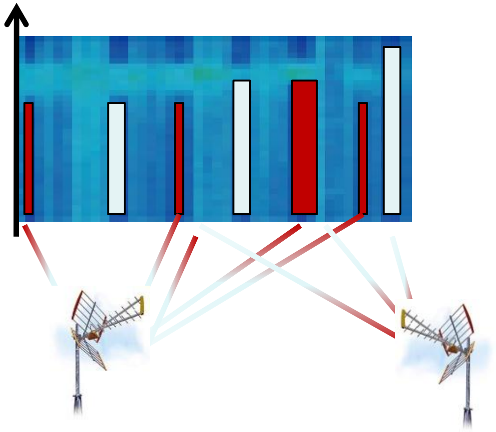
tweet simple, quantized measurements of local spectrum

…and "map" the spectrum!

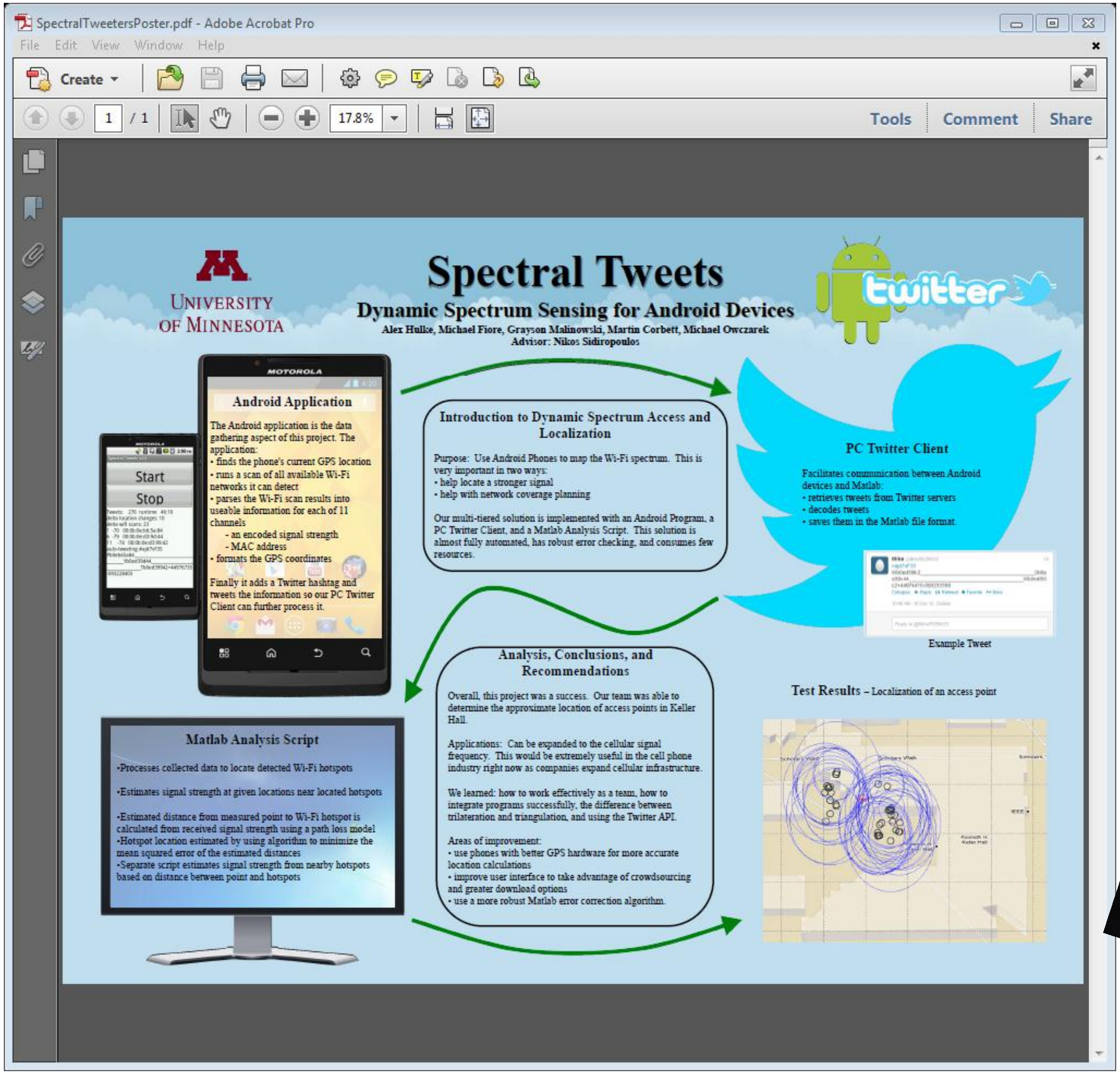
Spectral Tweets: Research Thrusts

- **Nonparametric power spectrum compression**
  - Distributed power spectrum compression and sensing
  - Dimensionality reduction – quantized canonical correlation analysis
- **Dictionary learning for blind primary user fingerprinting and tracking**
  - Distributed DL
  - Dynamic DL
  - Quantized DL and CS
- **Measurement-based spectrum management**
  - Joint CR power control and interference mitigation
  - Cognitive resource management





Proof of concept prototyping



Spectral Tweets

Dynamic Spectrum Sensing for Android Devices

Alex Hulke, Michael Fiore, Grayson Malinowski, Martin Corbett, Michael Owczarek
Advisor: Nikos Sidiropoulos

Android Application

The Android application is the data gathering aspect of this project. The application:

- finds the phone's current GPS location
- runs a scan of all available Wi-Fi networks it can detect
- parses the Wi-Fi scan results into useable information for each of 11 channels
  - an encoded signal strength
  - MAC address
- formats the GPS coordinates

Finally it adds a Twitter hashtag and tweets the information so our PC Twitter Client can further process it.

Introduction to Dynamic Spectrum Access and Localization

Purpose: Use Android Phones to map the Wi-Fi spectrum. This is very important in two ways:

- help locate a stronger signal
- help with network coverage planning

Our multi-tiered solution is implemented with an Android Program, a PC Twitter Client, and a Matlab Analysis Script. This solution is almost fully automated, has robust error checking, and consumes few resources.

PC Twitter Client

Facilitates communication between Android devices and Matlab:

- retrieves tweets from Twitter servers
- decodes tweets
- saves them in the Matlab file format.

Matlab Analysis Script

- Processes collected data to locate detected Wi-Fi hotspots
- Estimates signal strength at given locations near located hotspots
- Estimated distance from measured point to Wi-Fi hotspot is calculated from received signal strength using a path loss model
- Hotspot location estimated by using algorithm to minimize the mean squared error of the estimated distances
- Separate script estimates signal strength from nearby hotspots based on distance between point and hotspots

Analysis, Conclusions, and Recommendations

Overall, this project was a success. Our team was able to determine the approximate location of access points in Keller Hall.

Applications: Can be expanded to the cellular signal frequency. This would be extremely useful in the cell phone industry right now as companies expand cellular infrastructure.

We learned: how to work effectively as a team, how to integrate programs successfully, the difference between trilateration and triangulation, and using the Twitter API.

Areas of improvement:

- use phones with better GPS hardware for more accurate location calculations
- improve user interface to take advantage of crowdsourcing and greater download options
- use a more robust Matlab error correction algorithm.

Test Results – Localization of an access point

http://youtu.be/zfYs8vON-pA

Power Spectrum Sensing

- Only *power spectrum* (PSD) needed for cognitive radio
  - No need to reconstruct the spectrum of the original signal
  - Can estimate from Fourier transform of truncated autocorrelation → finite parameterization
  - Sampling rate requirements significantly decreased without requiring frequency-domain sparsity[1,2]
- Collaborative spectrum sensing
  - Exploit spatial diversity in distributed sensors to avoid hidden terminal problem, mitigate fading, enhance sensing reliability

***Challenge**: collaborative **power** spectrum sensing using low-end sensors with limited communication capabilities*

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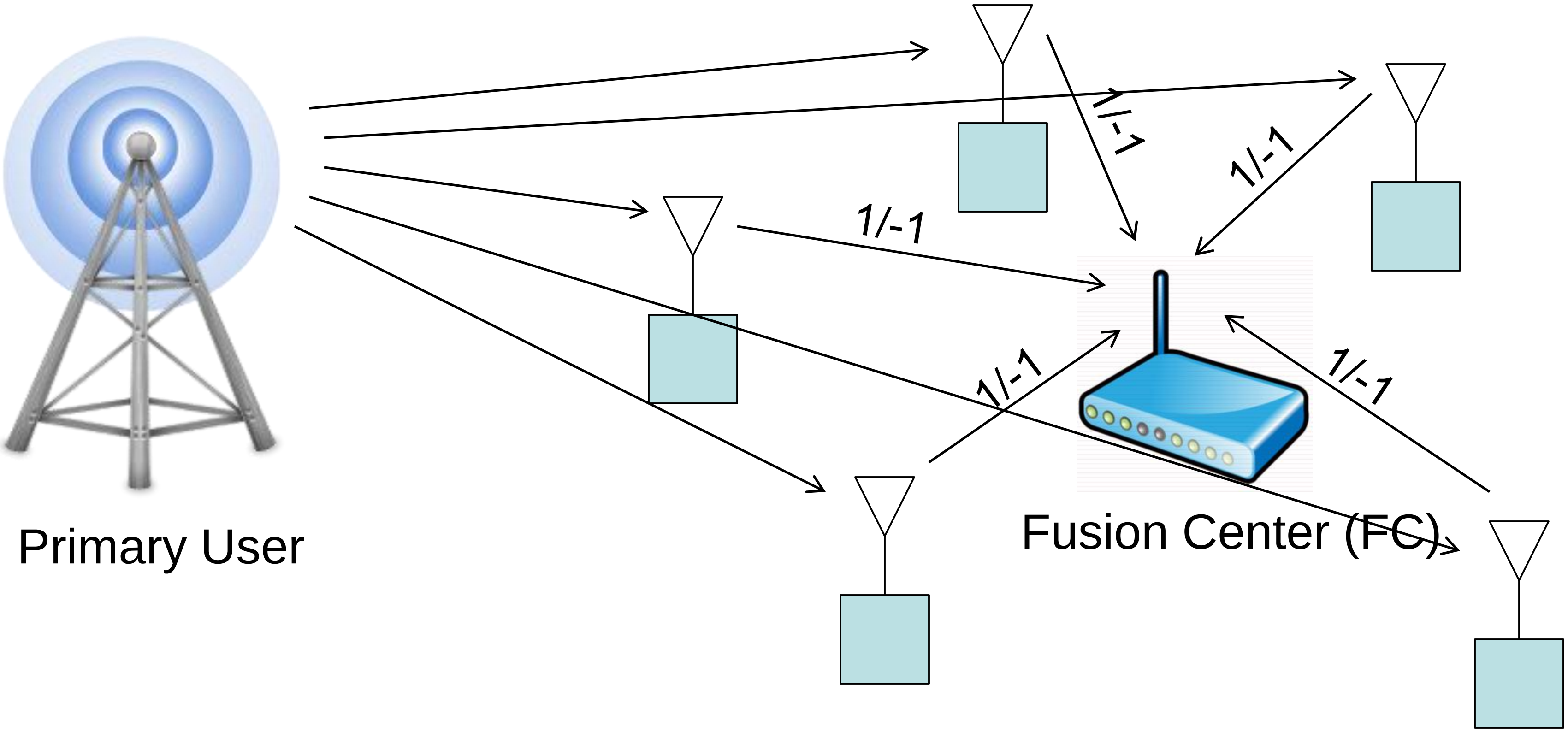
[1] D.D. Ariananda, and G. Leus, "Compressive wideband power spectrum estimation," *IEEE Transactions on Signal Processing, vol. 60, no. 9, pp. 4775–4789, Sept. 2012.*

[2] M. Lexa, M. Davies, J. Thompson, and J. Nikolic, "Compressive power spectral density estimation," *Proc. ICASSP, pp.3884–3887, Prague, Czech Republic, May 2011.*

Frugal Sensing



Primary User

Fusion Center (FC)

M sensors

Estimate the power spectrum from few bits

O. Mehanna, and N.D. Sidiropoulos, “Frugal Sensing: Wideband Power Spectrum Sensing from Few Bits”, *IEEE Trans. on Signal Processing*, vol. 61, no. 10, pp. 2693-2703, May 2013.

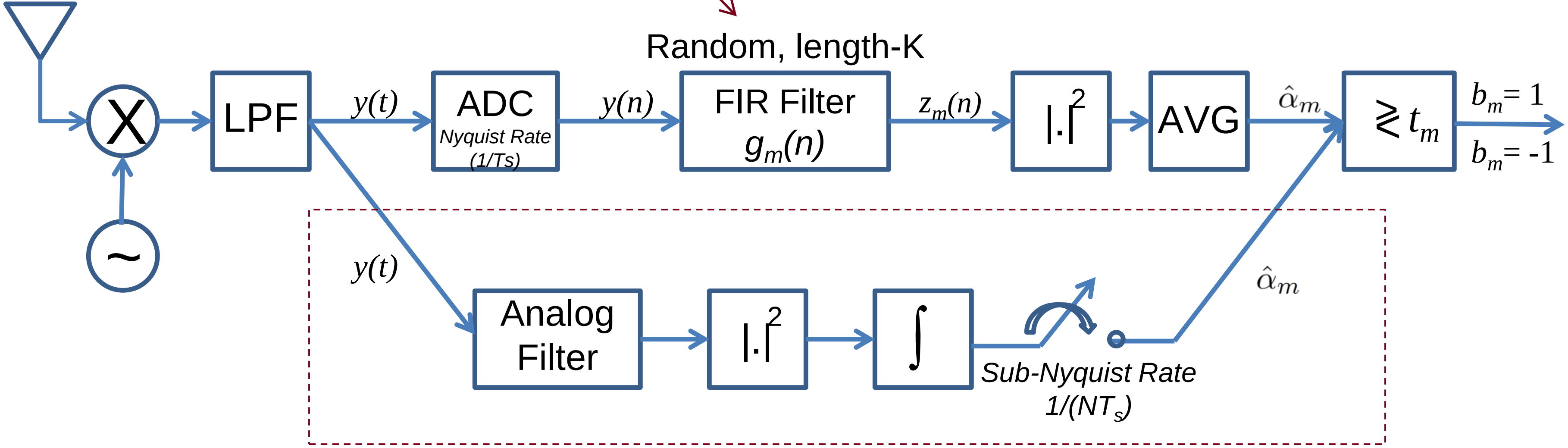
Sensor Measurement Chain

Complex PN - known at the FC

$$g_m(n) = \begin{cases} (1/\sqrt{2K})(\pm 1 \pm j) & \text{if} \quad 0 \leq n \leq K-1 \\ 0 & \text{otherwise} \end{cases}$$

$$\alpha_m := \mathbb{E}[|z_m(n)|^2]$$

$$\hat{\alpha}_m = \frac{1}{N} \sum_{n=0}^{N-1} |z_m(n)|^2$$



Equivalent analog measurement

Model-Based Power Spectrum

- Model-based power spectrum

known spectral density primitives

$$S_x(\omega) = \sum_{\ell=1}^{L} \rho_\ell \Psi_\ell(\omega)$$

unknown positive weights

- Received signal at sensor *m*

$$y_m(n) = \sum_{\ell=1}^{L} h_m(\ell) \sqrt{\rho_\ell} x_\ell(n)$$

Random fading

- Random filter output

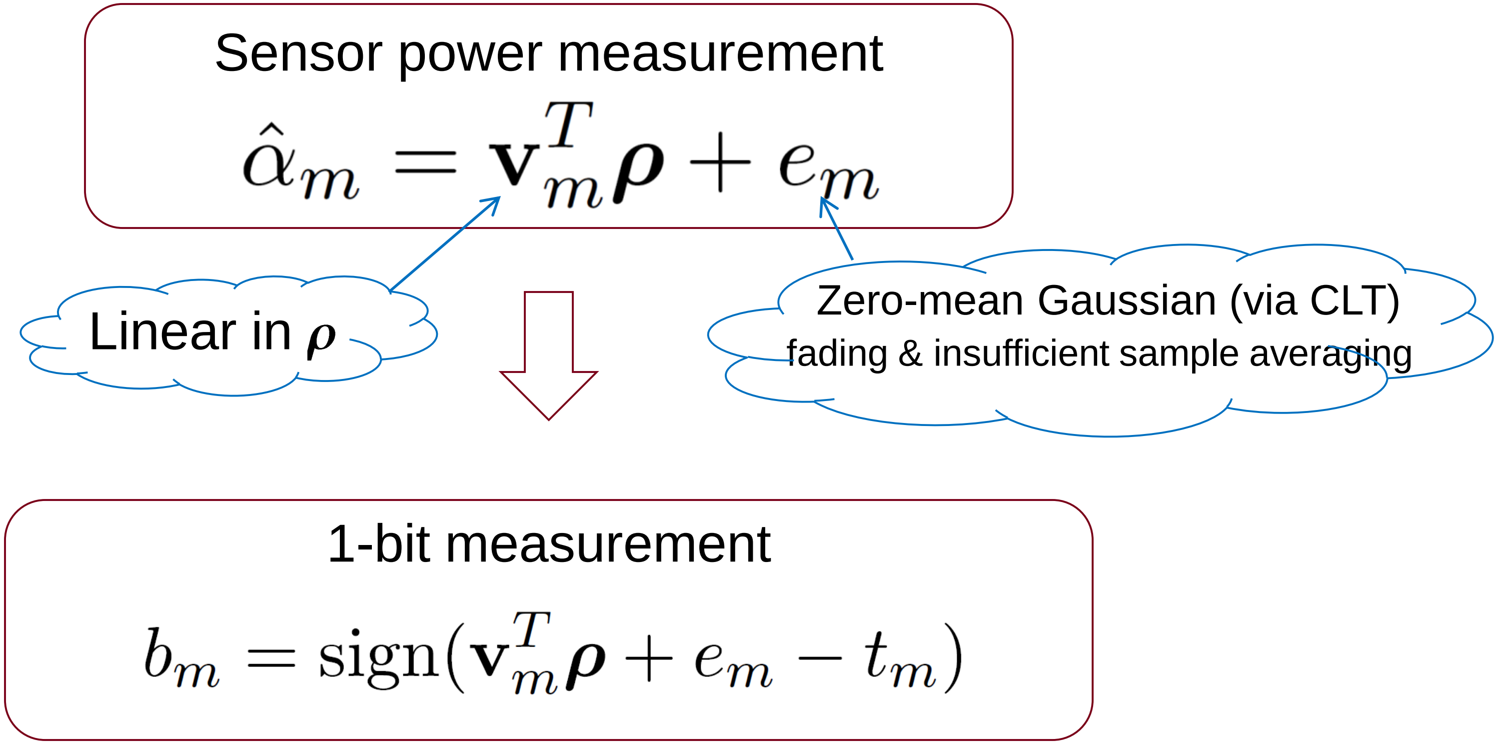
$$z_m(n) = \sum_{k=0}^{K-1} g_m(k) y_m(n-k) \quad \Rightarrow \quad \alpha_m = \mathbb{E}[|z_m(n)|^2] = \sum_{\ell=1}^{L} |h_m(\ell)|^2 \rho_\ell v_{m,\ell}$$

$$v_{m,\ell} := \sum_{k=1-K}^{K-1} \psi_\ell(k) e^{jk\omega_\ell} q_m^*(k)$$

I-DTFT of $\Psi(\omega)$

Deterministic filter autocorrelation

1-Bit Power Measurement



Sensor power measurement

$$\hat{\alpha}_m = \mathbf{v}_m^T \boldsymbol{\rho} + e_m$$

Linear in $\boldsymbol{\rho}$

Zero-mean Gaussian (via CLT)

fading & insufficient sample averaging

1-bit measurement

$$b_m = \mathrm{sign}(\mathbf{v}_m^T \boldsymbol{\rho} + e_m - t_m)$$

Spectral estimation from inequalities instead of equalities

Omar Mehanna, Nicholas D. Sidiropoulos, Efthymios Tsakonas (2013). *MODEL-BASED POWER SPECTRUM SENSING FROM A FEW BITS*. 21st European Signal Processing Conference - EUSIPCO 2013. Marrakech, Morocco.

Convex ML Formulation

$$b_m = \mathrm{sign}(\mathbf{v}_m^T \boldsymbol{\rho} + e_m - t_m)$$

i.i.d Gaussian

$$\mathcal{M}_+ := \{m | b_m = 1\}$$

$$\mathcal{M}_- := \{m | b_m = -1\}$$

$$f(b_1, \ldots, b_M | \boldsymbol{\rho}) = \prod_{m \in \mathcal{M}_+} \Pr(\mathbf{v}_m^T \boldsymbol{\rho} + e_m \geq t_m) \prod_{m \in \mathcal{M}_-} \Pr(\mathbf{v}_m^T \boldsymbol{\rho} + e_m < t_m)$$

$$= \prod_{m \in \mathcal{M}_+} \Phi\left(\frac{\mathbf{v}_m^T \boldsymbol{\rho} - t_m}{\sigma_m}\right) \prod_{m \in \mathcal{M}_-} \Phi\left(-\frac{\mathbf{v}_m^T \boldsymbol{\rho} - t_m}{\sigma_m}\right)$$

Gaussian CDF

- Convex (sparse) ML

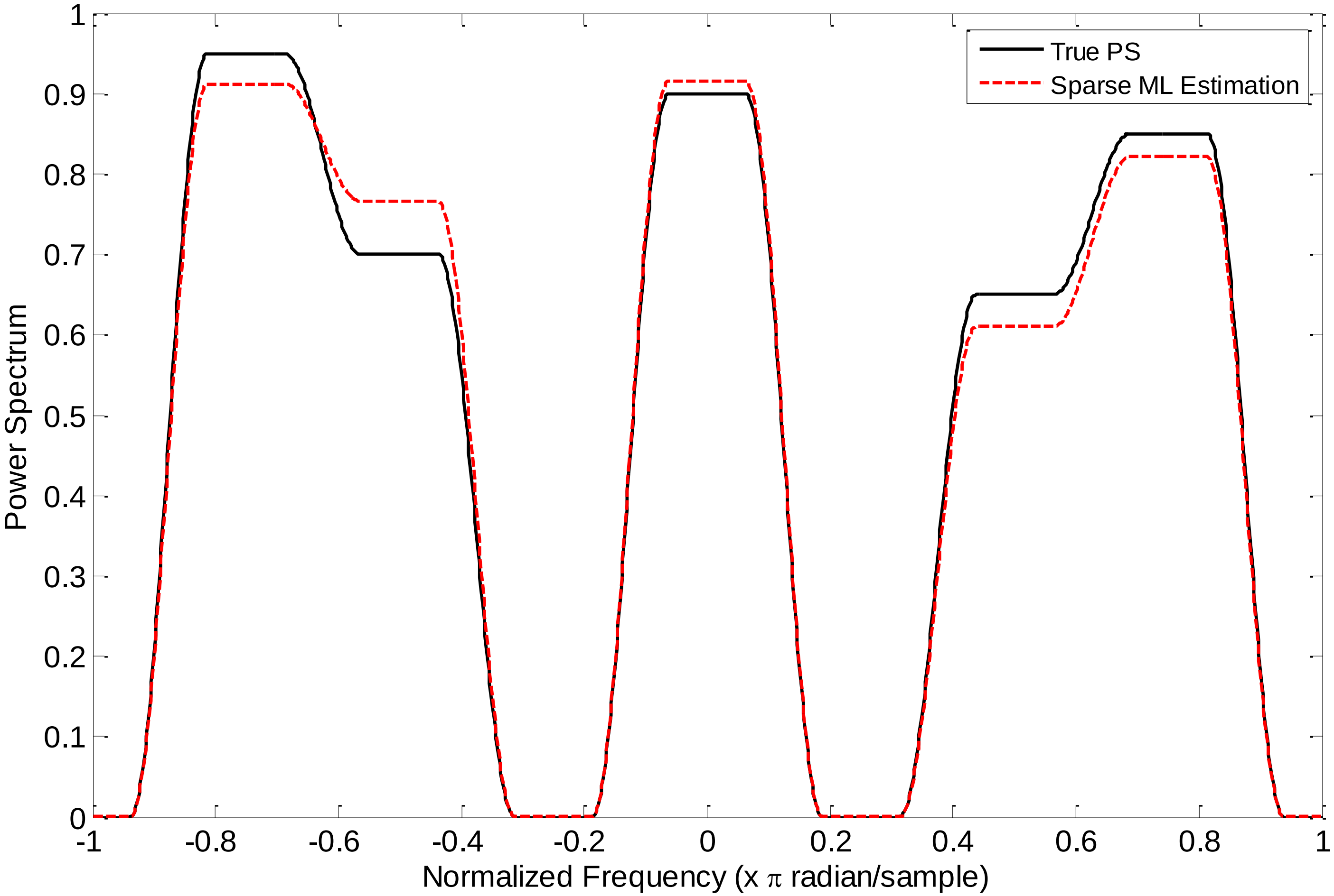
control sparsity

$$\boxed{\max_{\rho \in \mathcal{B}} \sum_{m=1}^{M} \log \Phi\left(\frac{b_m(\mathbf{v}_m^T \boldsymbol{\rho} - t_m)}{\sigma_m}\right) - \lambda \sum_{\ell=1}^{L} \rho_\ell}$$

Omar Mehanna, Nicholas D. Sidiropoulos, Efthymios Tsakonas (2013). *MODEL-BASED POWER SPECTRUM SENSING FROM A FEW BITS*. 21st European Signal Processing Conference - EUSIPCO 2013. Marrakech, Morocco.

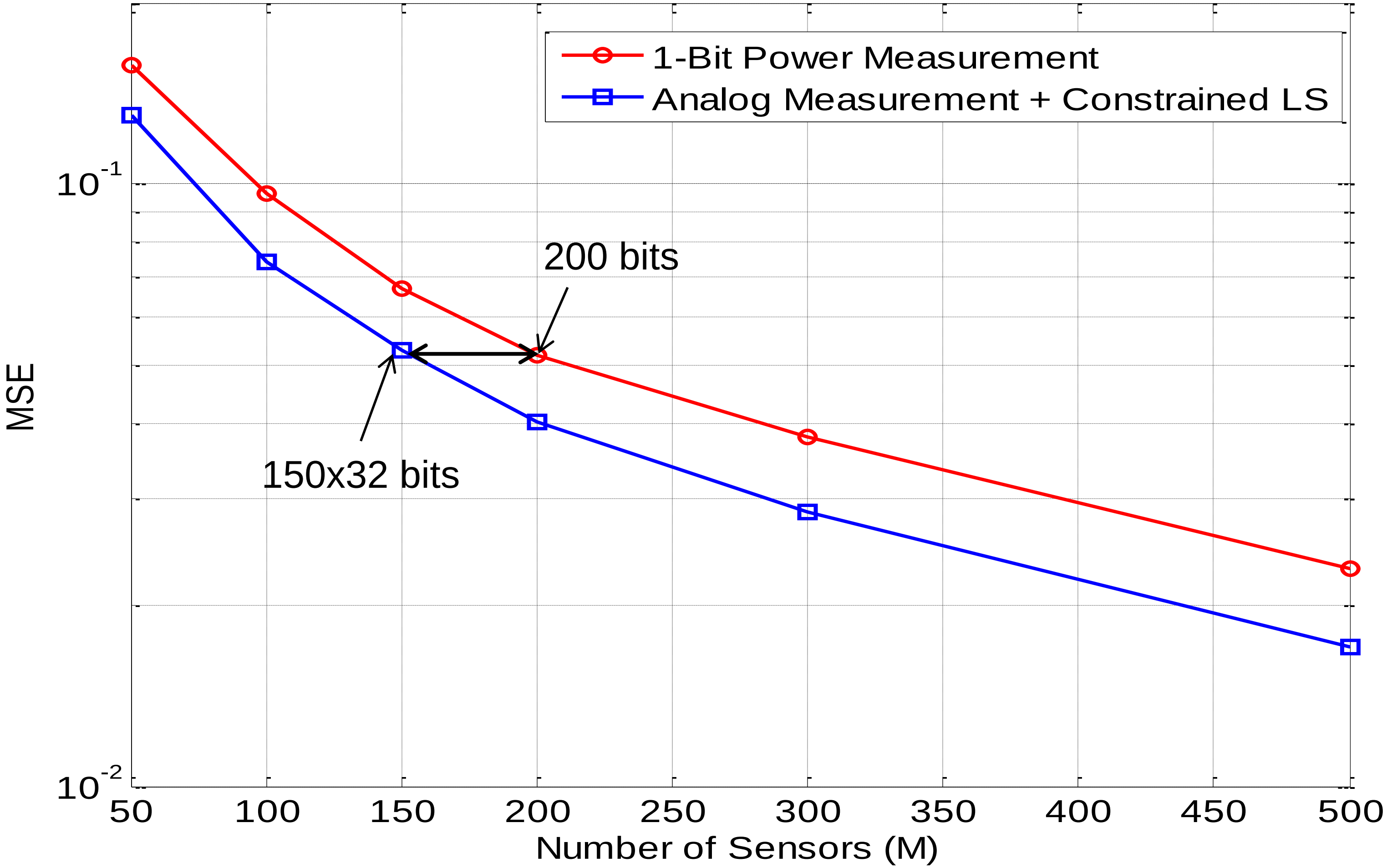
Example

L = 8 equispaced raised-cosine $\Psi_\ell(\omega)$, M = 150 sensors, t_m=t, 50 sensors send b_m=1, random errors flipped 10 sensor measurement bits, sparsity parameter λ = 50



1-Bit Quantization Loss

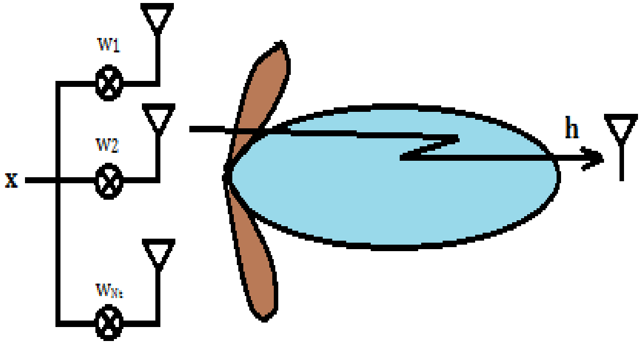
Rayleigh fading: random errors flipped 30% of sensor measurement bits on average



Omar Mehanna, Nicholas D. Sidiropoulos, Efthymios Tsakonas (2013). *MODEL-BASED POWER SPECTRUM SENSING FROM A FEW BITS*. 21st European Signal Processing Conference - EUSIPCO 2013. Marrakech, Morocco.

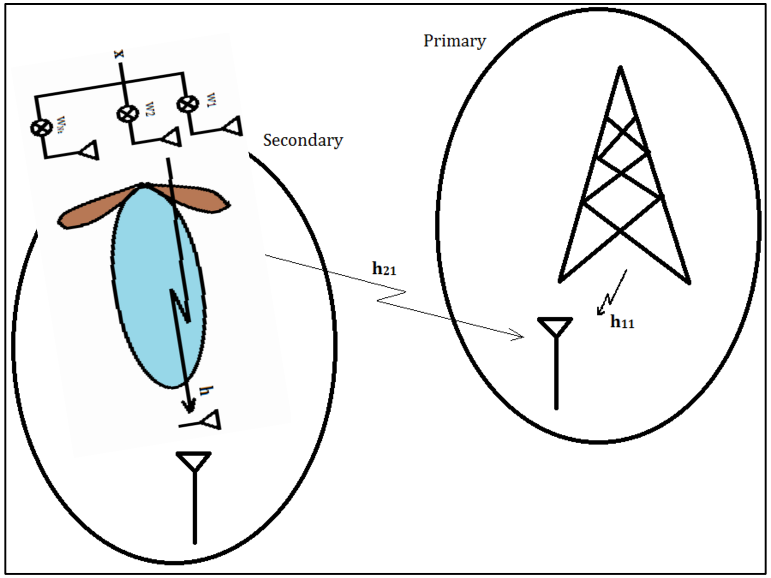
Cognitive Transmit Beamforming

- **Transmit beamforming -** Use multiple antennas to steer radiated power along specific directions that provide good QoS @ Rx
- Also need to protect primary Rx



- Need CSI @ Tx – for both secondary `target' Rx, and primary Rx to avoid
- Impractical, especially in cognitive radio networks where the primary Rx has no incentive (or ability) to cooperate
- CSI feedback overhead ~ number of users and antennas

Cognitive Transmit Beamforming

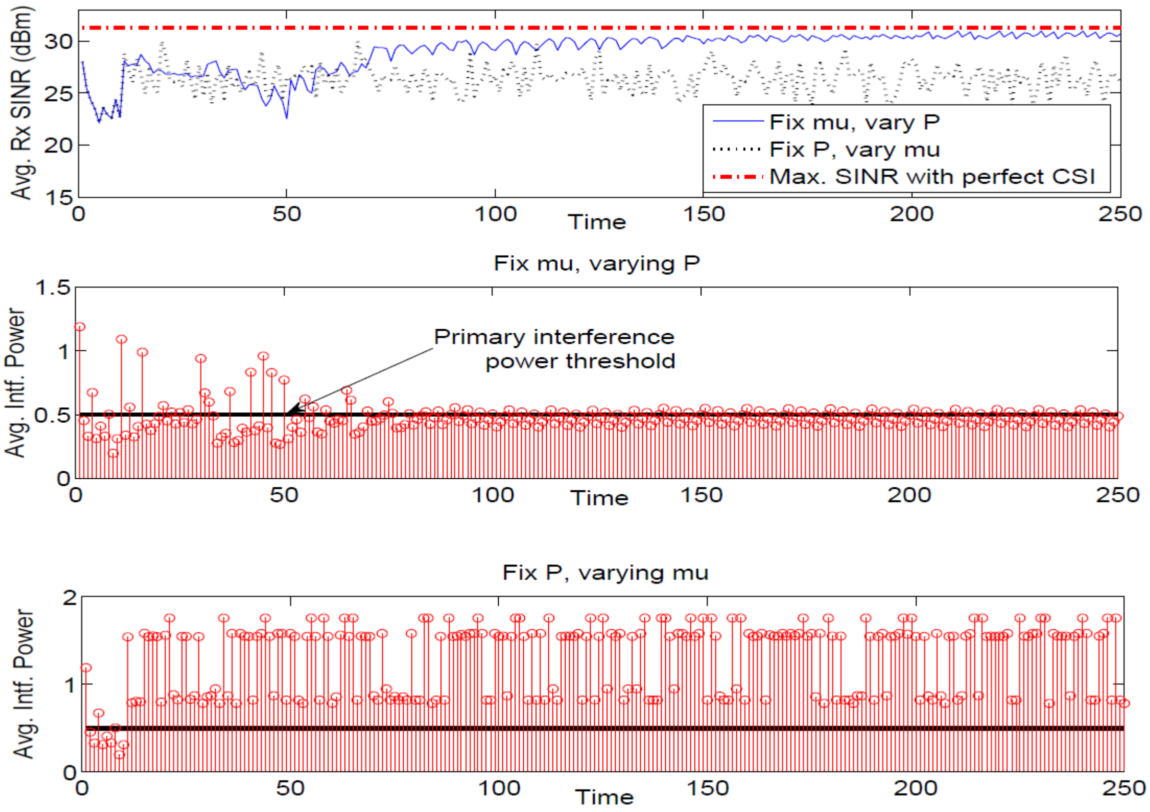


- **Wish list:**
  1. Low overhead transmit beamforming techniques that ***learn*** sTx-sRx ***and*** sTx-pRx channel correlation matrices and ***approach*** near-optimal performance ***without*** explicit CSI feedback or changing legacy protocols …
- Free lunch?

Balasubramanian Gopalakrishnan, and Nicholas D. Sidiropoulos, submitted.

Almost! – exciting preliminary results!

Cognitive Transmit Beamforming $N_t = 5$



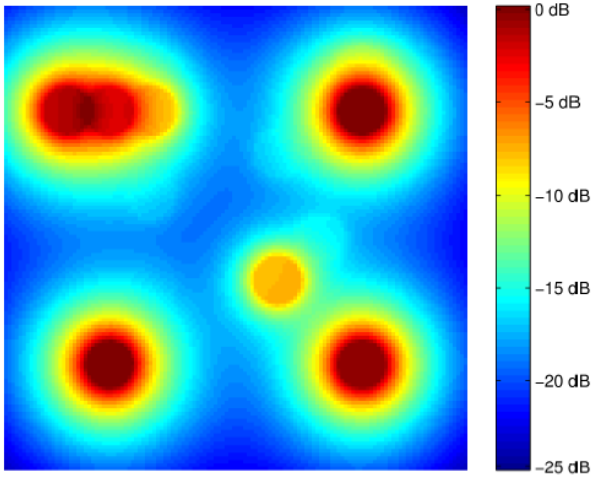
- Avg. Rx SINR at secondary asymptotically converges to max. SINR with perfect CSI!

- The interference power for Fix mu varying P method, converges to the primary interference threshold (not known at sec. Tx)!

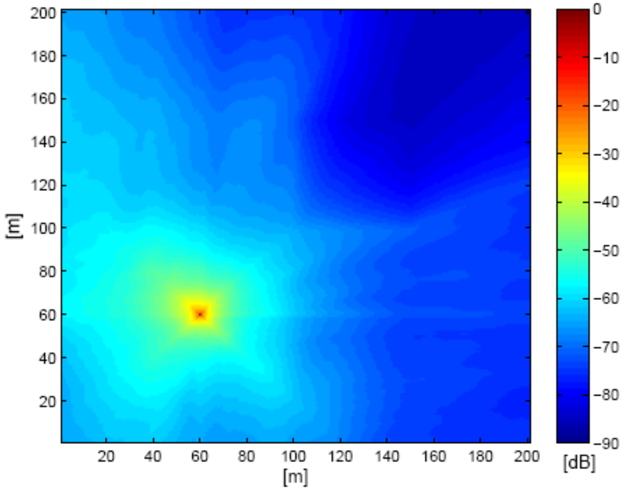
Balasubramanian Gopalakrishnan, and Nicholas D. Sidiropoulos, submitted.

PHY sensing via RF cartography

- Power spectral density (PSD) maps
  - Capture ambient power in space-time-frequency
  - Identify regions with high interference temperature



- Channel gain (CG) maps
  - Time-frequency channel from any-to-any point
  - CRs adjust Tx power to minimize PU disruption



S.-J. Kim, E. Dall'Anese, J. A. Bazerque, K. Rajawat, and G. B. Giannakis, "Advances in Spectrum Sensing and Cross-Layer Design for Cognitive Radio Networks," *EURASIP, E-Ref. Signal Processing*, Nov. 2012.

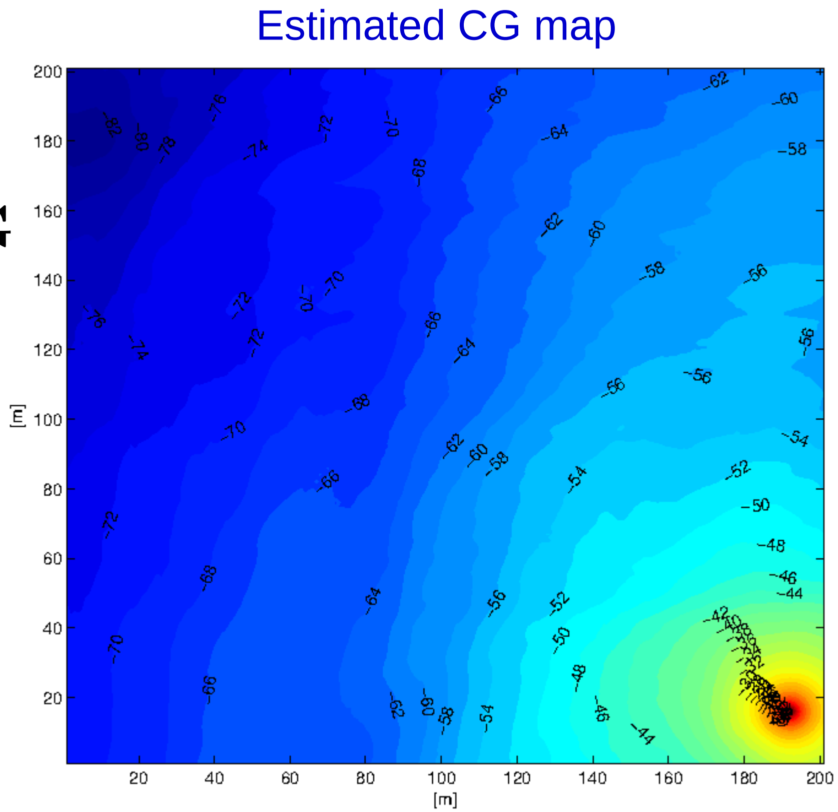
Any-to-any channel gain estimation

- Shadowing model-free approach
  - Slow variations in shadow fading
  - Low-rank any-to-any CG matrix $\hat{\mathbf{G}}$

Approach: low-rank matrix completion

$$\min_{\mathbf{C},\mathbf{W}} \|\mathcal{P}_{\mathcal{S}}(\mathbf{G}-\mathbf{C}\mathbf{W}')\|_F^2 + \lambda(\|\mathbf{C}\|_F^2 + \|\mathbf{W}\|_F^2)$$

Payoffs: global view of any-to-any CG real-time propagation metrics; efficient resource allocation



Estimated CG map

Outlook: kernel-based extrapolator for missing CR-to-PU measurements, look-ahead intervals; quantized DL tweets

S.-J. Kim and G. B. Giannakis, “Dynamic Network Learning for Cognitive Radio Spectrum Sensing,” *Proc. of Intl. Workshop on Comp. Advances in Multi-Sensor Adaptive Process.*, Saint Martin, 2013.

PU power and CR-PU link learning

- Reduce overhead in any-to-any CG mapping
  - Learn CGs only between CRs and PUs
  - Online detection of active PU transmitters

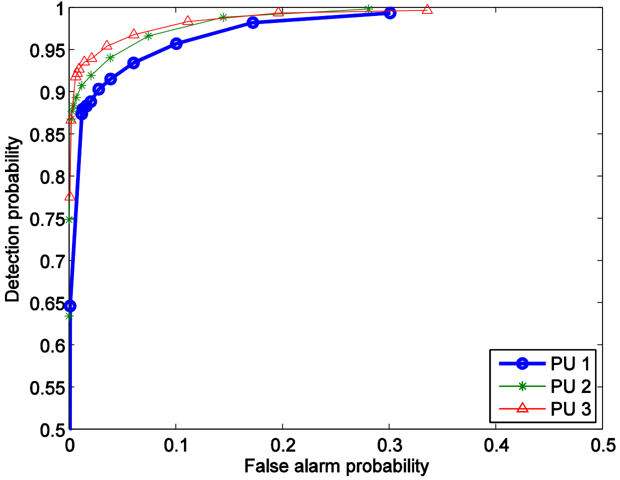
Approach: DL (RX-power=CG x TX power); blind estimation

$$\min_{\mathbf{G},\mathbf{P}} \|\mathbf{\Pi} - \mathbf{G}\mathbf{P}\|_F^2 + \lambda_1 \|\mathbf{P}\|_1$$

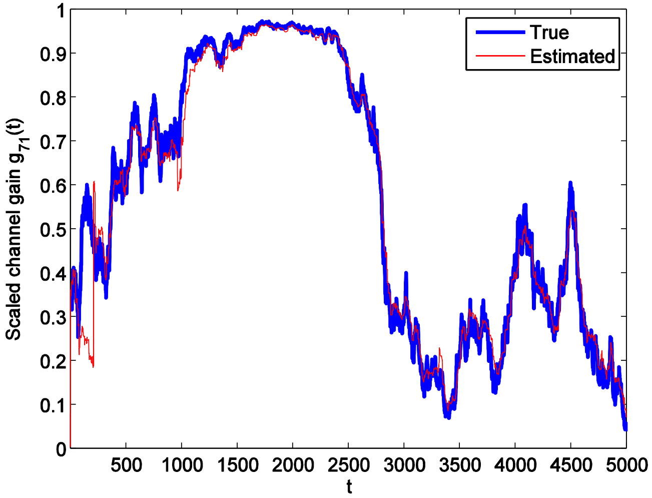
Payoffs: tracking PU activities; and efficient resource allocation

Outlook: missing data due to limited sensing; distributed robust algorithms

Detection of PU activity



Estimated CG



S.-J. Kim, N. Jain, and G. B. Giannakis, "Joint Link Learning and Cognitive Radio Sensing," *IEEE Trans. on SP*, Nov. 2013 (submitted); also in *Proc. of Asilomar Conf.* , Pacific Grove, CA, Nov. 2012.

Publications, dissemination, outreach

- Journal
  1. B. Gopalakrishnan, and N.D. Sidiropoulos (2013). Joint Back-Pressure Power Control and Interference Cancellation in Wireless Multi-Hop Networks. *IEEE Trans. on Wireless Communications*. 12 (7), 3484.
  2. Daniele Angelosante, Georgios B. Giannakis, and Nicholas D. Sidiropoulos (2013). Sparse Parametric Models for Robust Nonstationary Signal Analysis. *IEEE Signal Processing Magazine,* to appear.
  3. S.-J. Kim, N. Y. Soltani, and G. B. Giannakis (2013). Resource Allocation for OFDMA Cognitive Radios under Channel Uncertainty. *IEEE Transactions on Wireless Communications*. 12 (10).
  4. A. G. Marqués, E. Dall'Anese, and G. B. Giannakis (2014). Cross-Layer Optimization and Receiver Localization for Cognitive Networks Using Interference Tweets. *IEEE Journal of Selected Topics in Communications,* submitted.
- Conference
  1. Omar Mehanna, Nicholas D. Sidiropoulos, Efthymios Tsakonas (2013). *MODEL-BASED POWER SPECTRUM SENSING FROM A FEW BITS*. 21st European Signal Processing Conference - EUSIPCO 2013. Marrakech, Morocco.
  2. S.-J. Kim and G. B. Giannakis (2013). *Cognitive Radio Spectrum Prediction using Dictionary Learning*. Globecom Conference. Atlanta, GA.
- Plenaries
  1. IEEE SPAWC 2013, Darmstadt, Germany, June 2013 (Sidiropoulos)
  2. IFAC Workshop on Distr. Est. & Control in Networked Systems, Santa Barbara, CA, Sept. 2012 (Giannakis)
  3. ISWCS 2013, Ilmenau, Germany (Giannakis)