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

Nikos Sidiropoulos, Georgios Giannakis, Jarvis Haupt

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Spectral Tweeters

Nikos Sidiropoulos, Georgios Giannakis, Jarvis Haupt

Balasubramanian Gopalakrishnan
Omar Mehanna
Emiliano Dall’Anese
Akshay Soni
Brian Baingana
Swayambhoo Jain

Grayson Malinowski, Michael Owczarek, Michael Fiore, Martin Corbett, Alex Hulke
Spectral Tweets: A Community Paradigm for Spatio-temporal Cognitive Sensing and Access

**Research Goals**
- Crowdsourcing 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
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

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

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

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Frugal Sensing

Primary User

Fusion Center (FC)

M sensors

Estimate the power spectrum from few bits

Sensor Measurement Chain

Complex PN - known at the FC

\[ g_m(n) = \begin{cases} 
(1/\sqrt{2K})(\pm1 \pm j) & \text{if } 0 \leq n \leq K - 1 \\
0 & \text{otherwise} 
\end{cases} \]

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

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

Equivalent analog measurement
Model-Based Power Spectrum

- Model-based power spectrum
  \[ S_x(\omega) = \sum_{\ell=1}^{L} \rho_\ell \Psi_\ell(\omega) \]
  known spectral density primitives
  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
  \[ z_m(n) = \sum_{k=0}^{K-1} g_m(k) y_m(n-k) \]
  \[ \alpha_m = \mathbb{E}[|z_m(n)|^2] = \sum_{\ell=1}^{L} |h_m(\ell)|^2 \rho_\ell v_{m,\ell} \]

\[ v_{m,\ell} := \sum_{k=1-K}^{K-1} \psi_\ell(k)e^{i\omega_\ell k} q_m^*(k) \]
I-DTFT of \( \Psi(\omega) \)
Deterministic filter autocorrelation
1-Bit Power Measurement

Sensor power measurement

\[ \hat{\alpha}_m = \mathbf{v}_m^T \mathbf{\rho} + e_m \]

1-bit measurement

\[ b_m = \text{sign}(\mathbf{v}_m^T \mathbf{\rho} + e_m - t_m) \]

Spectral estimation from inequalities instead of equalities

Convex ML Formulation

\[ b_m = \text{sign}(v_m^T \rho + e_m - t_m) \]

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

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

\[ f(b_1, \ldots, b_M | \rho) = \prod_{m \in \mathcal{M}_+} \Pr(v_m^T \rho + e_m \geq t_m) \prod_{m \in \mathcal{M}_-} \Pr(v_m^T \rho + e_m < t_m) \]

\[ = \prod_{m \in \mathcal{M}_+} \Phi \left( \frac{v_m^T \rho - t_m}{\sigma_m} \right) \prod_{m \in \mathcal{M}_-} \Phi \left( -\frac{v_m^T \rho - t_m}{\sigma_m} \right) \]

- Convex (sparse) ML

\[ \max_{\rho \in \mathcal{B}} \sum_{m=1}^{M} \log \Phi \left( \frac{b_m (v_m^T \rho - t_m)}{\sigma_m} \right) - \lambda \sum_{\ell=1}^{L} \rho_{\ell} \]

Example

$L = 8$ equispaced raised-cosine $\Psi_r(\omega)$, $M = 150$ sensors, $t_m = t$, 50 sensors send $b_m = 1$, random errors flipped 10 sensor measurement bits, sparsity parameter $\lambda = 50$
1-Bit Quantization Loss

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

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
• **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

Any-to-any channel gain estimation

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

**Approach:** low-rank matrix completion

$$\min_{C,W} \left\| \mathcal{P}_S(G - CW') \right\|_F^2 + \lambda (\|C\|_F^2 + \|W\|_F^2)$$

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

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

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

\[
\min_{G,P} \| \Pi - GP \|_F^2 + \lambda_1 \| P \|_1
\]

**Payoffs:** tracking PU activities; and efficient resource allocation

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

Publications, dissemination, outreach

• Journal

• Conference

• 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)