Using Multiple Power Spectrum Measurements to Sense Signals with Partial Spectral Overlap

Mihir Laghate and Prof. Danijela Cabric

7th March 2017

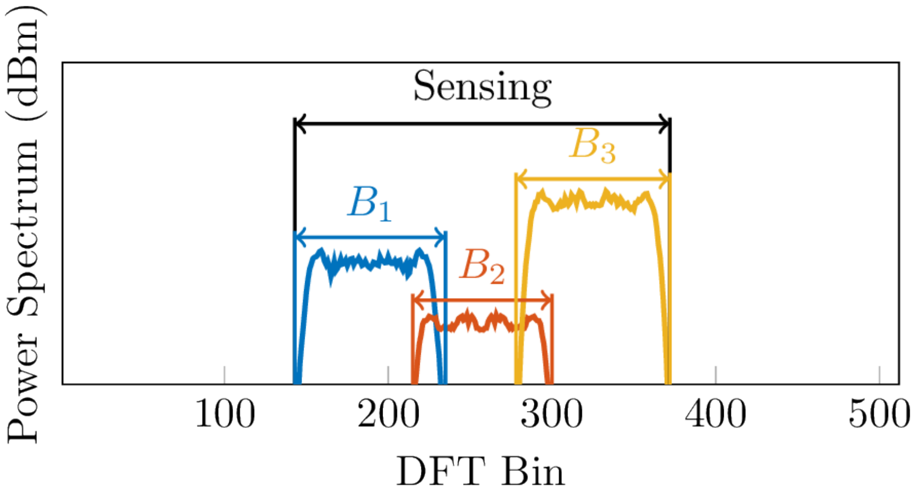
IEEE DySPAN 2017, Baltimore

Outline

- **Goals, Motivation, and Existing Work**
- **System Model**
  - Assumptions
  - Time-Frequency Map
- **Non-Negative Matrix Factorization (NNMF)**
  - Challenges with existing algorithms
- **Proposed Algorithm: Greedy Energy Minimizing NNMF**
- **MATLAB Simulation Results**
- **USRP Measurement Results**
- **Conclusions and Future Work**

Goals

Distinguish Signals with Spectral Overlap

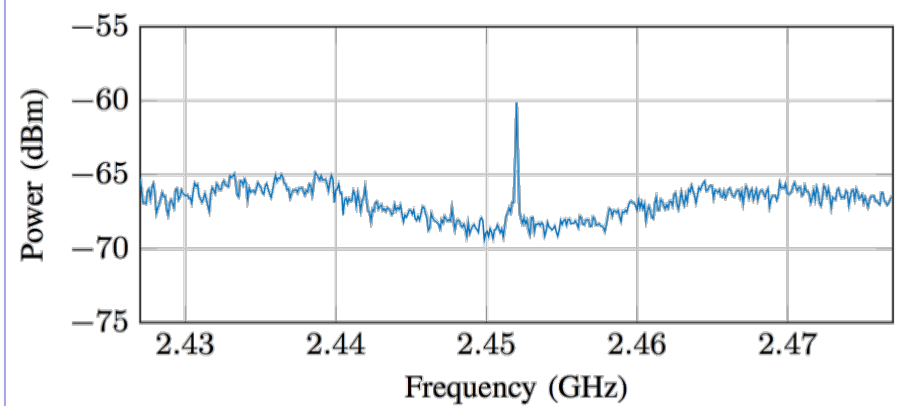


That is,

- Count number of signals rcvd
- Detect <u>sets</u> of discrete Fourier transform bins occupied by each signal

[1] M. Laghate and D. Cabric, "Using the Time Dimension to Sense Signals with Partial Spectral Overlap," in *IEEE GLOBECOM*, Washington, USA, 2016.

Estimate noise power spectrum



Challenges:

– Colored noise

– Spurs and always-on interferers

Motivating Applications

Spectral overlap by design

– IEEE 802.11b/g channels in 2.4GHz

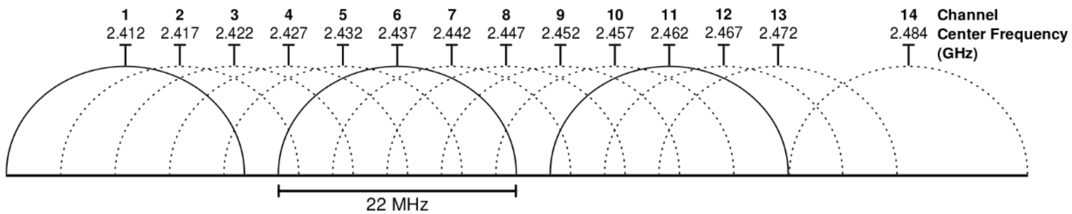
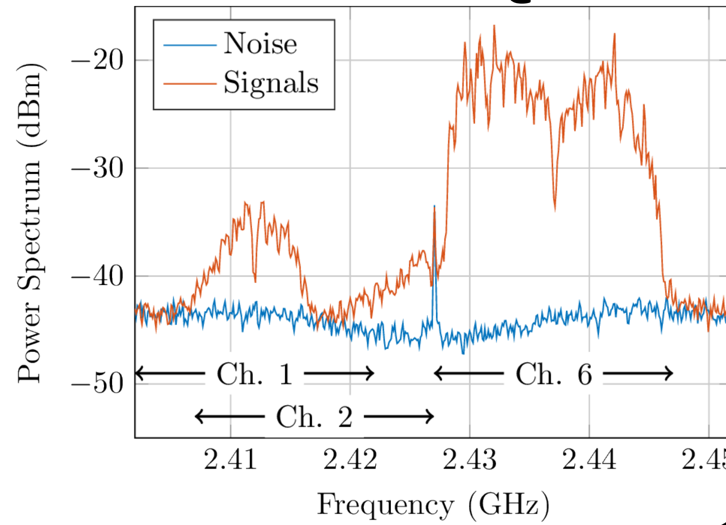


Image Source: Wikipedia “List of WLAN channels”

– Channel bonding in IEEE 802.11n

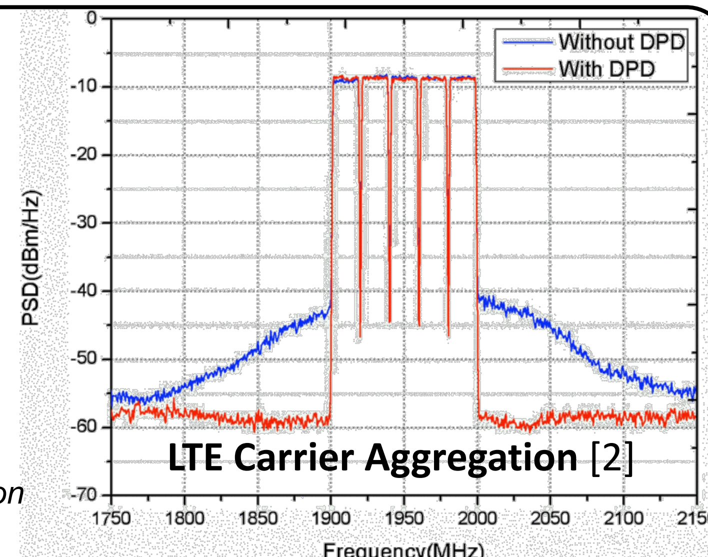
Measurements @ UCLA



Lack of Guard Bands

– IEEE 802.11n in 5GHz bands

– LTE-Advanced



[2] H. J. Wu *et al.*, “A wideband digital pre-distortion platform with 100 MHz instantaneous bandwidth for LTE-advanced applications,” in *2012 Workshop on Integrated Nonlinear Microwave and Millimetre-Wave Circuits*, 2012, pp. 1–3.

Existing Work for Distinguishing Signals

Based on	Blind	Single Antenna	Spectral Overlap	Detect Bands	Blind to Channel
Transmission protocols [4],[5]	✗	✓	✓	✓	✓
Cyclic frequency [7]	✗	✓	✓	✗	✓
Channel model & location [6]	✗	✓	✓	✗	✗
Angle of Arrival [8]	✓	✗	✓	✗	✗
Random Matrix Theory [9]	✓	✗	✓	✗	✓
Multiple CRs [10],[11]	✓	✗	✗	✓	✓
Power Spectrum Threshold [12]	✓	✓	✗	✓	✓
Multiple Power Spectrum Measurements	✓	✓	✓	✓	✓

Proposed method and our prior work [1]

System Model

Wideband sensor

- Baseband bandwidth W Hz
- Additive wide sense stationary Gaussian noise $\nu[t] \in \mathbb{R}_+^F$
- Welch power spectrum estimator using FFT of length F

Incumbent Users

- M distinct frequency bands
- m^{th} band has U_m transmitters with freq. support B_m DFT bins
  - Power spectrum received from u^{th} transmitter: $X_{m,u} \in \mathbb{R}_+^F$
  - Activity $a_{m,u}[t] \in [0,1]$ is fraction of t^{th} measurement that u^{th} transmitter in m^{th} band is active

- **Received power spectrum:** $Y[t] = \sum_{m=1}^{M} \sum_{u=1}^{U_m} a_{m,u}[t] X_{m,u}[t] + \nu[t]$

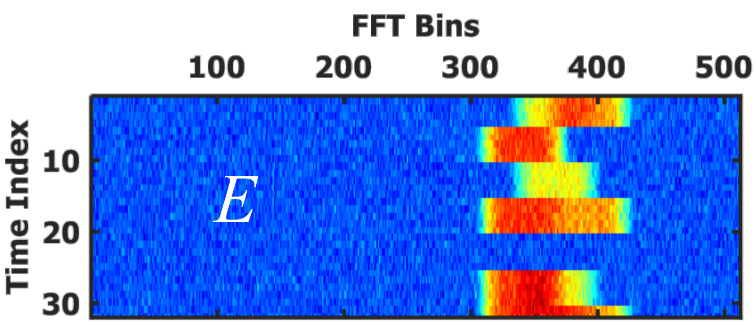
Time-Frequency Map: 1 user/band

- **Time-Freq. map E of received energy:** $E = [Y[1]\ Y[2]\ \dots\ Y[T]]^T$
- **Define matrices:** $A_{tm} = a_m[t]$, $\Sigma_{mf} = X_m(f)$, **and** $\Delta_{tf} = v[t](f)$

$$Y[t] = \sum_{m=1}^{M}\sum_{u=1}^{U_m} a_{m,u}[t]X_{m,u}[t] + v[t] \Longrightarrow E = A\Sigma + \Delta$$

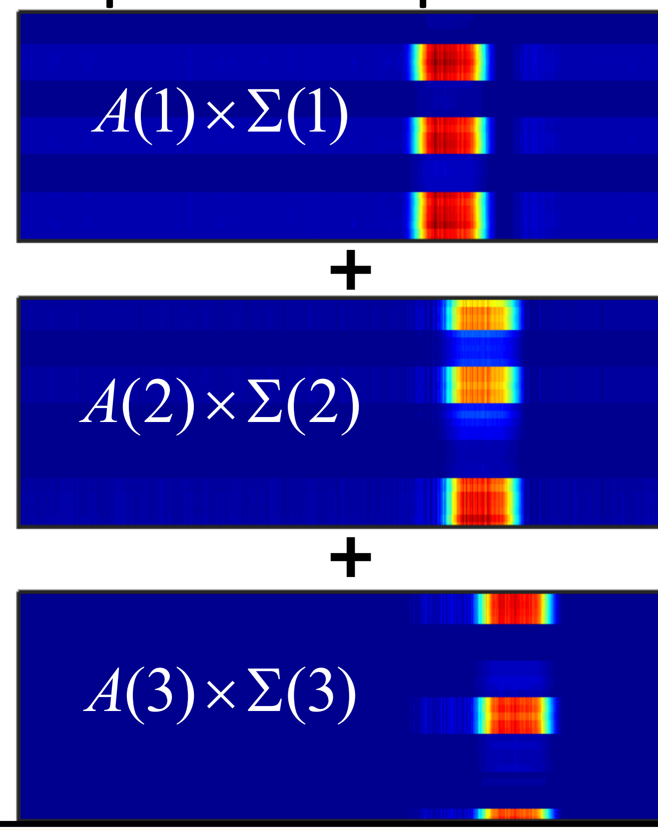
Example: $M = 3,\ F = 512,\ T = 30$

Input: Simulated Power Spectrum



=

Output: Time-Freq of Each Tx



Output computed by Non-Negative Matrix Factorization (NNMF) when given $M = 3$

Non-Negative Matrix Factorization (NNMF)

- **Let $\widehat{M}$ = Estimated number of received signals**
- **NNMF finds $\hat{A} \in \mathbb{R}_{+}^{T \times \hat{M}}$, $\hat{\Sigma} \in \mathbb{R}^{\hat{M} \times F}$ to minimize $\left\| E - \hat{A}\hat{\Sigma} \right\|_F^2$**

Challenges:

- **Estimating $\widehat{M}$ is hard when $T < F$**

- **Non-convex cost function**

  $\Rightarrow$ convergence to global minima not guaranteed

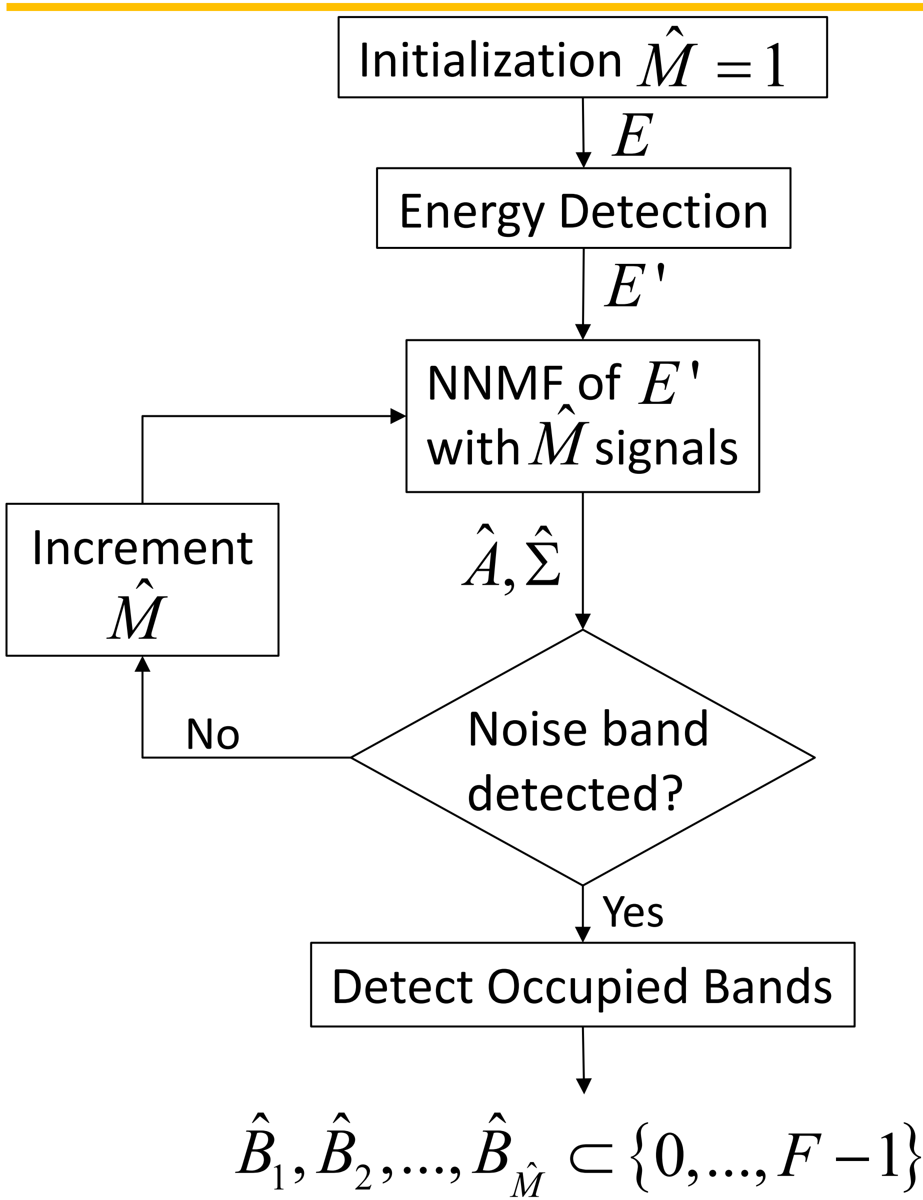
- **Cost function is not probabilistic**

  $\Rightarrow$ Not robust to noise

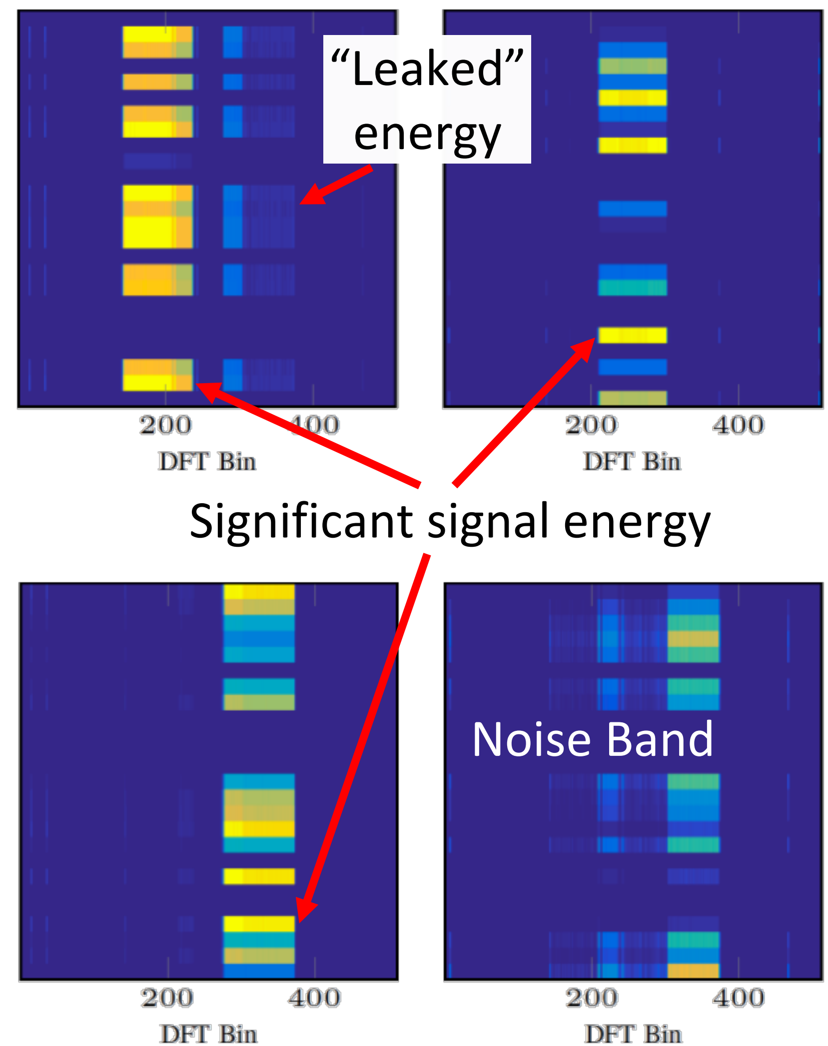
- **Non-unique solution and $\hat{A}$ is not binary**

  $\Rightarrow$ $\hat{\Sigma} \not\approx \Sigma$, i.e., thresholding $\hat{\Sigma}$ will not detect all occupied DFT bins

Prior Work: NNMF-based Algorithm



Reconstructed Factors for $\hat{M} = 4$



Motivating NNMF Algorithm: Robust XRay

$$E\left[Y[t] \mid a[t]\right] = \sum_{m=1}^{M} \sum_{u=1}^{U_m} a_{m,u}[t] E\left[X_{m,u}[t]\right] + E\left[v[t]\right]$$

i.e., cone with received power spectra as extreme rays

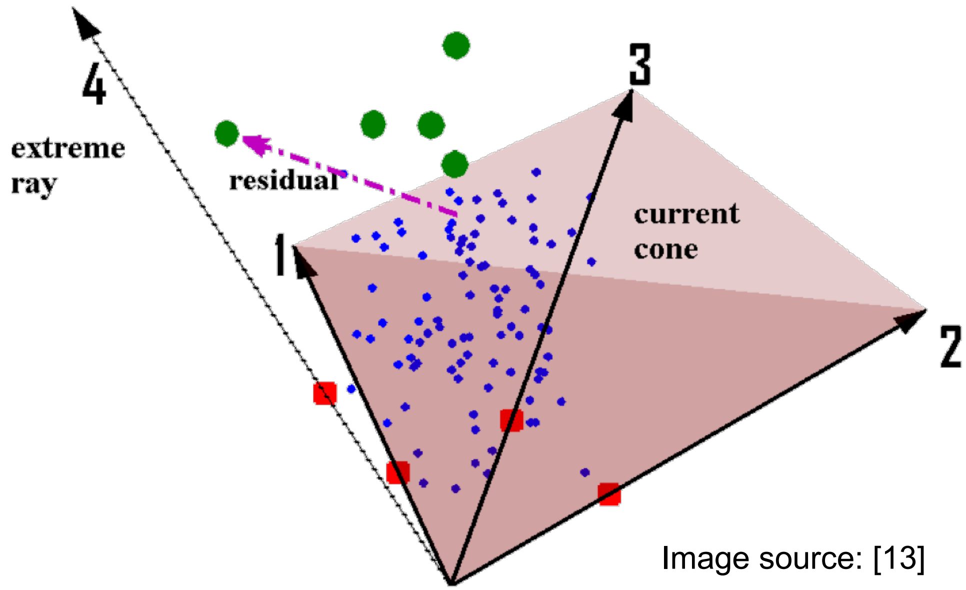


Image source: [13]

Recursive Algorithm:

1. Choose point with maximum residual as extreme ray
2. Measure residual to all measurements
3. Repeat 1 until all measurements lie within cone

[13] A. Kumar, V. Sindhwani, and P. Kambadur, "Fast conical hull algorithms for near-separable non-negative matrix factorization," in *International Conference on Machine Learning*, 2013.

Separability Assumption

$$E\left[Y[t] \mid a[t]\right] = \sum_{m=1}^{M} \sum_{u=1}^{U_m} a_{m,u}[t] E\left[X_{m,u}[t]\right] + E\left[v[t]\right]$$

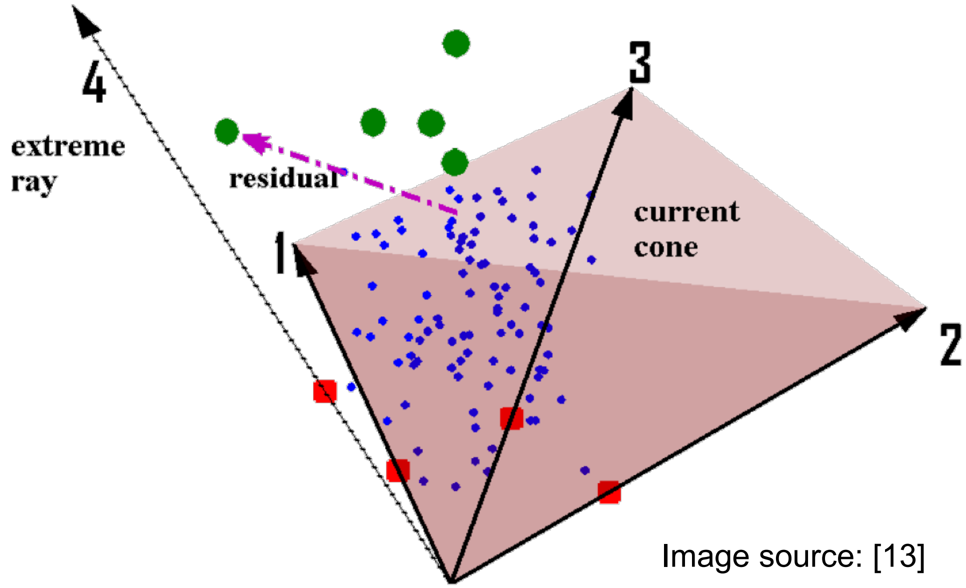


Image source: [13]

i.e., cone with received power spectra as extreme rays

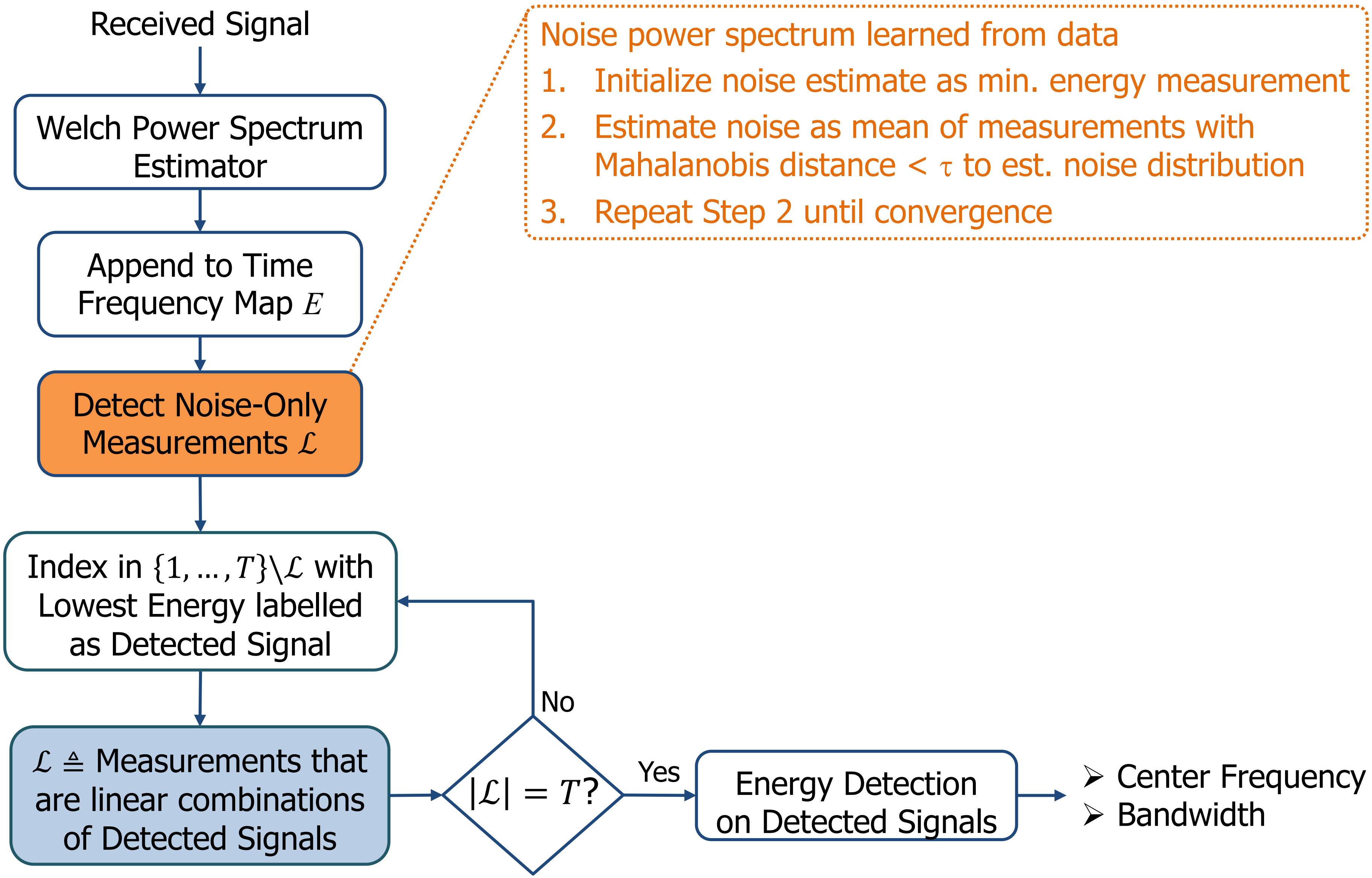
Separability Assumption:

Requires at least one measurement of each extreme ray

- At least one noise only measurement
- For each transmitter, at least one measurement where it is the only active transmitter

[14] D. Donoho and V. Stodden, “When Does Non-Negative Matrix Factorization Give a Correct Decomposition into Parts?,” in *Advances in Neural Information Processing Systems*, MIT Press, 2004, pp. 1141–1148.

Proposed Greedy Energy Minimizing NNMF



Proposed Greedy Energy Minimizing NNMF

Received Signal

→ Welch Power Spectrum Estimator

→ Append to Time Frequency Map E

→ Detect Noise-Only Measurements $\mathcal{L}$

→ Index in $\{1, \ldots, T\} \backslash \mathcal{L}$ with Lowest Energy labelled as Detected Signal

→ $\mathcal{L} \triangleq$ Measurements that are linear combinations of Detected Signals

→ $|\mathcal{L}| = T$?

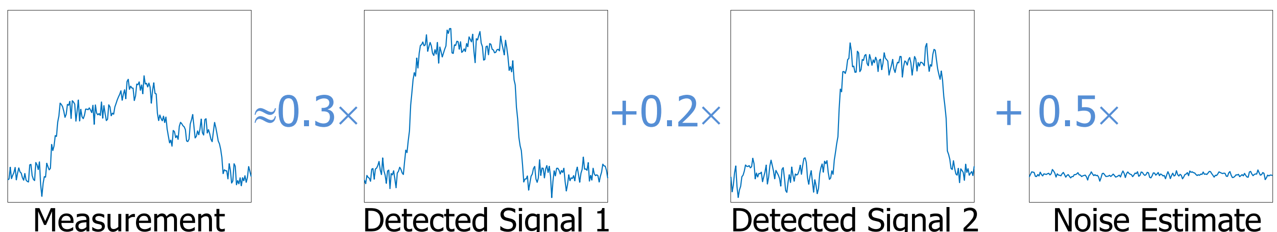
- No → Index in $\{1, \ldots, T\} \backslash \mathcal{L}$ with Lowest Energy labelled as Detected Signal
- Yes → Energy Detection on Detected Signals →
  - ➢ Center Frequency
  - ➢ Bandwidth

Noise power spectrum learned from data

1. Initialize noise estimate as min. energy measurement
2. Estimate noise as mean of measurements with Mahalanobis distance < τ to est. noise distribution
3. Repeat Step 2 until convergence

Constrained least squares minimization estimates activity

1. Activity for noise $\in (-\infty, 1]$
2. Activity for detected signals $\in [0, \infty)$



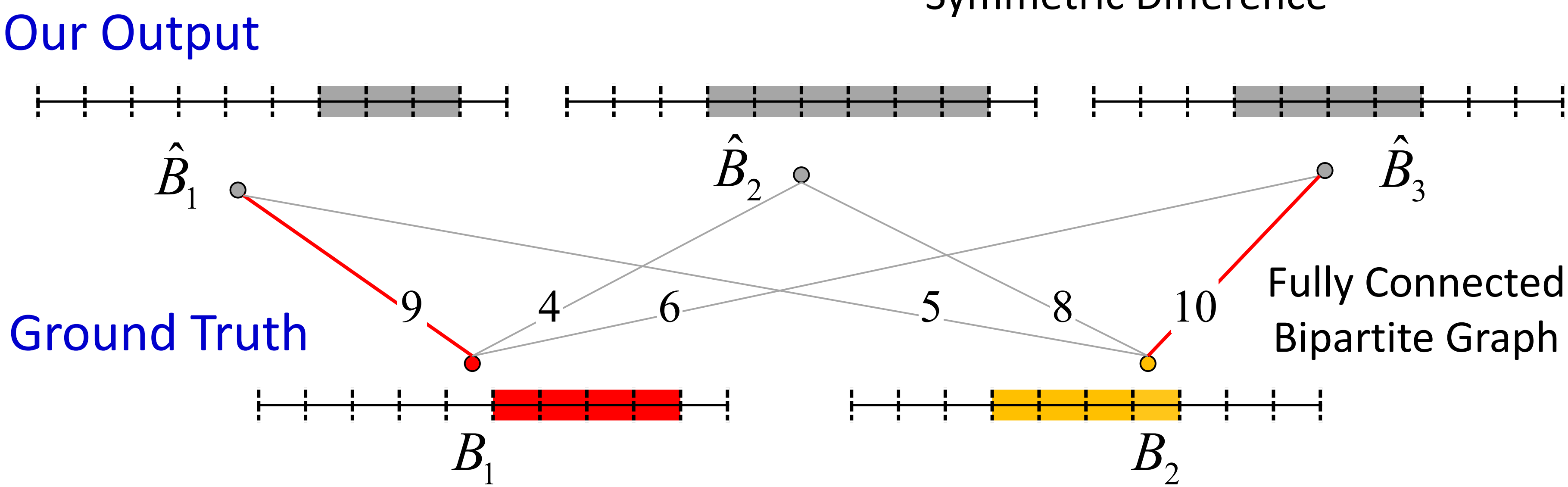
Performance Metrics

- **Number of detected bands**
- **Number of extra bands detected**
- **Relative Errors in Center Frequency and Bandwidth**

Performance Metrics

- **Number of detected bands**
- **Number of extra bands detected**
- **Relative Errors in Center Frequency and Bandwidth**

Edge Weights: $\delta\left(B_{m_1}, \hat{B}_{m_2}\right) = F - \left|\underbrace{B_{m_1} \ominus \hat{B}_{m_2}}_{\text{Symmetric Difference}}\right|$



Computed using Maximum Weight Matching

MATLAB Simulations: Performance vs. T

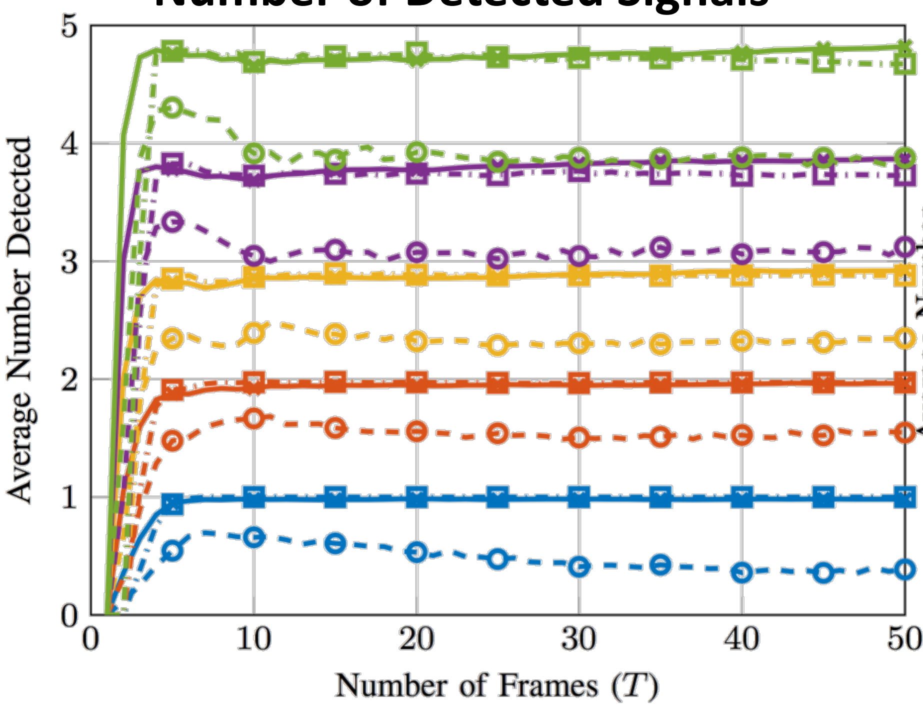
Receiver:

- Bandwidth 100 MHz
- 512 length FFT, average of 64 windowed overlapping segments
- Up to 50 measurements, i.e., 8.32ms
- Parameters: $P_{\mathrm{fa}} = 0.01$, $\tau_{\mathrm{r}} = 0.1$

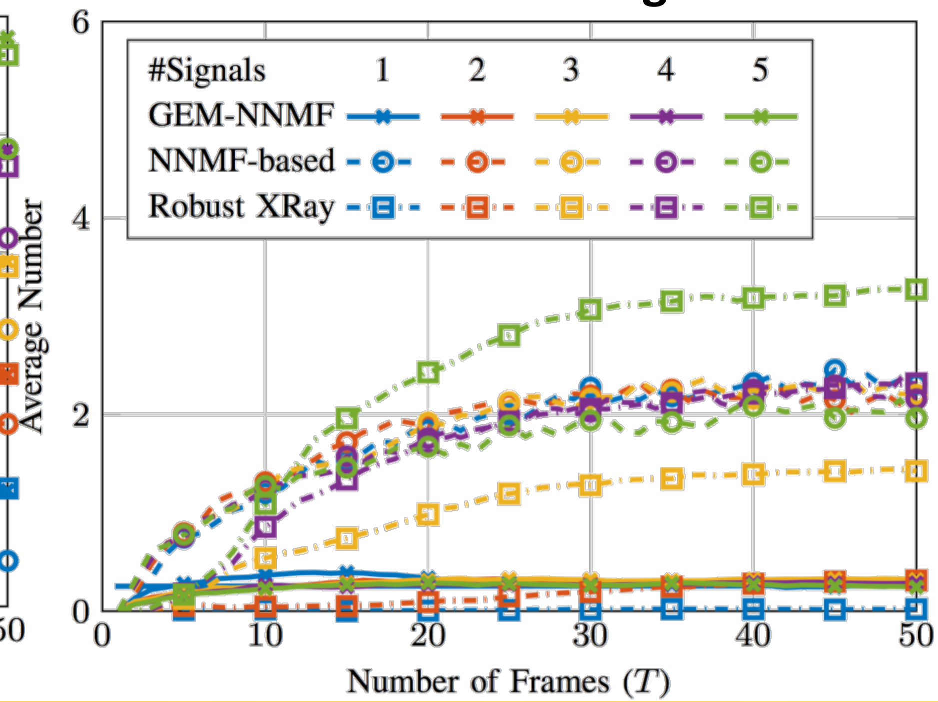
802.11g Transmitters:

- Each network = 1 AP + 2 STAs
- Channels 1, 4, 6, 8, 11
- Saturated uplink and downlink flows
- Shadow fading channels with 6dB variance

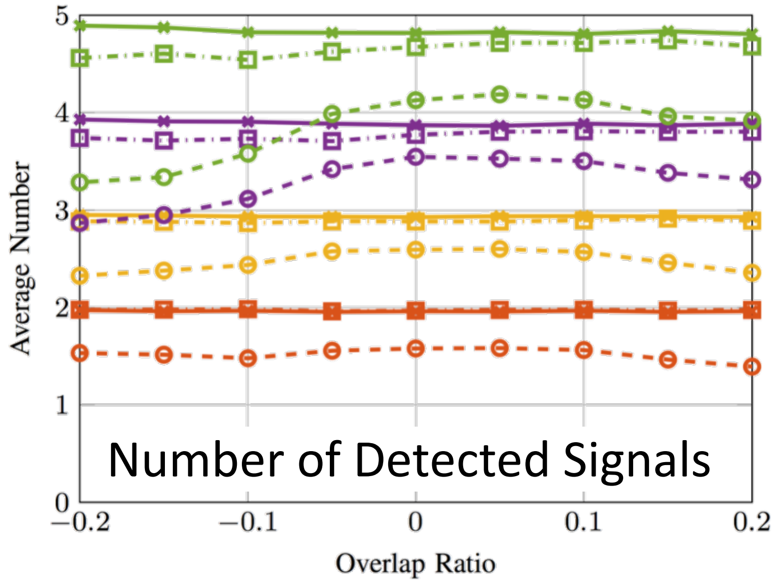
Number of Detected Signals

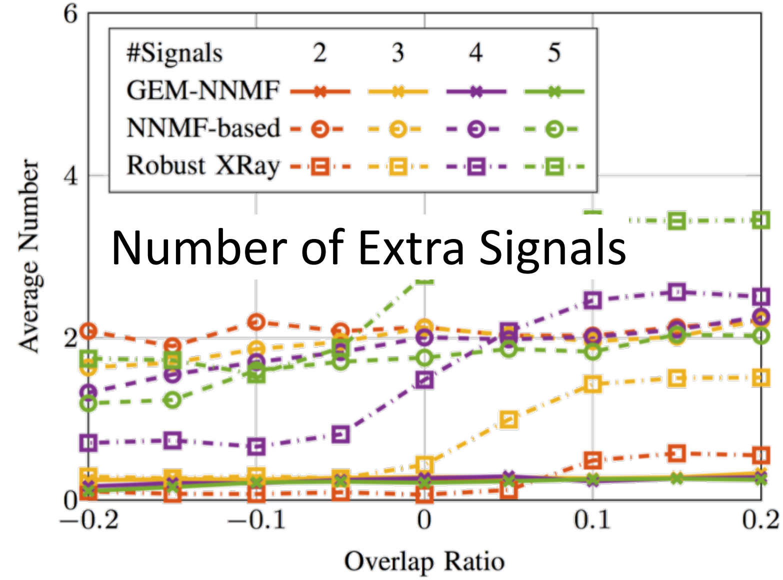


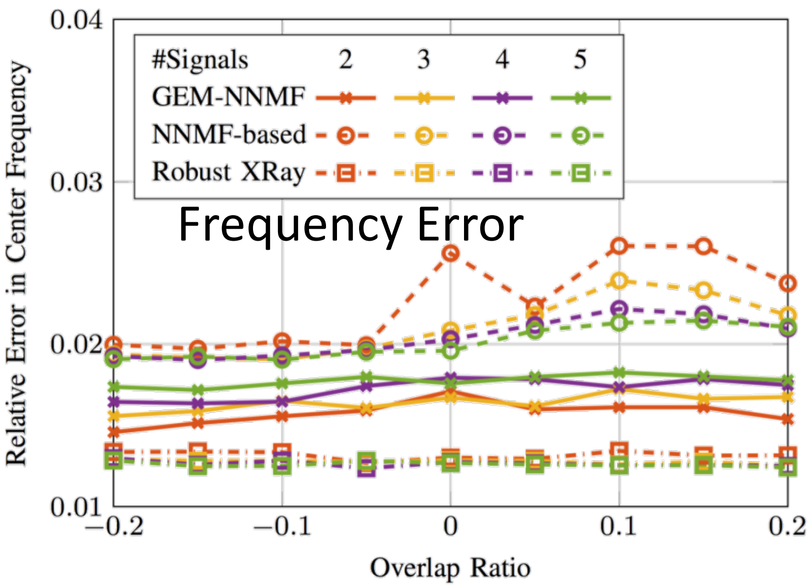
Number of Extra Signals

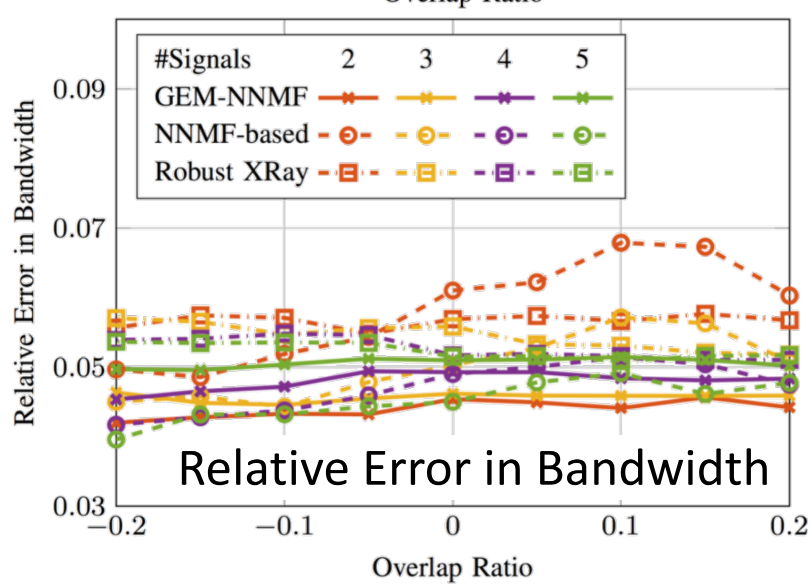


Simulation: Performance vs. Spectral Overlap



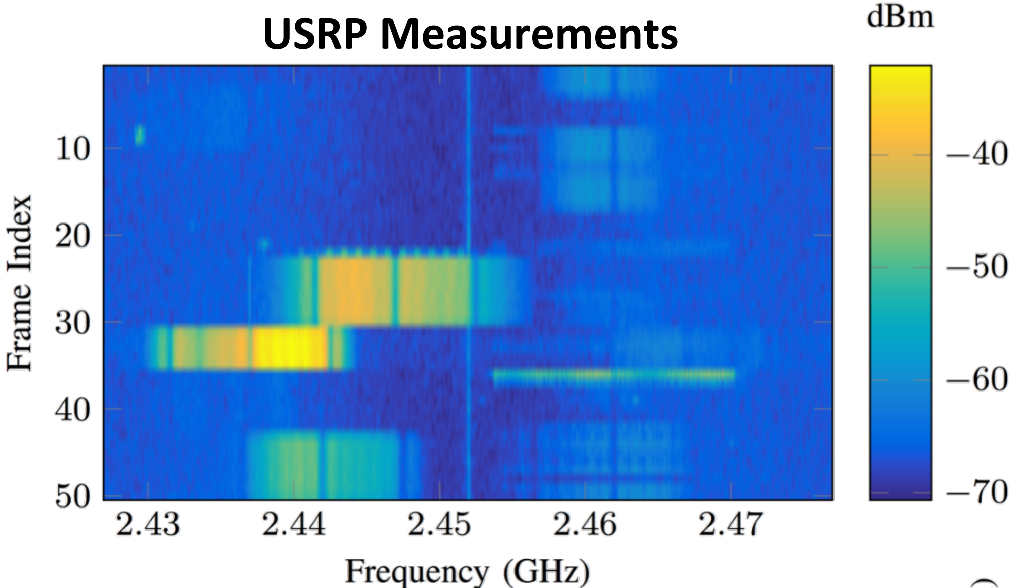






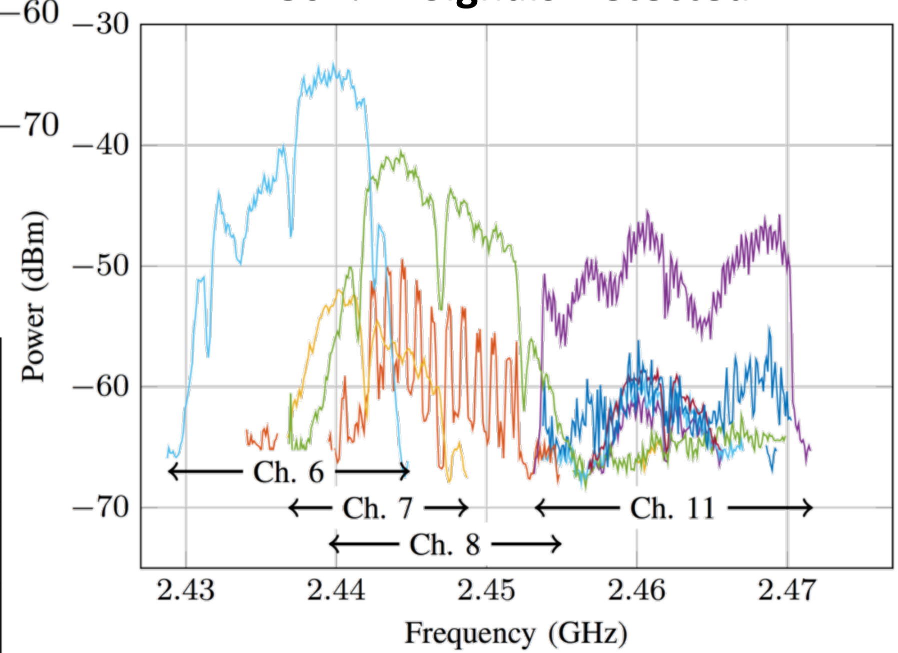
USRP Measurements: Example

USRP Measurements

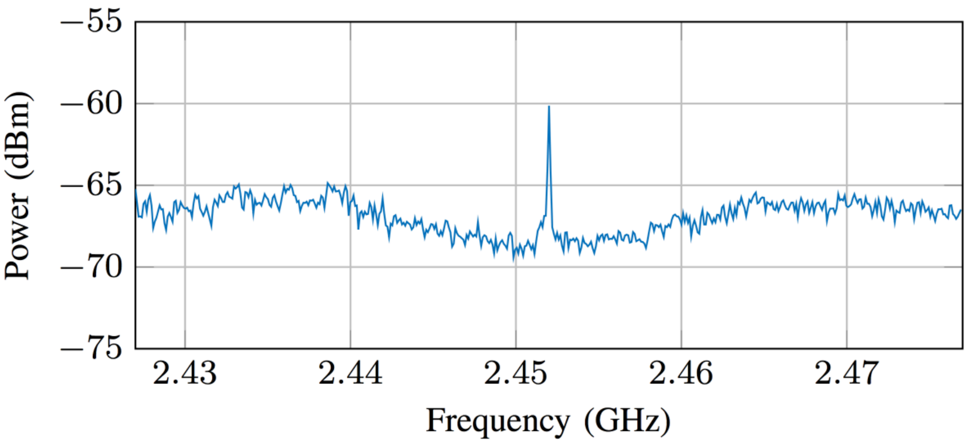


- Device: USRP N210 with CBX daughtercard
- Measurements at 2.452 GHz
- 8-bit samples @ 50 MS/s

802.11 Signals Detected



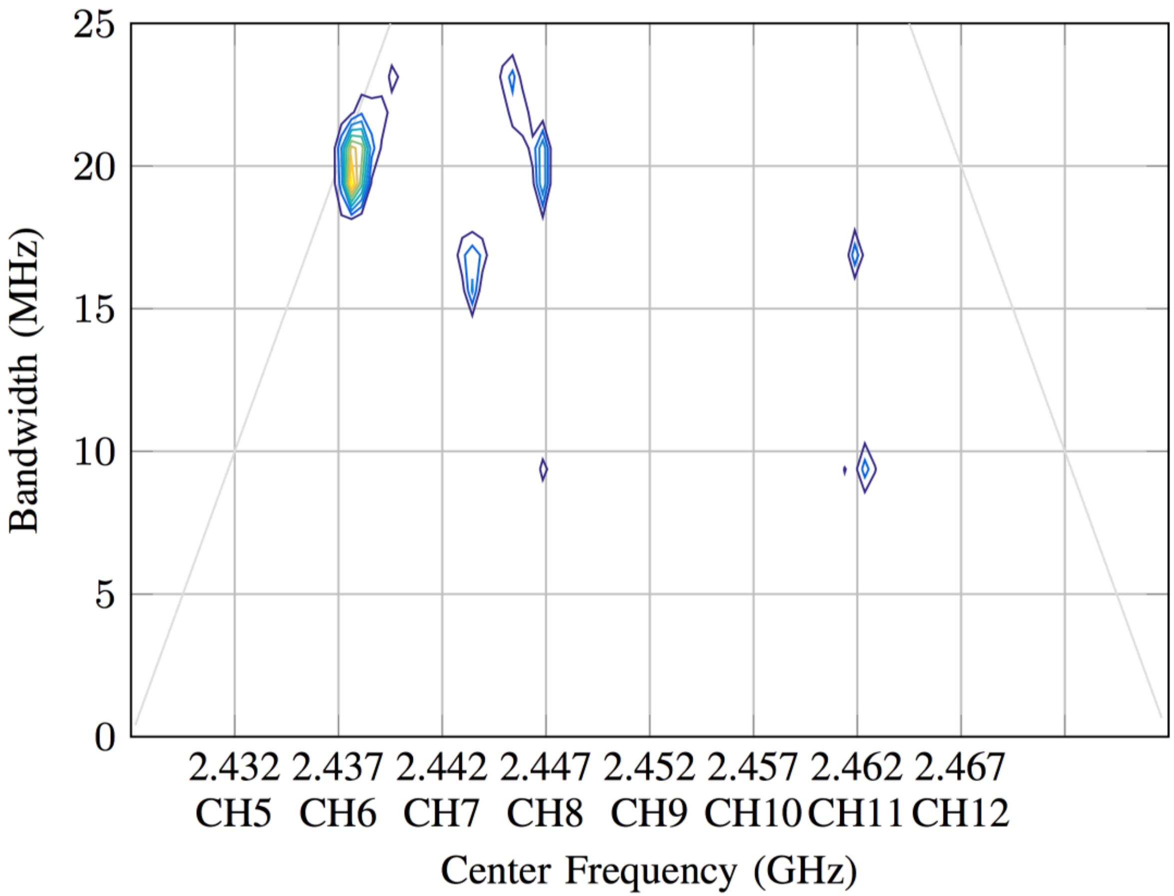
Colored Noise Learnt



Black arrows: detected supports
Labels: corresponding 802.11 channels

Multiple USRP Measurements

- **Contour plot of 2D histogram of detected center frequencies and bandwidths**
- **1000 realizations of 50 MHz measurements @ 2.452 GHz at UCLA**



Android WiFiAnalyzer used to confirm 802.11 channels 6, 7, 8, and 11 in use

Conclusions and Future Work

- Noise power spectrum can be estimated automatically when sensing communicating incumbent users
- Multiple power spectrum measurements can distinguish real world spectrally overlapped signals even in unknown channels
- Conventional signal detection and estimation theory may not be sufficient

Future Work:

- Find structural properties of optimization problem to reduce computational complexity
- Estimate time of activity, i.e., $\hat{A}$, for use in traffic estimation

Thank you!

Questions?

This material is based upon work supported by the National Science Foundation under Grant No. 1527026: Dynamic Spectrum Access by Learning Primary Network Topology

UCLA CORES

Selected References

[1] M. Laghate and D. Cabric, “Using the Time Dimension to Sense Signals with Partial Spectral Overlap,” in IEEE GLOBECOM, Washington, USA, 2016.

[2] H. J. Wu *et al.*, “A wideband digital pre-distortion platform with 100 MHz instantaneous bandwidth for LTE-advanced applications,” in *2012 Workshop on Integrated Nonlinear Microwave and Millimetre-Wave Circuits*, 2012, pp. 1–3.

[3] Z. Quan, S. Cui, A. H. Sayed, and H. V. Poor, “Optimal Multiband Joint Detection for Spectrum Sensing in Cognitive Radio Networks,” *IEEE Transactions on Signal Processing*, 2009.

[4] I. Bisio, M. Cerruti, F. Lavagetto, M. Marchese, M. Pastorino, A. Randazzo, and A. Sciarrone, “A Trainingless WiFi Fingerprint Positioning Approach Over Mobile Devices,” IEEE Antennas Wirel. Propag. Lett., vol. 13, pp. 832–835, 2014.

[5] M. Ibrahim and M. Youssef, “CellSense: An Accurate Energy-Efficient GSM Positioning System,” Veh. Technol. IEEE Trans. On, vol. 61, no. 1, pp. 286–296, Jan. 2012.

[6] H. Yilmaz, T. Tugcu, F. Alago¨z, and S. Bayhan, “Radio environment map as enabler for practical cognitive radio networks,” IEEE Commun. Mag., vol. 51, no. 12, pp. 162–169, Dec. 2013.

[7] S. Chaudhari and D. Cabric, “Cyclic weighted centroid localization for spectrally overlapped sources in cognitive radio networks,” in 2014 IEEE Global Communications Conference (GLOBECOM), Dec. 2014, pp. 935–940.

[8] J. Wang and D. Cabric, “A cooperative DoA-based algorithm for localization of multiple primary-users in cognitive radio networks,” in IEEE GLOBECOM, Dec. 2012, pp. 1266–1270.

[9] L. Wei, P. Dharmawansa, and O. Tirkkonen, “Multiple Primary User Spectrum Sensing in the Low SNR Regime,” IEEE Transactions on Communications, vol. 61, no. 5, pp. 1720–1731, May 2013.

[10] M. Laghate and D. Cabric, “Identifying the presence and footprints of multiple incumbent transmitters,” in 2015 49th Asilomar Conference on Signals, Systems and Computers, 2015, pp. 146–150.

[11] M. Laghate and D. Cabric, “Cooperatively Learning Footprints of Multiple Incumbent Transmitters by Using Cognitive Radio Networks,” submitted to IEEE Transactions on Cognitive Communications and Networking, Sept. 2015.

[12] T.-H. Yu, O. Sekkat, S. Rodriguez-Parera, D. Markovic, and D. Cabric, “A Wideband Spectrum-Sensing Processor With Adaptive Detection Threshold and Sensing Time,” IEEE Transactions on Circuits and Systems I: Regular Papers, vol. 58, no. 11, pp. 2765–2775, Nov. 2011.

[13] A. Kumar, V. Sindhwani, and P. Kambadur, “Fast conical hull algorithms for near-separable non-negative matrix factorization,” in International Conference on Machine Learning, 2013.

[14] D. Donoho and V. Stodden, “When Does Non-Negative Matrix Factorization Give a Correct Decomposition into Parts?,” in Advances in Neural Information Processing Systems, MIT Press, 2004, pp. 1141–1148.