# Localization of Unknown Signals over Multipath Channels

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# At a Glance

- Goal: Localization (geolocation) of <u>unknown</u> RF emitters in multipath environments
- Challenges:
  - Conventional methods such as TDOA based on line-of-sight (LOS)
  - Non-line-of-sight (NLOS) paths
  - Blocked LOS paths (e.g. indoor source)
- Applications:
  - Defense applications
  - Location based services
  - E911



# **Problem Statement**

# Goal

Estimate emitters locations

### **Sensor assumptions**

- Network of distributed sensors with fixed, known locations
- Sensors have ideal communication with a fusion center
- Sensors are time synchronized

#### Source assumptions

- Emitter waveforms are unknown
- PSD is known

#### **Channel assumptions**

- Time-invariant unknown multipath channel
- No prior information on the multipath channel



### **Localization over LOS Channels**



# **Multipath Challenge**

- TDOA, DPD fail in multipath channels can not apply the principle that the shortest delay difference = LOS TDOA
- Very scarce literature on localizing emitters over multipath channels.





• Signal at n-th sensor

$$\tilde{z}_{n}(t) = \sum_{q=1}^{Q} \alpha_{nq} \tilde{s}_{q}(t - \tau_{n}(\mathbf{p}_{q})) + \sum_{q=1}^{Q} \sum_{m=1}^{M_{nq}} \beta_{nq}^{(m)} \tilde{s}_{q}(t - \tau_{nq}^{(m)}) + \tilde{w}_{n}(t)$$

$$LOS \qquad NLOS$$

- N sensors, Q emitters
- $\tilde{s}_q$  = source signal
- LOS
  - $\alpha_{nq}$  = complex gain LOS path
  - $\mathbf{p}_q$  = source location

NLOS

- $\beta_{nq}^{(m)}$  = complex gain NLOS path
- $\tau_{nq}^{(m)}$  = multipath time delay



### **Frequency Domain and PSD**

Signal model for n-th sensor (frequency domain)

$$\mathbf{Z}_{n}(f) = \sum_{q=1}^{Q} \alpha_{nq} \mathbf{S}_{q}(f) \mathbf{e}^{-j2\pi f\tau_{n}(\mathbf{p}_{q})} + \sum_{q=1}^{Q} \sum_{m=1}^{M_{nq}} \beta_{nq}^{(m)} \mathbf{S}_{q}(f) \mathbf{e}^{-j2\pi f\tau_{nq}^{(m)}} + W_{n}(f)$$

$$\mathbf{LOS} \qquad \mathbf{NLOS}$$

Covariance matrix

$$\mathbf{R}(f) = \mathbf{E}\left[\mathbf{z}(f)\mathbf{z}^{H}(f)\right]$$

Model of vectorized covariance matrix  $\gamma(f) = \operatorname{vec}(\mathbf{R}(f))$ 

$$\gamma_{n}(f) = \sum_{q=1}^{Q} x_{nq} S_{q}(f) e^{-j2\pi f \tau_{n}(\mathbf{p}_{q})} + \sum_{q=1}^{Q} \sum_{m=1}^{M_{nq}} y_{nq}^{(m)} S_{q}(f) e^{-j2\pi f \tau_{nq}^{(m)}} + W_{n}(f)$$
LOS NLOS

 $S_q(f)$  = known power spectral density

Covariance matrix depends on unknown parameters  $\gamma(f; \theta)$ 

$$\boldsymbol{\theta} = \left[ \boldsymbol{x}_{nq}, \boldsymbol{p}_{q}, \boldsymbol{M}_{nq}, \boldsymbol{y}_{nq}^{(m)}, \boldsymbol{\tau}_{nq}^{(m)} \right]$$

# **Covariance Matching Estimation Technique (COMET)** 8

- MLE of unknown parameters from covariance matrix is too difficult
- Simpler alternative: approximate cov mat with sample cov mat Compute the sample covariance matrix

$$\widehat{\mathbf{R}} = \frac{1}{J} \sum_{j=1}^{J} \mathbf{z}_{j} \mathbf{z}_{j}^{H}$$

Vectorize

$$\hat{\gamma} = \operatorname{vec}(\widehat{\mathbf{R}})$$

Solve optimization to find  $\boldsymbol{\theta}$ 

$$\min_{\boldsymbol{\theta}} \left( \hat{\boldsymbol{\gamma}} - \boldsymbol{\gamma}(\boldsymbol{\theta}) \right)^{H} \mathbf{C}^{-1} \left( \hat{\boldsymbol{\gamma}} - \boldsymbol{\gamma}(\boldsymbol{\theta}) \right)$$

C is the covariance matrix of the residue

$$\mathbf{C} = E\left[\left(\hat{\gamma} - \gamma\right)\left(\hat{\gamma} - \gamma\right)^{H}\right] \approx \frac{1}{J}\left(\widehat{\mathbf{R}} \otimes \widehat{\mathbf{R}}\right)$$



### **Localization from SCM**

Even applying COMET leads to very complex problem

- Measurements
- Unknown parameters related to LOS paths
- Unknown parameters related to NLOS paths

$$\min_{\substack{\mathbf{x}_{nq}, \mathbf{p}_{q} \\ \mathbf{M}_{nq} \\ \mathbf{y}_{nq}^{(m)}, \tau_{nq}^{(m)}}} \left\| \mathbf{C}^{-1/2} \left( \hat{\boldsymbol{\gamma}} - \boldsymbol{\gamma} \left( \mathbf{x}_{nq}, \mathbf{p}_{q}, \mathbf{M}_{nq}, \mathbf{y}_{nq}^{(m)}, \tau_{nq}^{(m)} \right) \right) \right\|^{2}$$

- Large pool of unknown parameters
- Impractical complexity

#### 1. A small number of sources Q to be localized

2. A large number of possible locations for the sources G >> Q

Sparsity



- Unique solution under sparsity assumption
- Efficient algorithms active area of research

- Emitters are sparse
- LOS originate from common location
- NLOS is local to the sensors
- Mixed norm optimization to control LOS vs. NLOS assignments

$$\begin{split} \min_{\mathbf{x}_{g},\mathbf{y}_{m}} \sum_{g=1}^{G} \mathbf{v} \|\mathbf{x}_{g}\|_{2} + \sum_{m=1}^{M} \|\mathbf{y}_{m}\|_{1} \\ \text{subject to } \|\mathbf{C}^{-1/2} \left(\hat{\gamma} - \gamma\right)\|_{2}^{2} \leq \varepsilon \\ \gamma &= \sum_{g=1}^{G} \Phi_{g}^{\text{LOS}} \mathbf{x}_{g} + \sum_{m=1}^{M} \Phi_{m}^{\text{NLOS}} \mathbf{y}_{m} \end{split}$$



### **Parameter Tuning**

# Design challenge

Explain received data with correct mixture of LOS and NLOS

$$\min_{\mathbf{x}_g, \mathbf{y}_m} \sum_{g=1}^{G} \mathbf{V} \| \mathbf{x}_g \|_2 + \sum_{m=1}^{M} \| \mathbf{y}_m \|_1$$

- Source is missed when LOS is explained as NLOS
- False alarm occurs when NLOS is explained as LOS

# Theorem

• Given measurements collected by *L* sensors and  $L_1 < L$ , if  $\sqrt{L_1(L_1 - 1) - 1} < v < \sqrt{L_1(L_1 - 1)}$ , then the optimization problem will seek a feasible solution that explains a source with no less than  $L_1$  LOS components

### Significance

- L<sub>1</sub> LOS components are not explained as NLOS (prevent missed source)
- Fewer than L<sub>1</sub> NLOS components are not explained as LOS (prevent false alarm)

## **Numerical Results**

- 10 MHz emitter (30 m ranging resolution)
- Multipath channel RMS delay spread is 500 ns (exponential profile, Poisson arrivals)
- Search area: 200 x 200 m
- 5 sensor and 1 emitter
- 1000 samples/sensor

#### Channel impulse response





# **Probability of Correct Recovery vs. SNR**

- Correct recovery if error smaller than 10 m
- Unknown signal



• Correct recovery if error smaller than 30 m



### **Probability of Correct Recovery vs. Error**

- Error normalized to 30m
- SNR = 30 dB per sample (1000 samples and 5 sensors)



# Probability of Correct Recovery vs. Delay Spread 17

► SNR = **3**0 dB per sample



### Summary

- A novel approach for localizing unknown emitters over multipath channels
- Solution developed directly from observations
- Solution relies on sparsity of emitters and of multipath
- Solution is blind with respect to transmitted signals and channel
- ✓ Mixed norm optimization exploits properties of LOS vs. NLOS