Cooperative localization using angle of arrival measurements in non-line-of-sight environments

BHARATH ANANTHASUBRAMANIAM AND UPAMANYU MADHOW

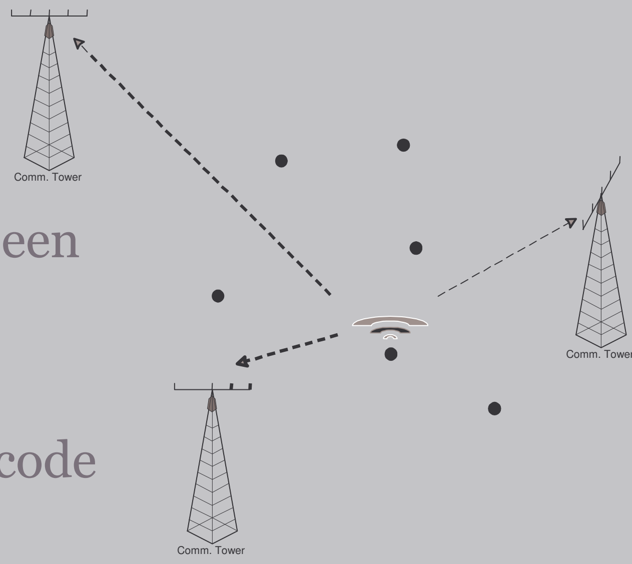
UNIVERSITY OF CALIFORNIA, SANTA BARBARA

Outline

- Why use angle of arrival measurements
- Line of sight scenarios
- Sequential algorithm for LOS scenarios
- Non – LOS narrowband and wideband scenarios
- ML localization in NLOS settings
- Robust localization algorithm
- Simulation results
- Conclusion and Future Work

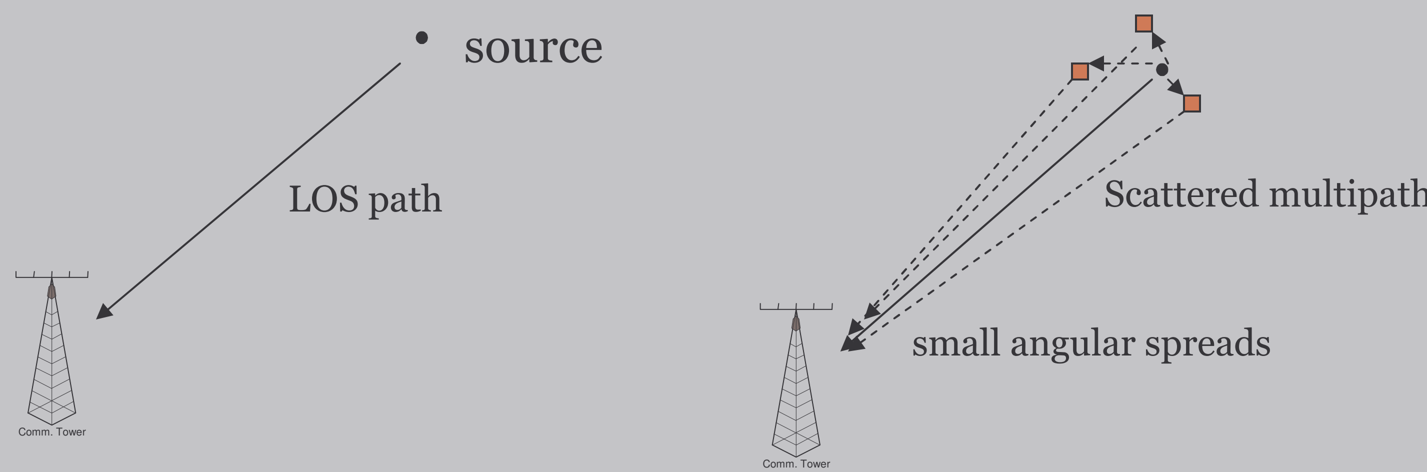
Why use AoA?

- AoA only requires calibrated antenna array at receivers
  - Time difference of arrival requires tight timing sync. between receivers
  - Received signal strength has lower reliability
  - However, other modalities if available can be used to augment performance
- Sensor-driven imaging sensor net
  - Sensors transmit when 'interesting' event is seen
  - No prior coordination between sensor and receivers
  - Receivers collaborate to locate sensor and decode data.



Line-of-sight scenario

- Direct path between source and receiver



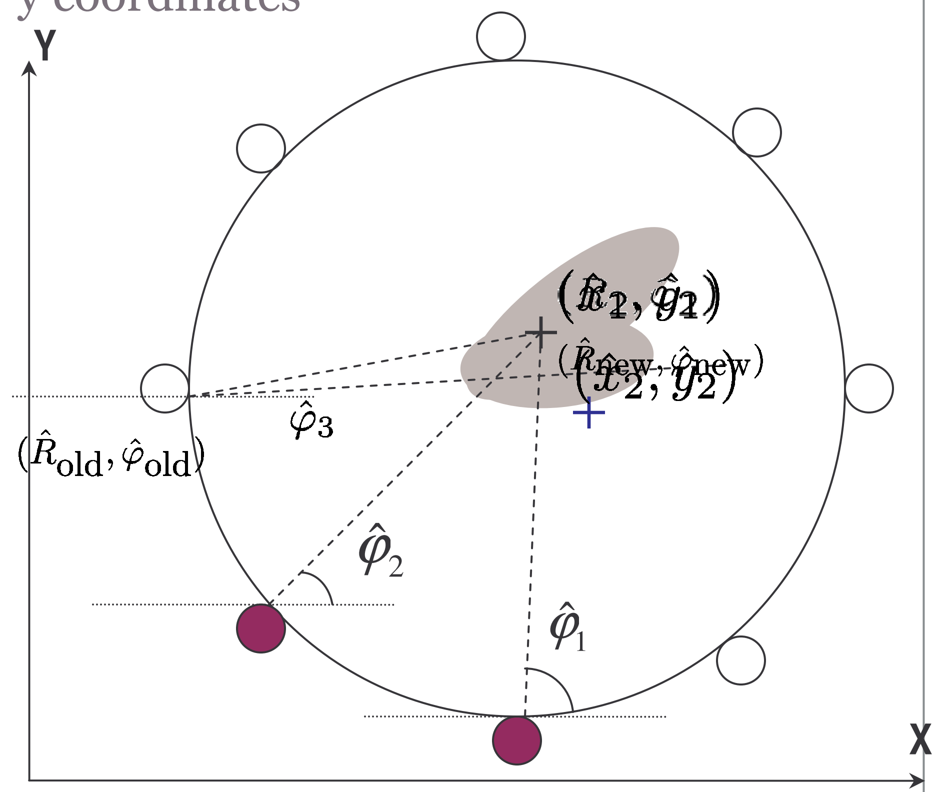
(a) True LOS (b) Local scattering

- Error in AoA modeled as zero-mean symmetric distributions, e.g., Gaussian, Laplacian
  - Variance is spatial spread in incoming paths

Sequential algorithm

- Given AOA estimates $\hat{\varphi}$ of variance $\hat{\Sigma}_{\theta\theta}$ at each receiver
  - receivers' location and orientation known.
  - Polar coordinates convenient
  - Need globally common reference: x-y coordinates

1. Bootstrap to get initial location estimate from 2 AoA
2. Transform location and covariance to global x-y coords.
3. Transform to polar coords. of next receiver or stop if no next receiver.
4. Update location and covariance
5. Goto 2



+ Estimated Sensor location + True Sensor location

Location & Covariance Update

- Receive old location estimate in global cartesian coordinates
- Convert to “local” polar coordinates.
  - Old location estimate $\hat{\mu}_{old} = [\hat{R}_{old} \quad \hat{\varphi}_{old}]^T$

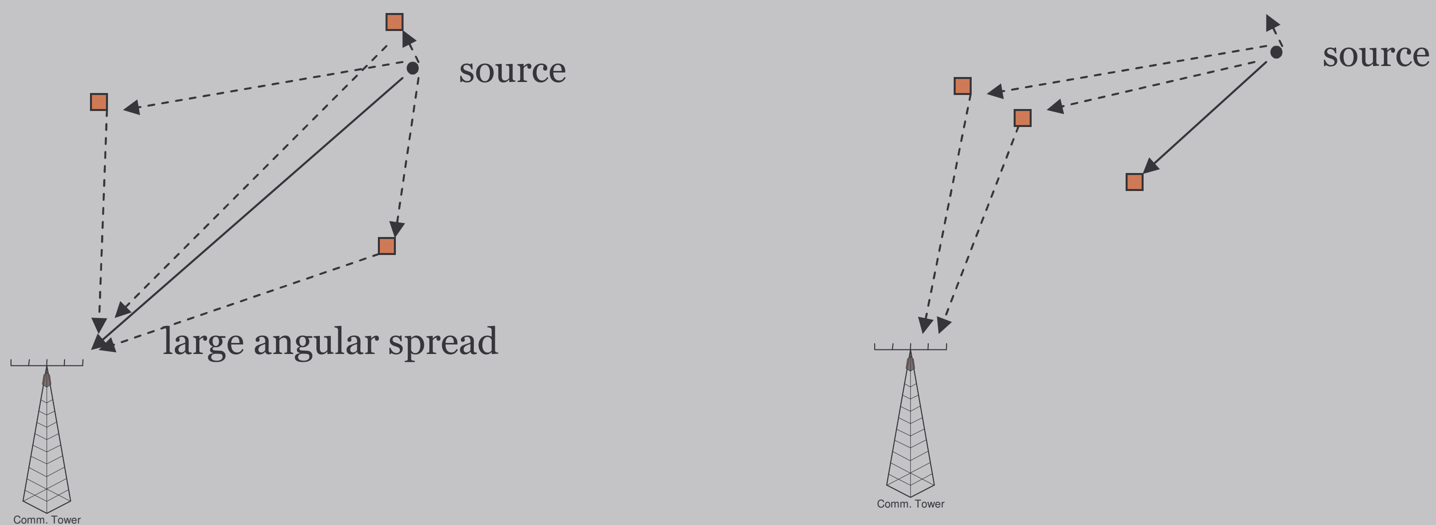
    and error covariance matrix $\hat{\mathbf{\Sigma}}_{old} = \begin{pmatrix} \Sigma^{(o)}_{RR} & \Sigma^{(o)}_{R\varphi} \\ \Sigma^{(o)}_{R\varphi} & \Sigma^{(o)}_{\varphi\varphi} \end{pmatrix}.$
- receiver’s AoA estimate is $\hat{\varphi}_{new}$ and variance $\Sigma^{(n)}_{\varphi\varphi}$
- Use linearized update equations – ML in Gaussian case.
  - The updated location $\hat{\mu} = [R \ \varphi]^T$ is

$$\begin{aligned} R &= \hat{R}_{old} + \frac{\Sigma^{(o)}_{R\varphi}(\hat{\varphi}_{new} - \hat{\varphi}_{old})}{\Sigma^{(o)}_{\varphi\varphi} + \Sigma^{(n)}_{\varphi\varphi}} \\ \varphi &= \frac{\Sigma^{(o)}_{\varphi\varphi}\ \hat{\varphi}_{new} + \Sigma^{(n)}_{\varphi\varphi}\ \hat{\varphi}_{old}}{\Sigma^{(o)}_{\varphi\varphi} + \Sigma^{(n)}_{\varphi\varphi}}. \end{aligned}$$

- Similarly, update the covariance matrix to get $\hat{\mathbf{\Sigma}}_{\text{new}}$

Non-line-of-sight scenario

- Reflections and scattering from surfaces can sometimes lead to large deviations



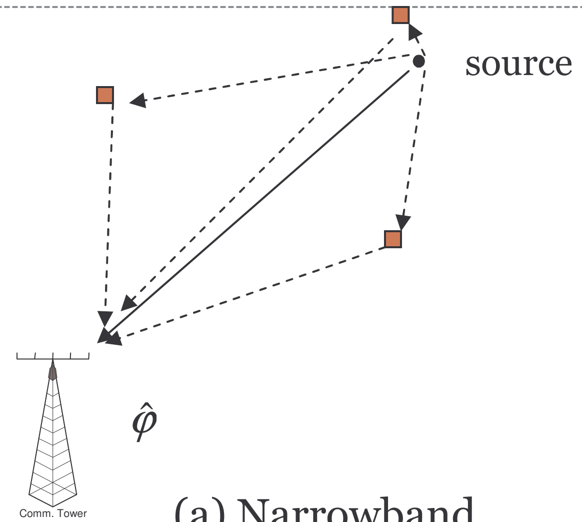
(a) Strong scatterers

(b) LOS blockage

- NLOS AoA estimates are often *outliers*
- LOS-blockage measurement model for AoA
  - chosen randomly in feasible set.

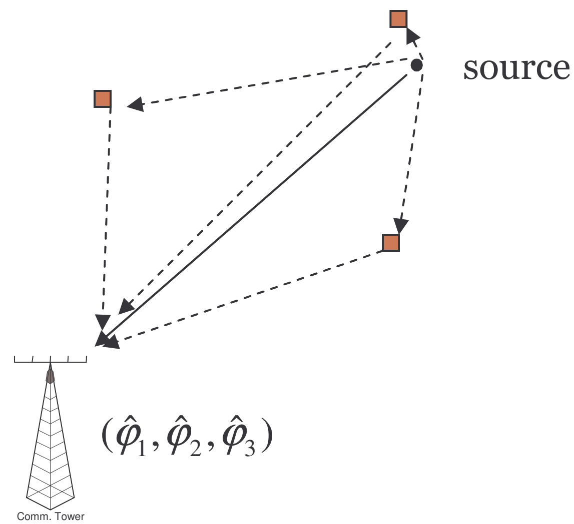
Narrowband versus Wideband

- Narrowband model
  - Cannot resolve incoming paths spatially
  - One estimate from superposition of paths
  - Either AoA estimate has LOS
    - Use zero-mean symmetric LOS models
  - Or, AoA estimate has no LOS
    - Use worst-case NLOS model



(a) Narrowband

- Wideband model
  - Can resolve multiple paths spatially
  - Multiple AoA estimates
    - One from LOS model
    - Other AoA from multipath
      - Use worst-case NLOS model



(b) Wideband

ML Estimate for Narrow band scenario

- Gaussian LOS model with blockage

$$p(\hat{\varphi} \mid \varphi) = \alpha . p_{block}(\hat{\varphi} \mid \varphi) + (1-\alpha) . p_{Gaussian}(\hat{\varphi} \mid \varphi)$$

- Solution: $\hat{X} = \arg\min \sum_{i=1}^{N} \min\{[\hat{\varphi}_i - \varphi_i(\hat{X})]^2, \Theta_{\max}^2\}$

  where threshold $\Theta_{\max}(\alpha, \sigma^2)$

- Insight: Solve least squares problem
  - but minimize only errors less than threshold
  - Suppresses effect of outliers
- ML estimator is exponentially complex in N

Narrowband NLOS Suppression

Modifications to the sequential algorithm

- Randomization
  - Start procedure with M random bootstraps
- Thresholding Errors
  - At each step, no observed angular errors exceed Θ_{max}
  - Observed angular error = angle between measured AoA and the bearing of the estimated location.
- Pick solution with lowest ML cost

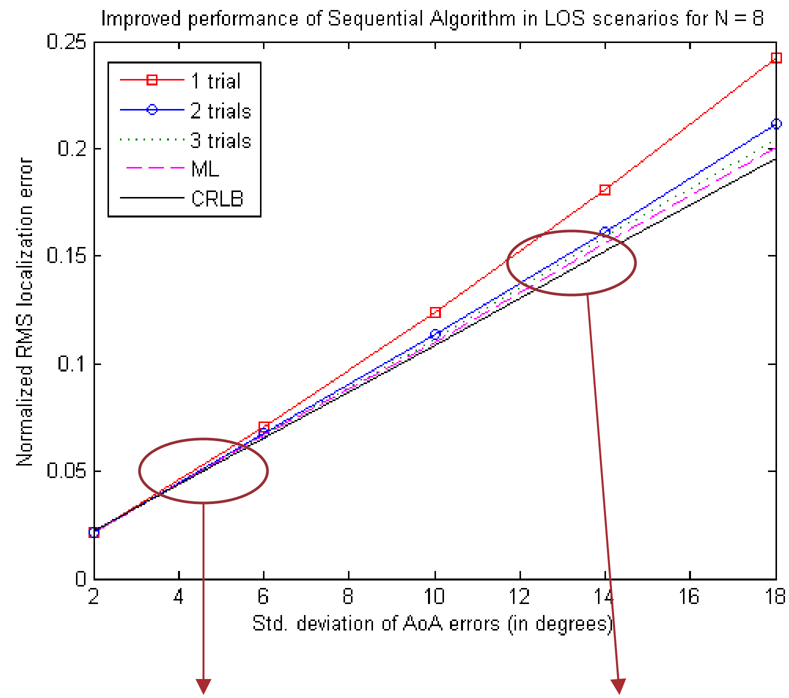
Note: In wideband setting, introduce virtual receivers

No. of Randomizations ‘M’

- Chosen to keep probability of bootstrap failure small.
- Bootstrap failure => initialization of algorithm with *outlier* in all `M’ attempts
  - At least two of initial receivers have NLOS
- Given limit on probability of bootstrap failure and fraction of receivers ‘N’ with NLOS,
  - M is independent of N
    - $O(MN^2)$ complexity of NLOS suppression

Performance under LOS

- Circular field of unit radius
- 8 receivers
- Sequential combining in random order
- Gaussian “errors” in AoA estimate.
- Close to ML performance
- Multiple bootstraps to achieve ML



Outdoor regime:

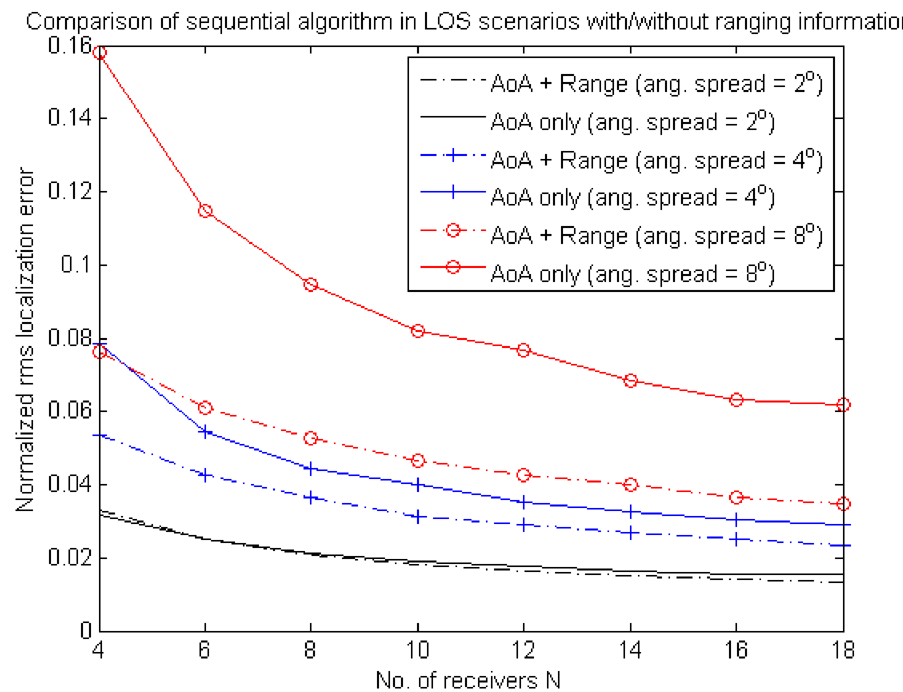
1x1 km area using 8 receivers ~ 6m

Indoor regime:

30x30m area using 8 receivers~0.75m

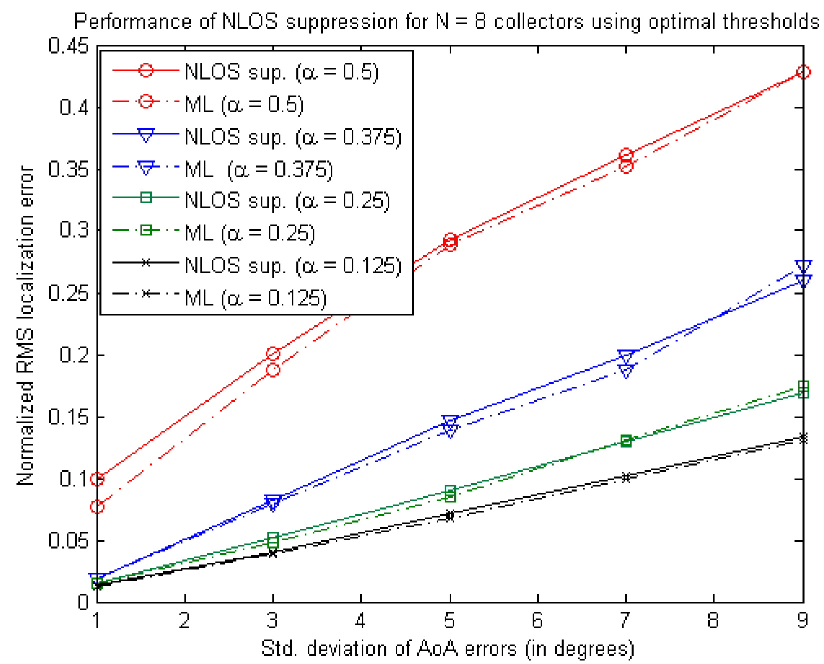
Using additional RSS information

- Easy incorporation of range information
- Substantial gains at large AoA spreads



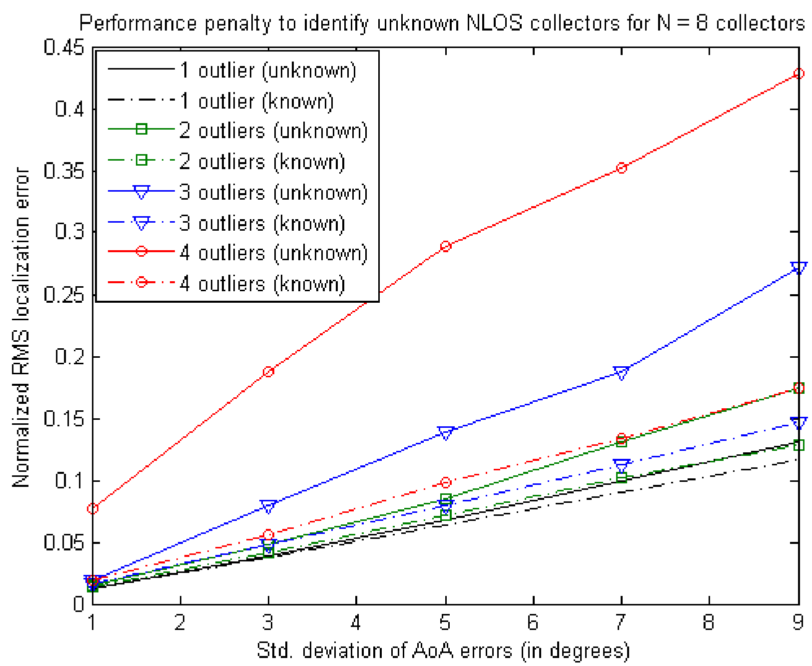
Performance under NLOS

- α fraction of receivers with NLOS (outliers) using narrowband model with Gaussian LOS errors.
- M = {4,7,11,13} for α= {0.125,0.25,0.375,0.5}
- NLOS suppression close to brute-force ML performance
- Poor performance for large α,
  - Need other forms of location info.?



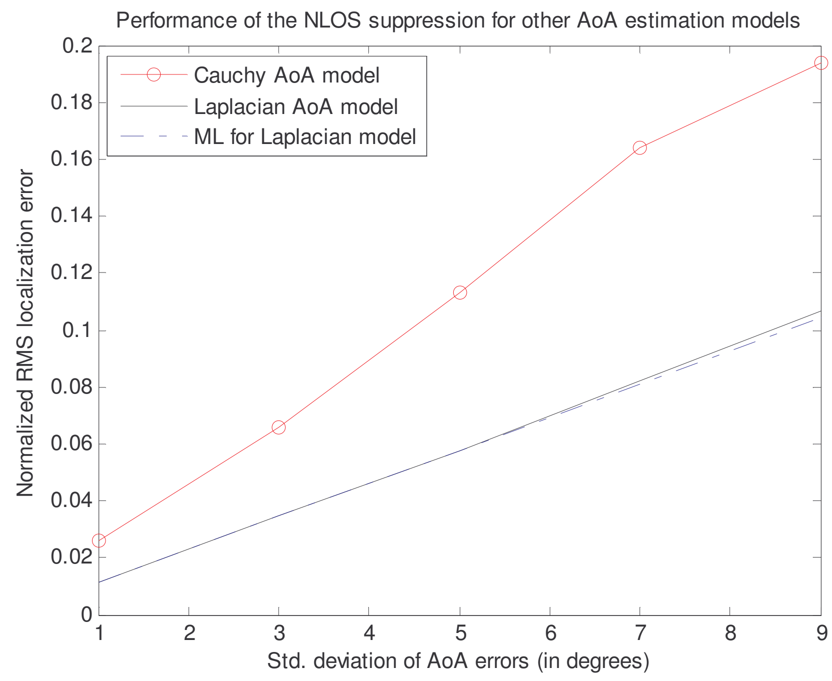
Loss due to NLOS

- Brute force ML with known outliers much better than ML with unknown outliers
- Cost to find outliers
- Small fraction of outliers/small angular spreads, algorithm performs well (e.g. outdoors).



Alternate AoA measurement models

- Algorithm robust to other heavy tailed AoA measurement models
- Laplacian model close to ML
- Cauchy with larger tails performs worse



Related Work

- Extensive literature on using combination of modalities assuming LOS
- Utilizing *robust* techniques
  - Identify outliers before localization
    - J.Borras et al. (1998), Cong et al. (2001), Venkatraman et al.(2002)
  - Robust localization
    - Chen(1999) - weighted LS using range/TOF
    - Casas et al. (2006) – least median squares using 3 “good” TOF measurements

Conclusions and Future Work

- Algorithm for NLOS environments
  - Robust and scalable
  - Achieves close to ML performance
  - Incorporates other localization modalities

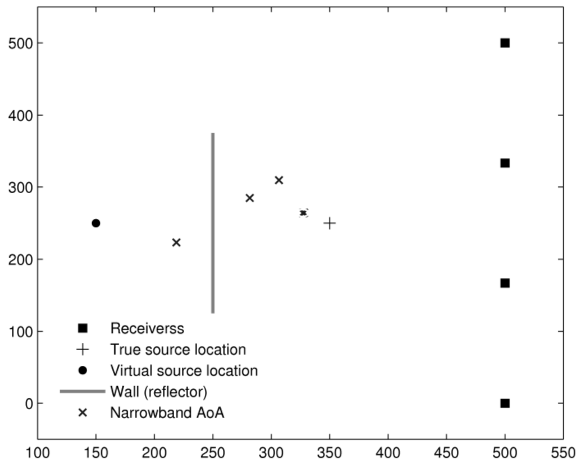
- Challenges
  - Theoretical guarantees on robust performance
  - Using time of arrival information
  - Further investigation of correlated scattering scenarios

THANK YOU !

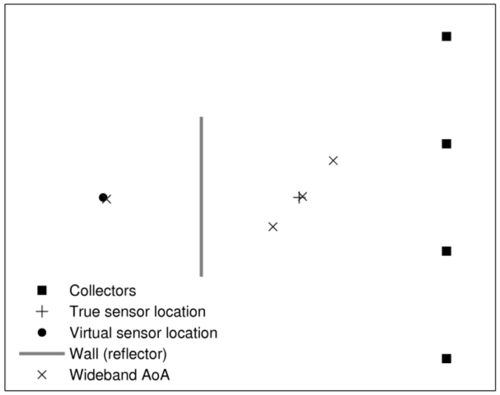
QUESTIONS?

Sample Environments

Virtual source in narrowband regime



Virtual source in wideband regime



Narrowband system with LOS blockage