Jamming Source Localization Using Augmented Physics-Based Model

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INTRODUCTION

The interference threat in GNSSs

Global Navigation Satellite Systems (GNSSs) are a critical and ubiquitous infrastructure. They are vital for countless PNT applications (e.g. intelligent transportations, critical network infrastructures, etc.). Not surprisingly, there is a growing concern about their vulnerabilities.

GNSS signals are weak and vulnerable. Because of their long transmitting distance, it is indeed easy to cause effective intentional interference, like **jamming** or **spoofing**. Moreover, due to spread-spectrum modulation, GNSS signals are below the receiver's noise floor.

Power observations can be used to detect jamming. In-band signal power higher than the noise floor could indicate a jamming signal in the surroundings.

Interference in Congested areas

Congested areas are sensitive to jamming attacks. It is therefore fundamental to develop interference monitoring systems that can detect and locate potential threats in a given area.

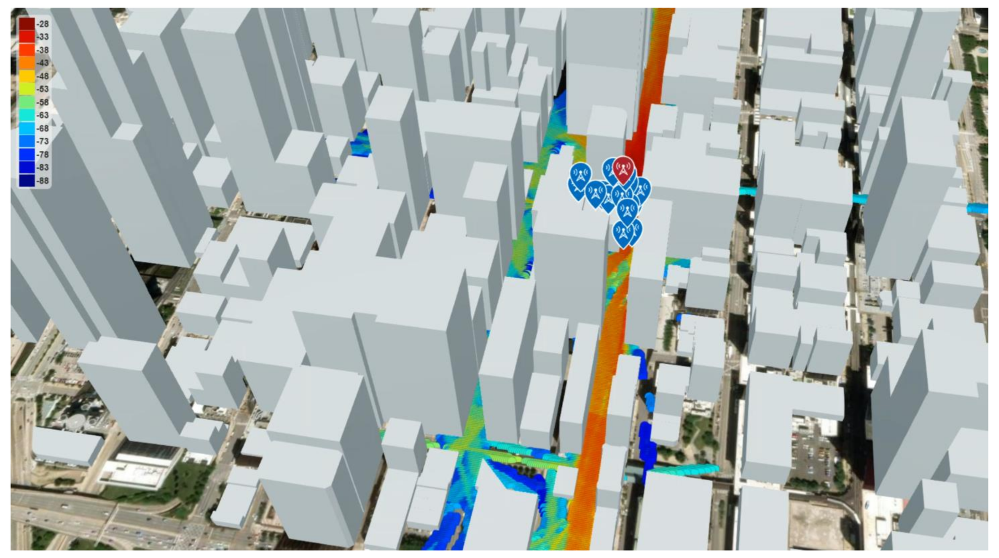
They also present an opportunity. Congested areas present an opportunity to leverage crowdsourced data to implement monitoring systems. [1][2]

How to do such an inference from crowdsourced data?

We foresee a system where **agents** within an area:

- can observe signal power in the GNSS frequency bands
- can communicate such measurements
- are aware of their position with some level of accuracy

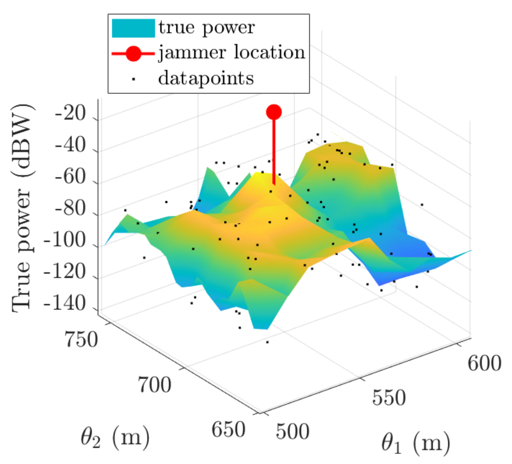
An **agent** can be any GNSS receiver embedded in a device able to communicate (e.g. **smartphones**, IoT devices, etc.).



MEASUREMENT MODEL

General Measurement Model

A jammer's location is estimated from N observations of the **jamming signal power**. An observation is related to the jammer location through a generic function that depends also on the agent's position. The measurement noise can be considered additive Gaussian [3][4].



n-th observation model

$$y_n = f(\mathbf{x}_n;\boldsymbol{\theta}) + \xi_n$$

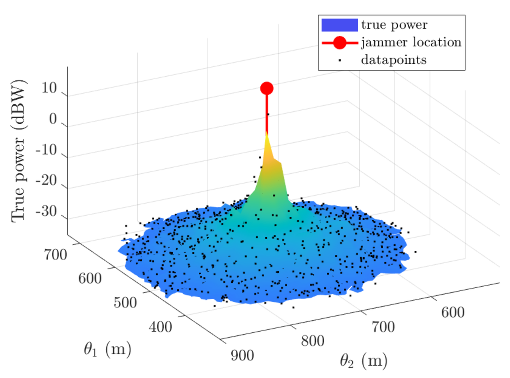
$\mathbf{x}_n = (x_n^{(1)},\dots,x_n^{(D)})^\top$ Agent location

$\boldsymbol{\theta} = (\theta_1,\dots,\theta_D)^\top$ Jammer state

$\xi_n \sim \mathcal{N}(0,\sigma^2)$ Meas. noise

Path Loss Model

The *Log-distance path loss* model is a widely adopted model for received signal strength (RSS) observations [5][6]. It depends on the jamming signal power and on the distance between jammer and agent.



Log-distance path loss model

$$f(\mathbf{x}_n;\boldsymbol{\theta}) = \underbrace{P_0}_{\text{Reference jammer power}} - \gamma 10\log_{10} \underbrace{d(\mathbf{x}_n,\boldsymbol{\theta})}_{\text{Euclidean distance}}$$

$$d(\mathbf{x}_n,\boldsymbol{\theta}) = \|\mathbf{x}_n - \boldsymbol{\theta}\| = \sqrt{(\mathbf{x}_n-\boldsymbol{\theta})^\top(\mathbf{x}_n-\boldsymbol{\theta})}$$

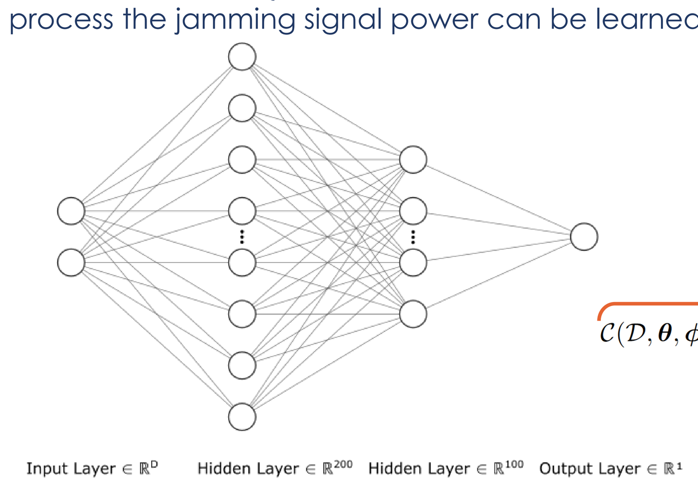
JAMMER LOCALIZATION

Augmented Physics-Based Model

The path loss model is effective for RSS in ideal open spaces. However, it does not account for **complex environments** with reflections and signal fading. The path loss model can be **augmented** by a data-driven component [7].

$$\overbrace{h(\mathbf{x}_n;\boldsymbol{\theta},\boldsymbol{\phi}) = f(\mathbf{x}_n;\boldsymbol{\theta}) + \underbrace{g(\mathbf{x}_n;\boldsymbol{\phi})}_{\text{Data-driven model (NN)}}}^{\text{Augmented model}}$$

The data-driven component can be implemented through a **Neural Network** (NN). Nonetheless, a NN alone would require much data to achieve the same performance. We can build a **cost function** whose minimization leads to the estimation of the jammer location and the NN parameters. Within the learning process the jamming signal power can be learned as well.



Updated Obs. model

$$y_n = h(\mathbf{x}_n;\boldsymbol{\theta},\boldsymbol{\phi}) + \xi_n$$

Cost function

$$\mathcal{C}(\mathcal{D},\boldsymbol{\theta},\boldsymbol{\phi}) = \sum_{n=1}^{N} |y_n - h(\mathbf{x}_n;\boldsymbol{\theta},\boldsymbol{\phi})|^2 + \underbrace{\beta\|\boldsymbol{\phi}\|_2^2}_{\text{regularization}}$$

APBM estimator

$$(\hat{\boldsymbol{\theta}},\hat{\boldsymbol{\phi}},\hat{P}_0) = \arg\min_{\boldsymbol{\theta},\boldsymbol{\phi},P_0} \mathbb{E}_{p(\mathcal{D})}\left\{\mathcal{C}(\mathcal{D},\boldsymbol{\theta},\boldsymbol{\phi})\right\}$$

Jammer's power information not needed in the model!

The Maximum Likelihood Estimator

As a benchmark solution, the *maximum likelihood estimator* (MLE) for the generic Gaussian measurement model can be used.

Log-likelihood (LLH)

$$\ln p(\mathbf{y}|\mathbf{X},\boldsymbol{\theta}) = -\frac{N}{2}\ln(2\pi\sigma^2) - \frac{1}{2\sigma^2}\sum_{n=1}^{N}(y_n - f(\mathbf{x}_n;\boldsymbol{\theta}))^2$$

Power Measurements $\mathbf{y} = (y_1,\dots,y_N)^\top$ Agents positions $\mathbf{X} = \{\mathbf{x}_1,\dots,\mathbf{x}_N\}$

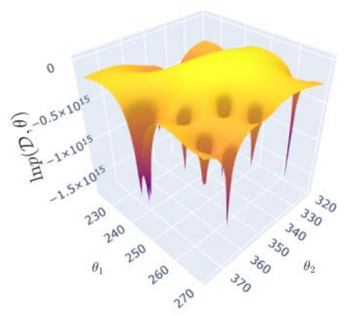
Dataset

$$\mathcal{D} = \{y_n,\mathbf{x}_n\}_{n=1}^{N}$$

$$\underbrace{\hat{\boldsymbol{\theta}}_{\text{MLE}} = \arg\max_{\boldsymbol{\theta}} \ln p(\mathbf{y}|\mathbf{X},\boldsymbol{\theta})}_{\text{MLE}}$$

A problem with the path loss model

The log-distance path loss model does not hold for **small values of distance**. Singularities (holes) arise in the LLH function. Such infinite values arise in the cost function and in the APBM estimator as well.

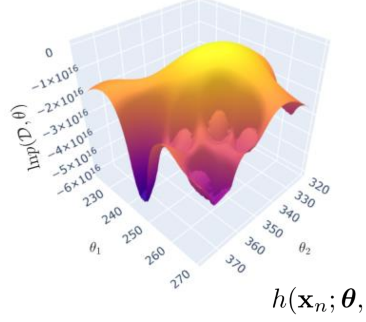


$$d(\mathbf{x}_n,\boldsymbol{\theta}) = \|\mathbf{x}_n-\boldsymbol{\theta}\| = \sqrt{(\mathbf{x}_n-\boldsymbol{\theta})^\top(\mathbf{x}_n-\boldsymbol{\theta})} \qquad f(\mathbf{x}_n;\boldsymbol{\theta}) = P_0 - \gamma 10\log_{10} d(\mathbf{x}_n,\boldsymbol{\theta})$$

$$d(\mathbf{x}_n,\boldsymbol{\theta}) \to 0 \qquad f(\mathbf{x}_n;\boldsymbol{\theta}) \to \infty$$

$$\ln p(\mathbf{y}|\mathbf{X},\boldsymbol{\theta}) = -\frac{N}{2}\ln(2\pi\sigma^2) - \frac{1}{2\sigma^2}\sum_{n=1}^{N}(y_n - f(\mathbf{x}_n;\boldsymbol{\theta}))^2$$

Bounding the loss at the *far-field distance* allows to obtain a smoother LLH function [5]. This modification is applied also to the APBM.



$$d(\mathbf{x}_n,\boldsymbol{\theta}) = \|\mathbf{x}_n-\boldsymbol{\theta}\| = \sqrt{(\mathbf{x}_n-\boldsymbol{\theta})^\top(\mathbf{x}_n-\boldsymbol{\theta})} \qquad \bar{f}(\mathbf{x}_n;\boldsymbol{\theta}) = P_0 - \gamma 10\log_{10}\boxed{\{\max(d(\mathbf{x}_n,\boldsymbol{\theta}),d_F)\}}$$

$$d(\mathbf{x}_n,\boldsymbol{\theta}) \to 0 \qquad \bar{f}(\mathbf{x}_n;\boldsymbol{\theta}) \to P_0 - \gamma 10\log_{10} d_F$$

$$\ln p(\mathbf{y}|\mathbf{X},\boldsymbol{\theta}) = -\frac{N}{2}\ln(2\pi\sigma^2) - \frac{1}{2\sigma^2}\sum_{n=1}^{N}(y_n - \bar{f}(\mathbf{x}_n;\boldsymbol{\theta}))^2$$

$$h(\mathbf{x}_n;\boldsymbol{\theta},\boldsymbol{\phi}) = \bar{f}(\mathbf{x}_n;\boldsymbol{\theta}) + g(\mathbf{x}_n;\boldsymbol{\phi}) \qquad \mathcal{C}(\mathcal{D},\boldsymbol{\theta},\boldsymbol{\phi}) = \sum_{n=1}^{N}\|\mathbf{y}_n - h(\mathbf{x}_n;\boldsymbol{\theta},\boldsymbol{\phi})\|_2^2 + \beta\|\boldsymbol{\phi}\|_2^2$$

The modified model affects APBM as well!

METHODOLOGY

Compared Estimators

- **APBM estimator**
- **APBM estimator (P_0-blind)**
- NN-only estimation
- PL-only learning
- MLE (path loss model)
- Cramér-Rao Bound (path loss model)

$$h(\mathbf{x}_n;\boldsymbol{\theta},\boldsymbol{\phi}) = \cancel{f(\mathbf{x}_n;\boldsymbol{\theta})} + g(\mathbf{x}_n;\boldsymbol{\phi})$$

$$h(\mathbf{x}_n;\boldsymbol{\theta},\boldsymbol{\phi}) = f(\mathbf{x}_n;\boldsymbol{\theta}) + \cancel{g(\mathbf{x}_n;\boldsymbol{\phi})}$$

CRB

$$\operatorname{var}(\hat{\theta}_1) \geq \frac{\sigma^2(\ln(10))^2}{100\gamma^2}\frac{\sum_{n=1}^{N}\frac{(\theta_2-x_n^{(2)})^2}{d^4(\mathbf{x}_n,\boldsymbol{\theta})}}{\left(\sum_{n=1}^{N}\frac{(\theta_1-x_n^{(1)})^2}{d^4(\mathbf{x}_n,\boldsymbol{\theta})}\right)\left(\sum_{n=1}^{N}\frac{(\theta_2-x_n^{(2)})^2}{d^4(\mathbf{x}_n,\boldsymbol{\theta})}\right)-\left(\sum_{n=1}^{N}\frac{(\theta_1-x_n^{(1)})(\theta_2-x_n^{(2)})}{d^4(\mathbf{x}_n,\boldsymbol{\theta})}\right)^2}$$

$$\operatorname{var}(\hat{\theta}_2) \geq \frac{\sigma^2(\ln(10))^2}{100\gamma^2}\frac{\sum_{n=1}^{N}\frac{(\theta_1-x_n^{(1)})^2}{d^4(\mathbf{x}_n,\boldsymbol{\theta})}}{\left(\sum_{n=1}^{N}\frac{(\theta_1-x_n^{(1)})^2}{d^4(\mathbf{x}_n,\boldsymbol{\theta})}\right)\left(\sum_{n=1}^{N}\frac{(\theta_2-x_n^{(2)})^2}{d^4(\mathbf{x}_n,\boldsymbol{\theta})}\right)-\left(\sum_{n=1}^{N}\frac{(\theta_1-x_n^{(1)})(\theta_2-x_n^{(2)})}{d^4(\mathbf{x}_n,\boldsymbol{\theta})}\right)^2}$$

Figures of merit

Root Mean Square Error (RMSE)

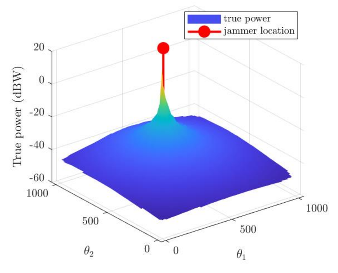
- Computed over 100 Monte Carlo simulations
- Evaluated against interference-to-noise ratio (INR)

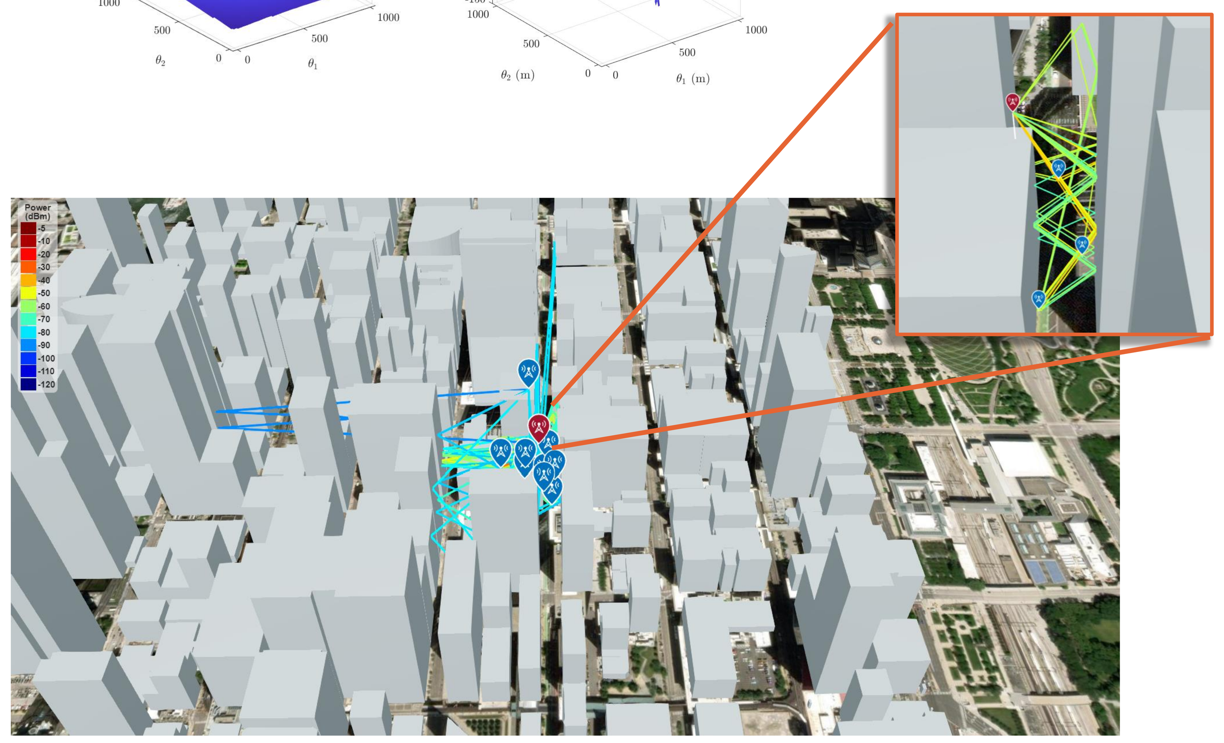
$$\text{RMSE}_{\theta_i} = \sqrt{\frac{1}{N_{\text{MC}}}\sum_{n=1}^{N_{\text{MC}}}(\theta_i - \hat{\theta}_{i,n})^2}$$

$$\text{INR} = 10\log_{10}\frac{P_0}{\sigma^2}$$

Propagation Scenarios

- Ideal path loss propagation
- Urban scenario (through ray-tracing [8])





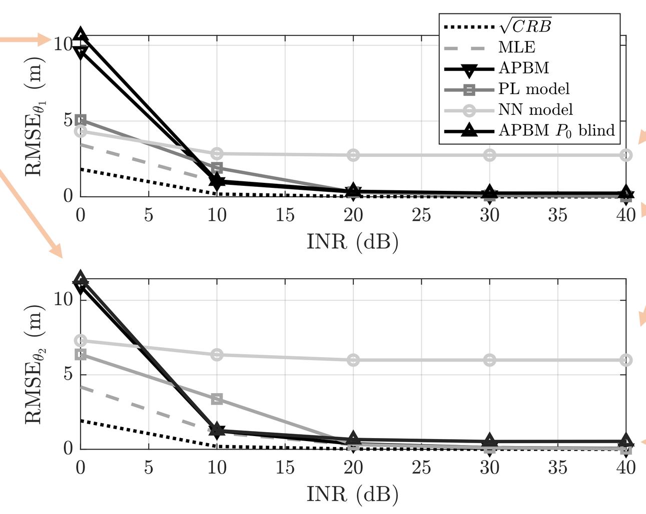
RESULTS

Path Loss Scenario

The use of NN alone struggles to accurately model path loss. The MLE and the PL-only estimator have a perfect knowledge of the propagation scenario. In this scenario, the **APBM approaches the CRB** despite its lack of information about the jammer.

APBM approaches the CRB

NN alone struggle to model path loss



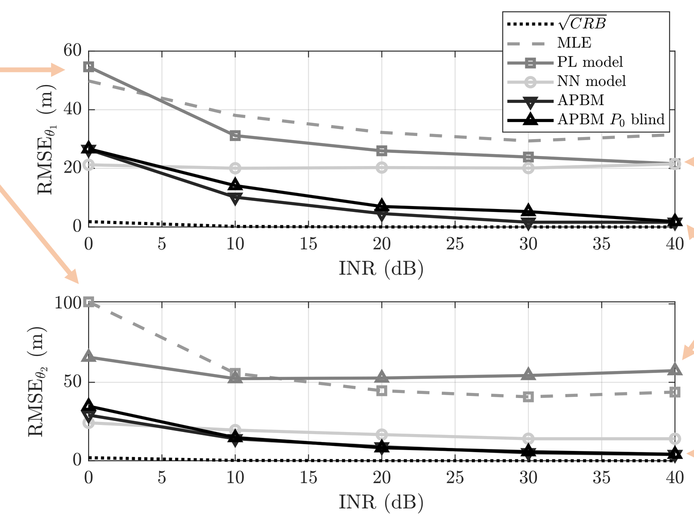
MLE and PL-only have perfect model knowledge

Urban Scenario

The MLE and the PL-only estimator mismodel the propagation field. Nonetheless, the NN needs a priori information about the propagation physics. Although not sufficient by itself, the path loss propagation is a relevant model also in this complex urban scenario, encouraging our approach. **APBM outperforms MLE, PL-only, and NN-only.**

MLE and PL-only mismodel the propagation field

NN needs a priori information about the model



APBM outperforms MLE, PL-only, and NN

CONCLUSIONS

Proposed a jamming localization strategy based on a physics-based model augmented with a data-driven component trained with crowdsourced data.

- It **seamlessly adapt** without tuning to very different propagation scenarios
- It is **unaware of jammer's characteristics** (i.e. transmitting power)

MAIN TAKEAWAYS

Ideal path loss propagation scenario:

- APBM as good as MLE, despite lack of P_0 knowledge
- APBM outperforms NN

Urban scenario:

- APBM outperforms MLE
- APBM outperforms NN

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