# Single-Antenna Sensor Localization with Reconfigurable Intelligent Surfaces

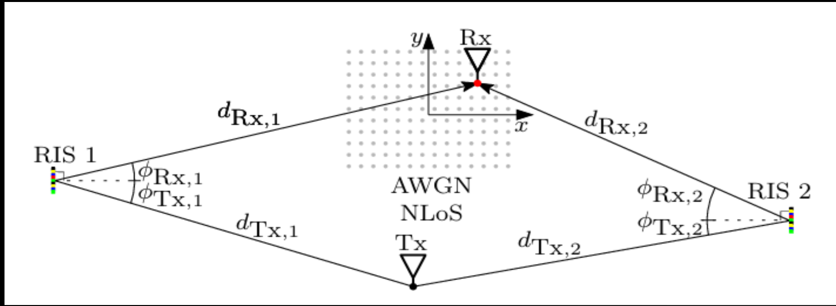
**Purnima Kumari**
22075066
**Praneeth Chandra**
22075088

# Introduction

- This paper tackles the challenge of sensor localization in wireless networks, aiming to accurately determine sensor positions with wireless signals. Traditional methods require multiple antennas or access points, which are costly and complex. To enhance space and energy efficiency, single-antenna sensors are used, but they provide limited observations (amplitude and phase) that alone do not enable precise localization.
- A novel solution is proposed using Reconfigurable Intelligent Surfaces (RIS), a low-cost technology with programmable reflecting elements that enhance signal control. The paper's contributions are two-fold: (1) it introduces RIS-reconfiguration protocols tailored for high-accuracy single-antenna localization, and (2) it derives the Fisher information and Cramér-Rao lower bound, demonstrating that centimeter-level accuracy is achievable in the SISO setting.

# System model

- The RIS-assisted SISO localization communication system consists of A **base station (BS)** with a single antenna that sends signals, A **single-antenna sensor** whose location needs to be determined and A **Reconfigurable Intelligent Surface** placed at a known position that reflects the signals from the base station.




- The total received channel is a combination of the direct link h Tx-Rx and the RIS-reflected link
- The RIS elements apply tunable phase shifts ϕn, which are designed to optimize the received signal by enhancing constructive interference between the direct and reflected paths.

$$h = \sum_{m} h_{R_k,m} \Omega_m h_{T_k,n}$$

- The paper incorporates **path-loss models** based on Friis transmission equations, accounting for the natural propagation attenuation and effective area of the elements as seen from the communication nodes.

$$(\beta_{\mathrm{Tx},m} = \sqrt{\frac{\varepsilon_{\mathrm{Tx},m}}{4\pi d^2_{\mathrm{Tx},m}}}) \qquad (h_{\mathbf{T},m} = \beta_{\mathrm{Tx},m}\left[e^{jkd^0_{\mathrm{Tx},m}}, e^{jkd^1_{\mathrm{Tx},m}}, \dots, e^{jkd^{N-1}_{\mathrm{Tx},m}}\right]^T)$$

$$(h(p) = \sum_m \alpha_m(p) G_r(p, \varrho_m))$$

p is the unknown and to be estimated position

# SISO Positioning with RIS

## RIS-reconfiguration protocol

- The RIS dynamically adjusts phase shifts $\theta_{l,m}^{n}$ at each time-slot based on the angles between the transmitter and receiver. This reconfiguration helps diversify signal paths, aiding in precise localization.
- At each time-slot, the receiver collects signal observations from the RIS with unique phase configurations, creating an L-dimensional vector of measurements ("fingerprints") that can be used for position estimation.

## Maximum Likelihood Estimator

- The receiver's position is estimated by maximizing the likelihood of observed signals over a grid of possible positions, pinpointing the most likely receiver location.

$$\Lambda(p) = -|r - h(p)|^2$$

# Cramér-Rao Lower Bound

## Evaluating Estimator Performance

To evaluate how close we are to the theoretical limit of accuracy

## CRLB

The Cramér-Rao Lower Bound (CRLB) sets a baseline for the possible error (variance) in our estimates.

.

## Decision

Use CRLB as a benchmark for the performance of our QML estimator.

## 1. Fisher Information Matrix (FIM)

- **Purpose**: Quantifies how much information observations provide about unknown parameters (receiver's position).
- **Parameters**:

$$\theta = [d_{Rx,1}, \phi_{Rx,1}, \ldots, d_{Rx,M}, \phi_{Rx,M}]^T$$

- **Why**: Helps us understand the achievable accuracy of our estimator.

## 2. Transformation to Cartesian Coordinates

## 3. Cramér-Rao Lower Bound (CRLB)

- **Definition**: Sets a lower bound on the variance of any unbiased estimator—indicating the best possible accuracy.
- **Formula**:

$$\sigma_{\hat{p}}^2 \geq \mathrm{tr}(I(p)^{-1})$$

- **Why**: Provides an accuracy benchmark to assess estimator performance.

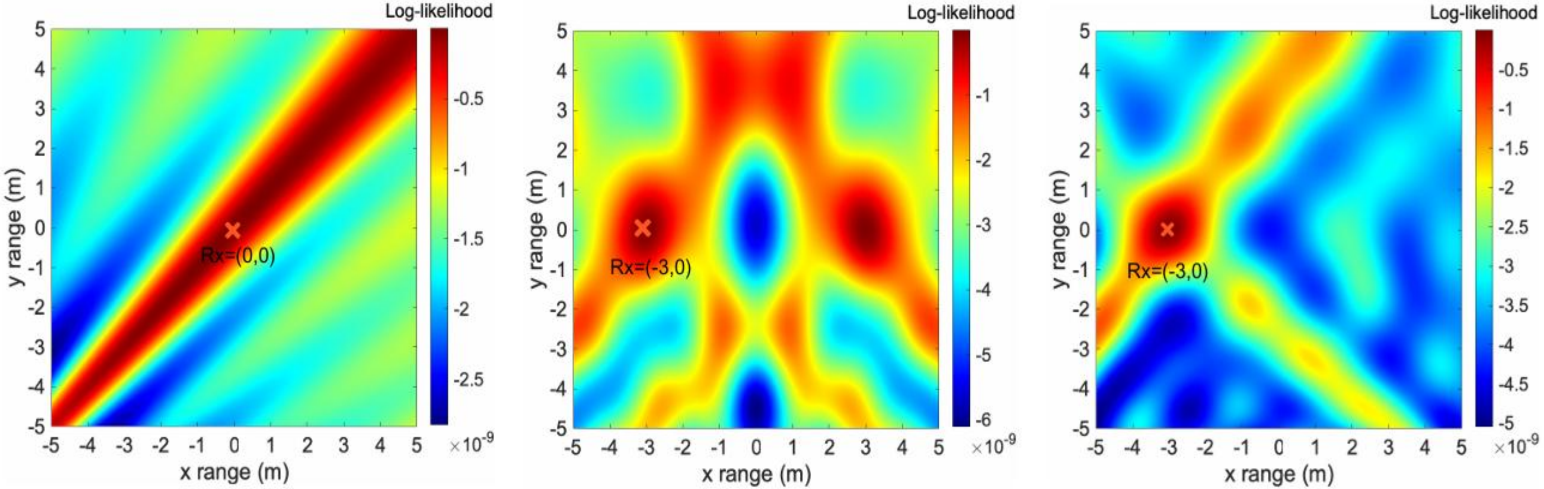
# Simulation Results

- **Single vs. Multiple RISs:** Multiple RISs significantly improve localization accuracy over a single RIS by resolving angular ambiguities, enhancing position estimation.

- **Reconfiguration Protocols:** A stochastic RIS phase configuration (RIS phases are randomly set across time slots) outperforms a deterministic protocol by around 4 dB, creating distinct signal patterns that boost accuracy.

- **Geometry Impact:** Closer RIS placement to the receiver yields better accuracy and robustness, meeting theoretical error bounds.

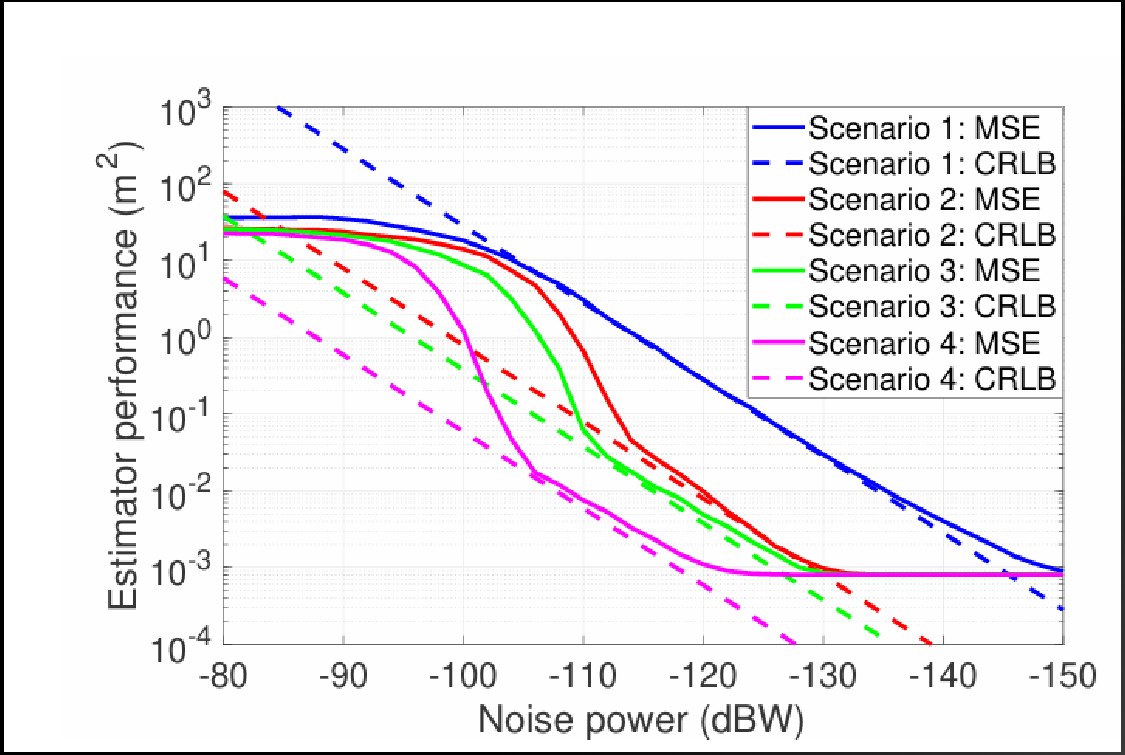
- **MLE and CRLB:** The Maximum Likelihood Estimator (MLE) nearly reaches the Cramér-Rao Lower Bound with fine grid spacing, achieving centimeter-level precision.




(a) A 1-RIS scenario. The receiver is located at (0,0). The RIS is deployed with central element at $(-15, -15)$.

(b) A 2-RIS scenario operating a *sequential* scheduling protocol $\phi_{l,m}$. The receiver is located at $(-3, 0)$. The RISs are deployed with central elements at $(-15, -15)$ and $(15, -15)$, respectively.

(c) A 2-RIS scenario operating a *stochastic* scheduling protocol $\phi_{l,m}$. The receiver is located at $(-3, 0)$. The RISs are deployed with central elements at $(-15, -15)$ and $(15, -15)$, respectively.



Scenario 1: MSE
Scenario 1: CRLB
Scenario 2: MSE
Scenario 2: CRLB
Scenario 3: MSE
Scenario 3: CRLB
Scenario 4: MSE
Scenario 4: CRLB
Estimator performance ($m^2$)
$10^3$
$10^2$
$10^1$
$10^0$
$10^{-1}$
$10^{-2}$
$10^{-3}$
$10^{-4}$
-80
-90
-100
-110
-120
-130
-140
-150
Noise power (dBW)

# Future Ideas

## Higher-Dimensional Positioning:

- Extend the localization framework from 2D to 3D (or even 4D with time), allowing accurate positioning in complex 3D spaces and tracking moving sensors in real-time.

## Machine Learning for Predictive Localization:

- Train machine learning models using historical RIS configurations and environmental data to predict optimal settings.
- Deploy the model to adjust RIS configurations proactively based on real-time conditions, refining accuracy over time through continuous learning.

# Implementation of our Ideas

- **Objective:**
  - Simulate and analyze RIS-assisted localization under three configurations:
    1. Single RIS.
    2. Dual RIS.
    3. Dual RIS with Stochastic Scheduling.
  - Compare the performance of Bayesian Estimation and Maximum Likelihood Estimation (MLE) techniques.
- **Purpose:**
  - Evaluate the localization accuracy (average error) and computational efficiency (execution time) of these techniques.
- **Approach:**
  - Utilize simulation-based grid search and stochastic phase reconfiguration for high-resolution signal-based localization.

# Simulation Setup

- **RIS Configurations:**
  - 1 RIS: Single RIS deployed with sequential signal processing.
  - 2 RIS: Two RIS units deployed in a non-stochastic configuration.
  - 2 RIS with Stochastic Scheduling: Dynamic phase reconfiguration for improved performance.
- **Parameters:**
  - Number of RIS Elements: $N=100$.
  - Time Slots: 10.
  - Transmitter and RIS Positions: Fixed at known coordinates.
  - Receiver Positions: Randomized in a 2D grid of $[-5,5]$ meters.
  - Signal Wavelength: $\lambda=0.03$m.
  - Noise Power: $\sigma 2=-80$dBm.

# Mathematical Framework

## Assumptions:

- The RIS is positioned at a known fixed location, the base station and the sensor are equipped with single antennas.
- RIS elements are programmable to adjust signal phase shifts dynamically.

## Path Loss Calculation:

- Follows the Friis Transmission Equation:

$$(PL(d) = \frac{P_t G_t G_r \lambda^2}{(4\pi d)^2})$$

## RIS Phase Configuration:

- For stochastic scheduling, phases $\theta_i$ are randomized per time slot:

$$\theta i \sim Uniform(0,2\pi)$$

## Signal Strength Simulation:

- Combines transmitter-RIS and RIS-receiver path strengths, adds Gaussian noise:

$$(y = \sum_{i=1}^{N} P\,L(d_i)e^{j\theta_i} + \mathcal{N}(0, \sigma^2))$$

## Localization Model:

- Computes signal strength variations as a function of RIS reconfiguration and distance.

# MLE Localization with Hierarchical Grid Search

## Process:

- **Coarse Search:**
  - Defines broad regions of interest.
  - Grid Spacing: 0.5m.

- **Refined Search:**
  - Narrows down the search with finer resolution.
  - Grid Spacing: 0.2m.

## Algorithm:

- Objective: Minimize error between observed and simulated signals:

$$MLE\ Estimate: (\hat{x} = \arg\max_{x} L\,(x))$$

Where,

$$(L(x) = \prod_{t=1}^{T} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{\left(y_t - \widehat{y_t}(x)\right)^2}{2\sigma^2}\right))$$

## Performance Metrics:

- Average Estimation Error (meters).
- Execution Time (seconds).

# Bayesian Estimation

- **Key Steps:**
  - **Prior:** Assume uniform distribution over the grid.
  - **Likelihood:**

$$(P(y \mid x) = \prod_{t=1}^{T} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{\left(y_t - \hat{y}_t(x)\right)^2}{2\sigma^2}\right))$$

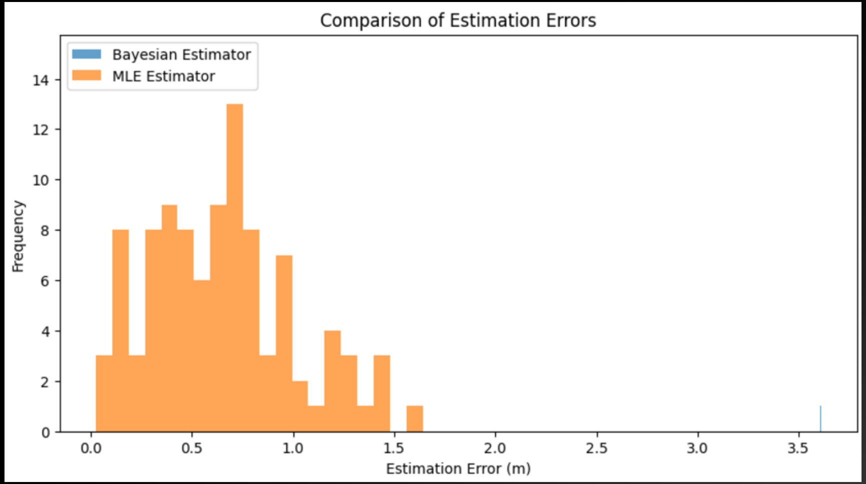
  - **Posterior:**

$$(P(x \mid y) \propto P(y \mid x) \cdot P(x))$$

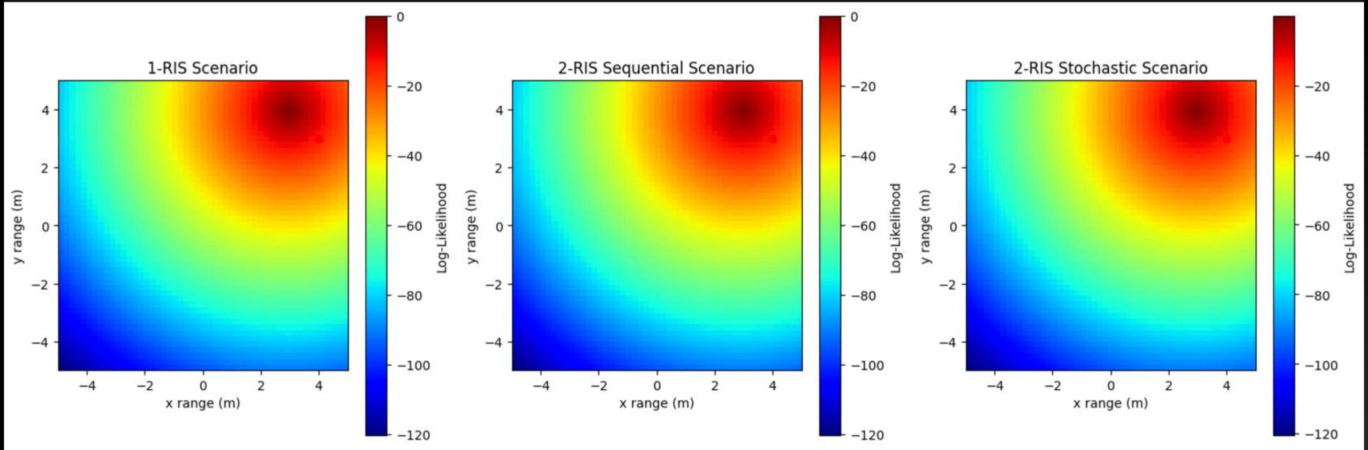
  - **Estimation:** Compute weighted mean of grid points based on posterior probabilities.
- **Output:**
  - Estimated Receiver Position.
  - Posterior Distribution Map.

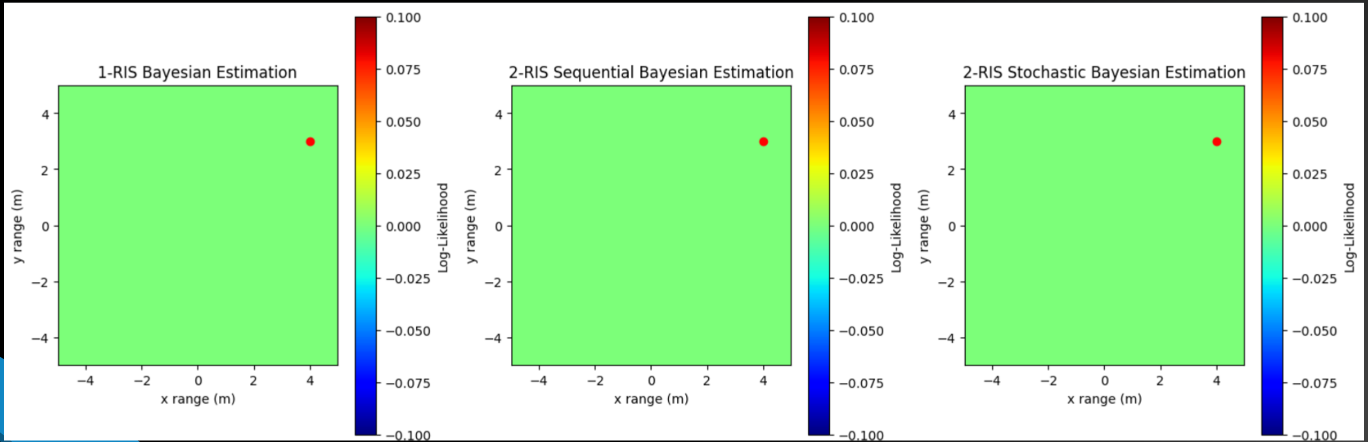
# Results - MLE vs Bayesian Estimation

- **Comparison of errors:**
  - MLE: Average error = 0.3m.
  - Bayesian: Average error = 0.25m.
- **Execution Time:**
  - Bayesian Estimation is 20% slower due to posterior computation.
- **Statistical Analysis:**
  - Variance in Error: Bayesian < MLE.
  - Median Error: Bayesian consistently closer to true position.



# Visualization of Results



# Conclusion

- Increased complexity with higher RIS elements and time slots.
- Need to optimize phase reconfiguration for minimal latency.

## Performance Analysis:

- Stochastic scheduling enhances localization accuracy.
- Bayesian Estimation outperforms MLE in error reduction, albeit slower.

## Applications:

- Suitable for real-time IoT localization with computational trade-offs.

LET'S END HERE !

# THANK YOU