

# Anchor-free Ranging-Likelihood-based Cooperative Localization

# ARLCL

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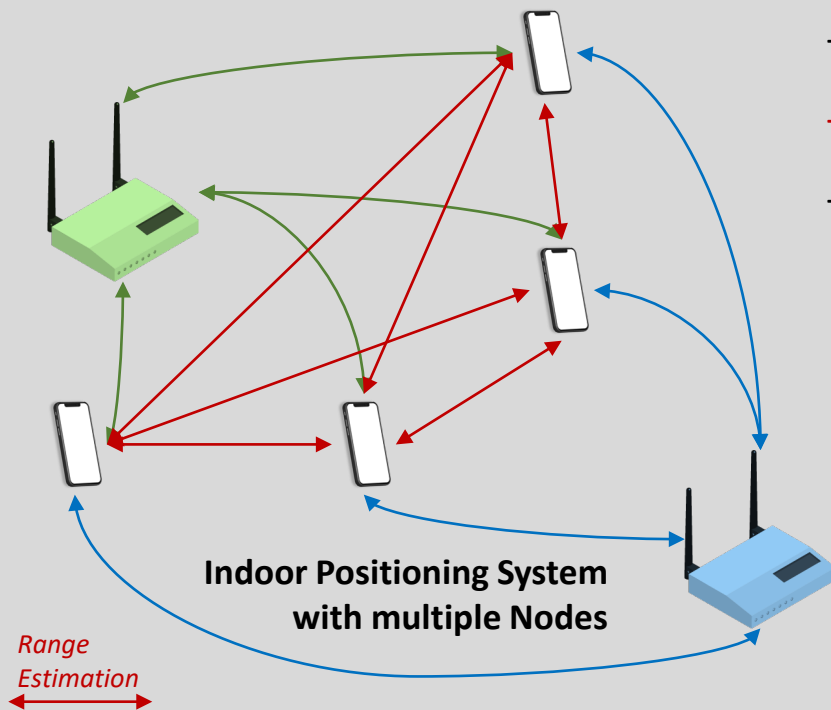
# Outline

- **Introduction** (*Recap since last year*)
  - *Background, Motivation & Current Solution*
- **Proposed Methodology**
  - *Creating the required Ranging-Likelihood model*
  - *How to perform positioning using ARLCL*
- **Assessing ARLCL**
- **Results**

# Introduction

## Motivation

- The more signals, the better
- Yet, no effective node cooperation
- Recent advances and opportunities

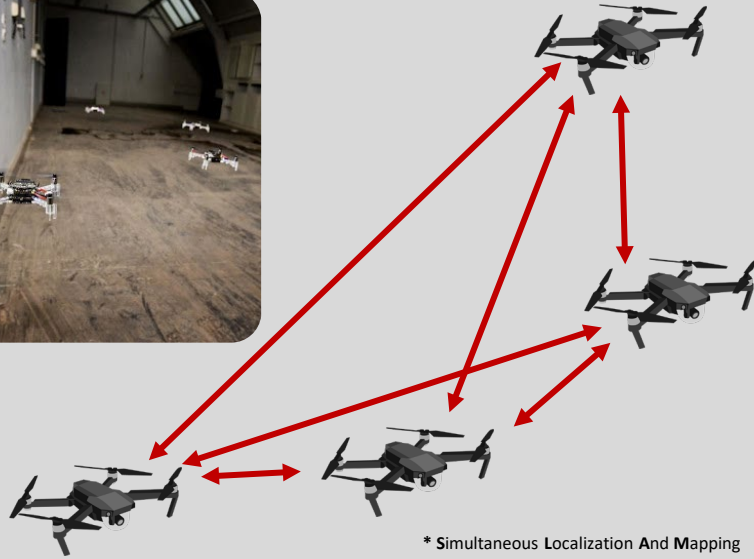


*(Samsung Ad for Galaxy S21 Ultra)*



# Introduction

## Various applications



\* Simultaneous Localization And Mapping  
**Cooperative SLAM\***  
using UAV's

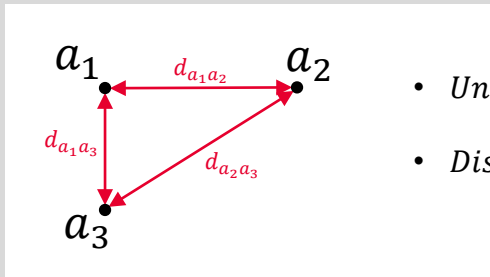
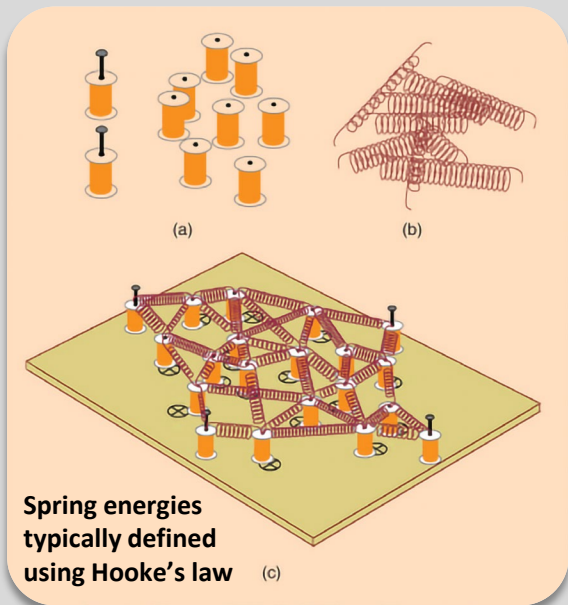
Range  
Estimation  
↔

- More information available  
→ Higher positioning accuracy
- Facilitates limited to **No-Infrastructure** positioning  
→ **Anchor Free localization**  
(where position estimations have arbitrary origin)
- Covid Tracking

# Introduction

## Anchor-free Ranging-based Cooperative Localization (ARLCL) today

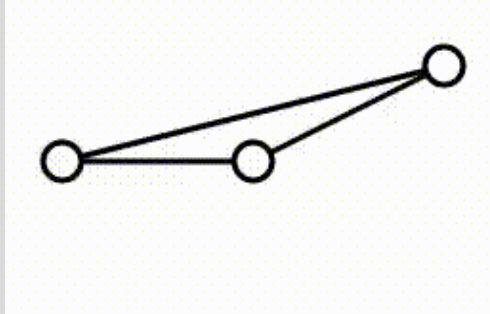
### Mass-Spring Localization



- Unknown position of agent  $\mathbf{a}_i$  at  $\text{Pos}(x_i, y_i)$
- Distance estimation  $d_{\mathbf{a}_i\mathbf{a}_j}$  based on noisy measurements

→ Non-Linear Optimization problem

Minimize the energy to reach equilibrium



**But..** are all measurements equally important?

Estimations of far distances → more uncertainty

- We need to model this uncertainty.

# Ranging likelihood as a requirement for ARLCL

A function to describe  $P(\text{Distance}; \text{Measurement})$

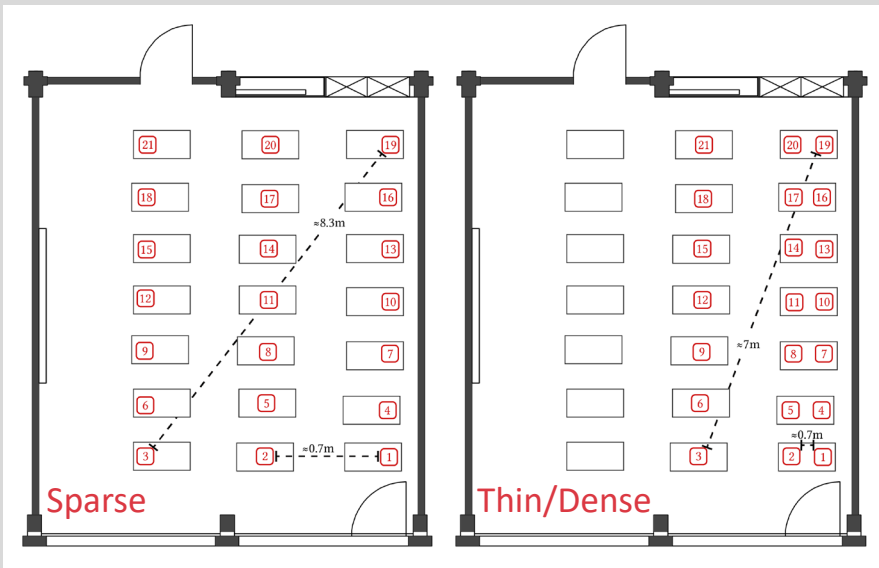
- **ARLCL utilizes iteratively the Density Function  $P_{\text{Measurement}}(\text{distance})$  to assign proper importance**
- **Method is technology-agnostic**  
(WiFi ranging, Ultrasonic ranging, BLE ranging, etc..)

*.. Given that Node-A received from Node-B this measurement,  
how likely is that Node-B is 5m far?*

# Modelling the ranging likelihood

## Sampling process

Collect **Received Signal Strength (RSS)** measurements between *all pairs* of 21 **BLE-Enabled Raspberries (RPI's)**

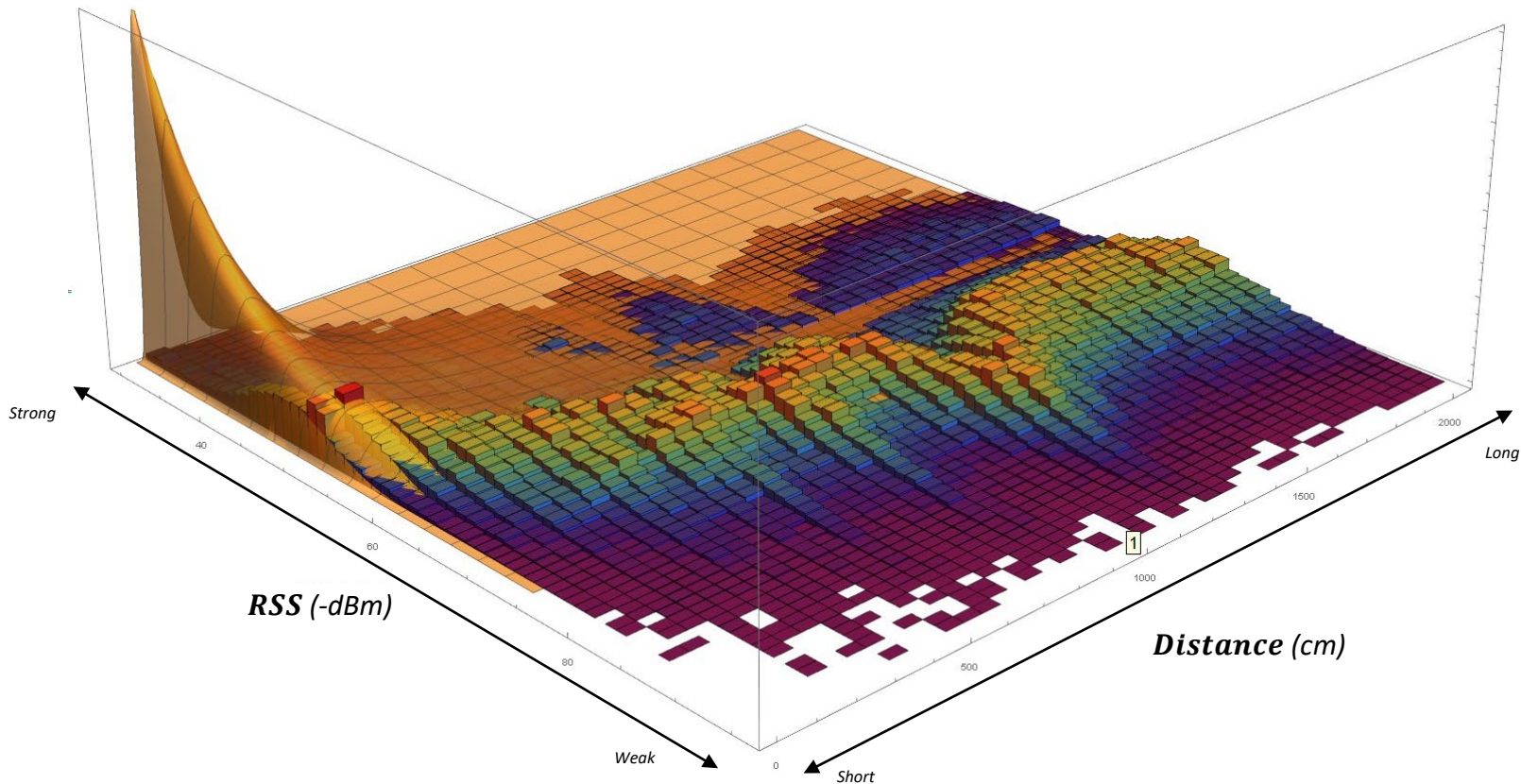


- **True Positions** recorded with **LiDAR Scanner** (*Leica BLK360*)
- **x2 deployment shapes** (Sparse & Thin/Dense)
- **x10 times** (@random RPI's orientations)
- **x 5mins**



# Modelling the ranging likelihood

## From Frequency Histogram to Final Model





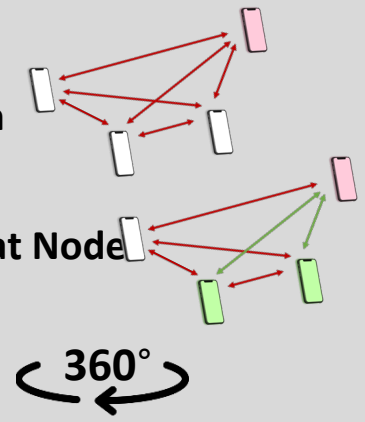
# Performing swarm positioning with ARLCL

## The methodology outline

### Init

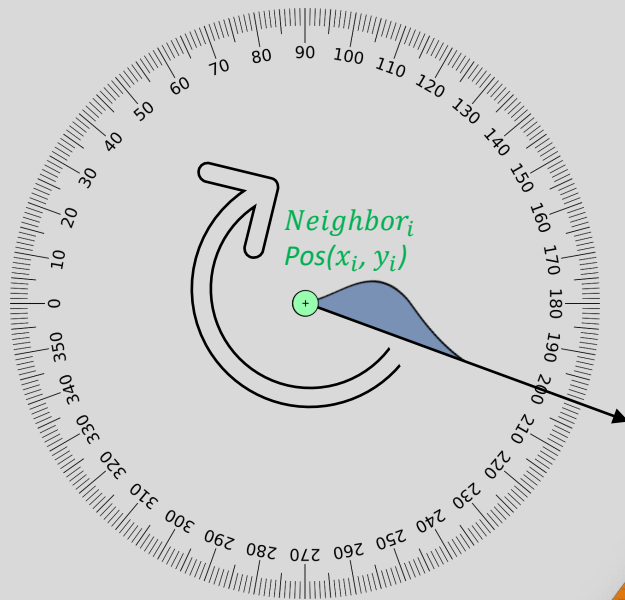
- Place the Nodes (*i.e. the Swarm*) randomly on space

### Cycle

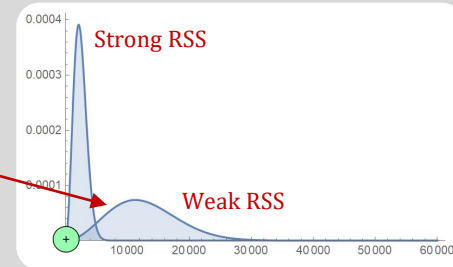
- Select the **1st Node** (according to some selection order) to correct his position
- Select all **Neighbor Nodes** that have effective measurements towards that Node
- Get each measurement's PDF and rotate it (*according to the modelled DoF*)   $360^\circ$
- Find the global max of the product of these PDFs and move the **1st Node** to that position
- Proceed with the 2<sup>nd</sup> Node and continue until the last one. *>> Repeat cycle until we converge..*

# Performing swarm positioning with ARLCL

## Rotating the Position's PDF



- Get the  $\mathbf{P}(x_c ; RSS)$  that corresponds to some measurement

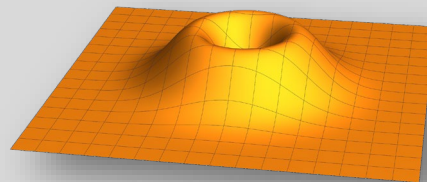
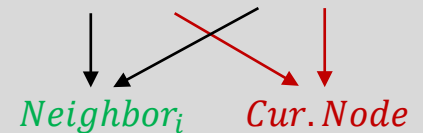


Current Node  $Pos(x_c)$  lies on this axis

Neighbor<sub>i</sub>  $Pos(x_i)$

- We expand considering 2-Dimensions  $\rightarrow$  i.e. go from  $Pos(x_c)$  to  $Pos(x_c, y_c)$

- Replace  $x$  in  $\mathbf{P}(x_c ; RSS)$  with the eq.  $\sqrt{(x_i - x_c)^2 + (y_i - y_c)^2}$



# Assessing ARLCL

## Compare against Mass Spring Method

- Using our developed **Ranging Model** and **True positions** of the 21 RPi's..
- Get a noisy **RSS measurement** between each pair

### Evaluated variables

- **Swarm shape** **x2** (*Sparse, Thin/Dense*)
- **Swarm size** **x19** (3..21)
- **Noise level** **x20** (1..20) (*PDF resamplings to get an average RSS*)

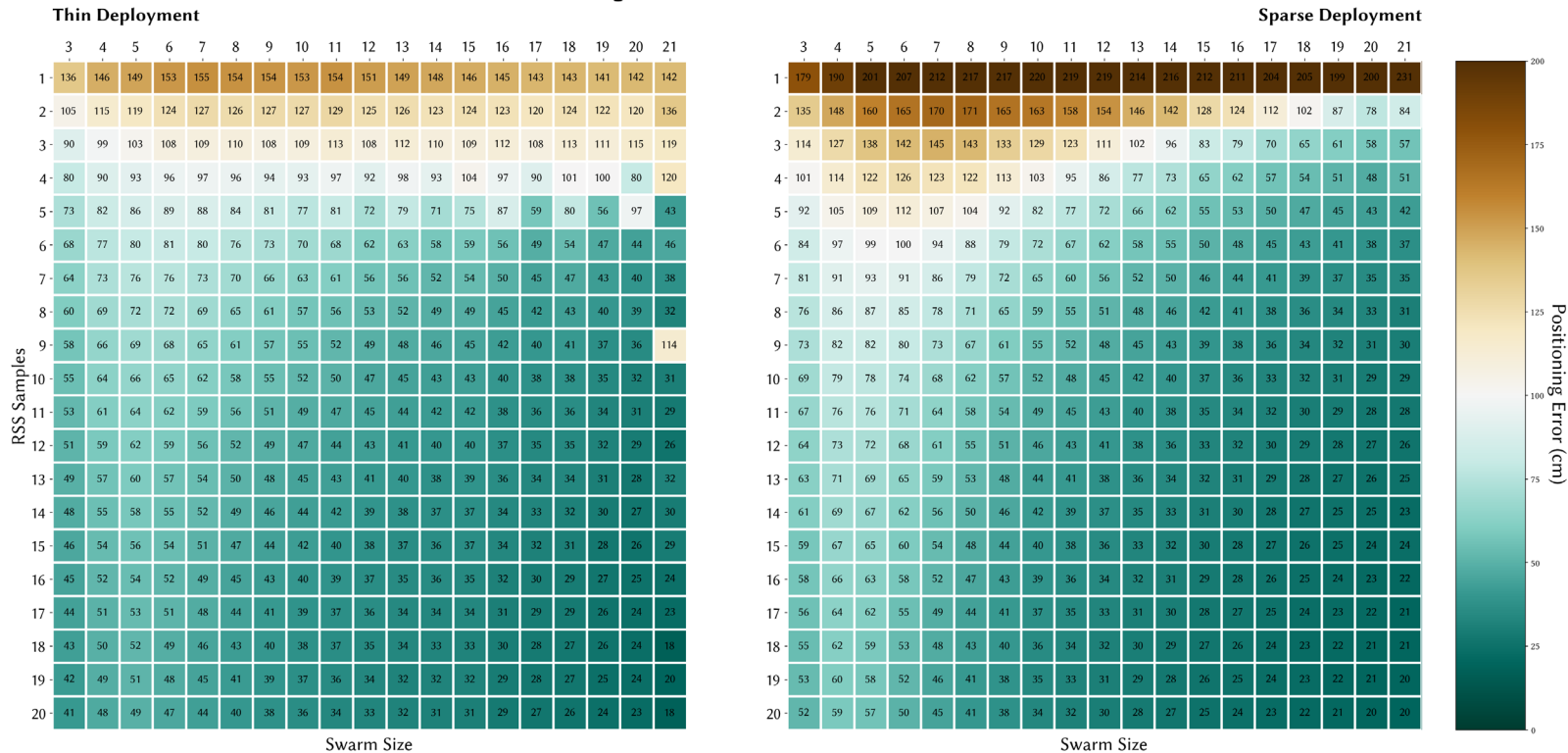
### Repetition parameters

- **Position initialization** **x100** (1..100) (*Random initial node placement*)
- **Node Combinations** **x200**

**= ~14m Evaluated cases**

# Results

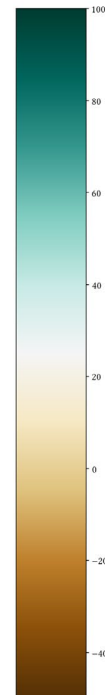
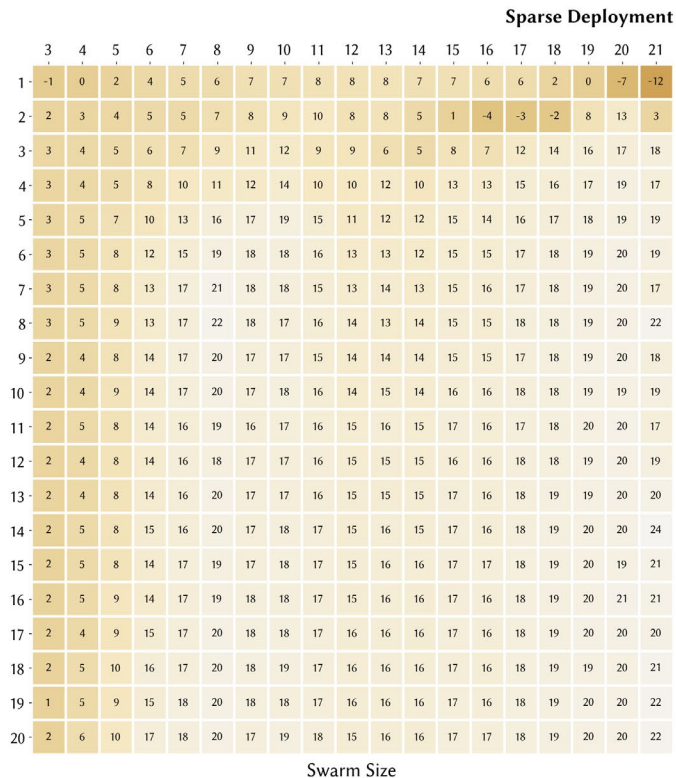
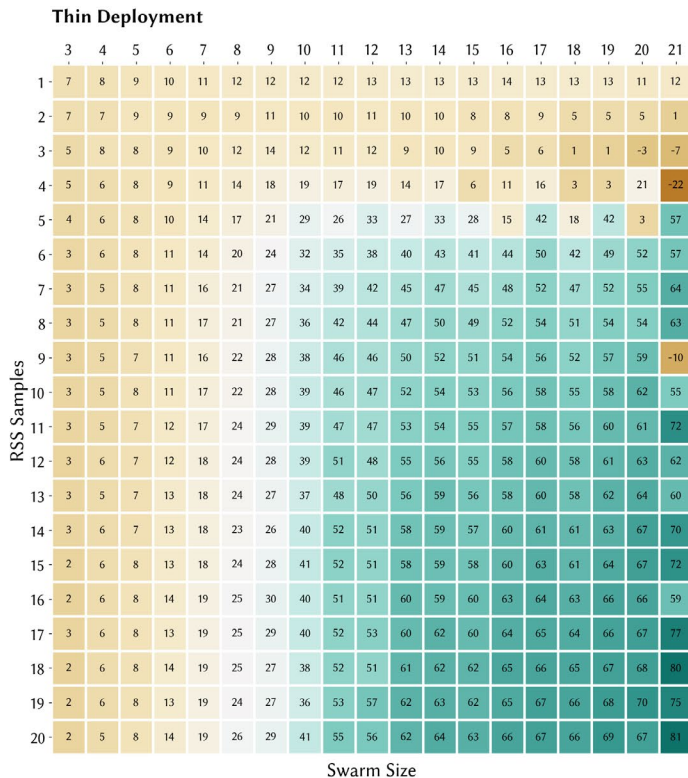
## Positioning Error of ARLCL at 75<sup>th</sup> Percentile



# Results

% Reduction of Error at 75<sup>th</sup> Percentile

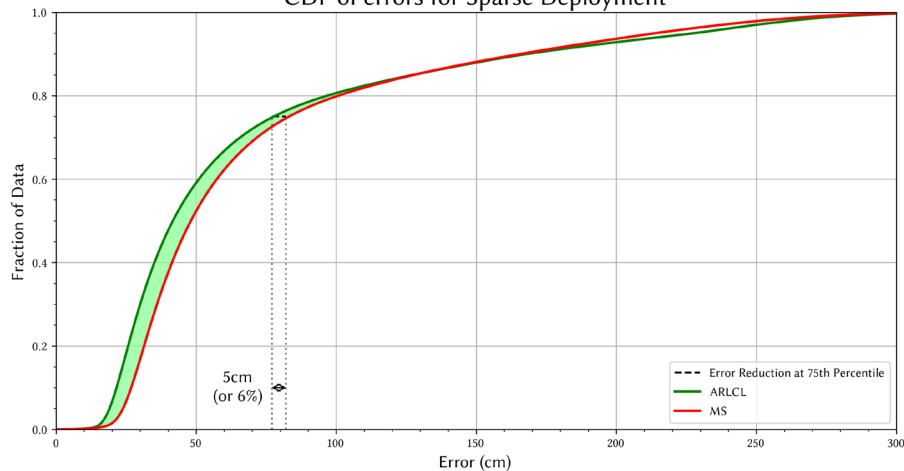
$$(E_{MS} - E_{ARLCL}) / E_{MS} \times 100$$



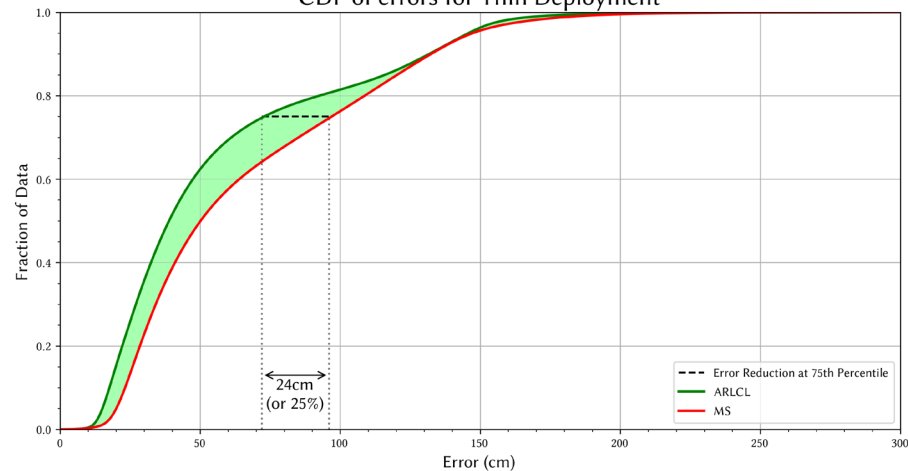
# Results

## Cumulative distribution function of the positioning errors

CDF of errors for Sparse Deployment

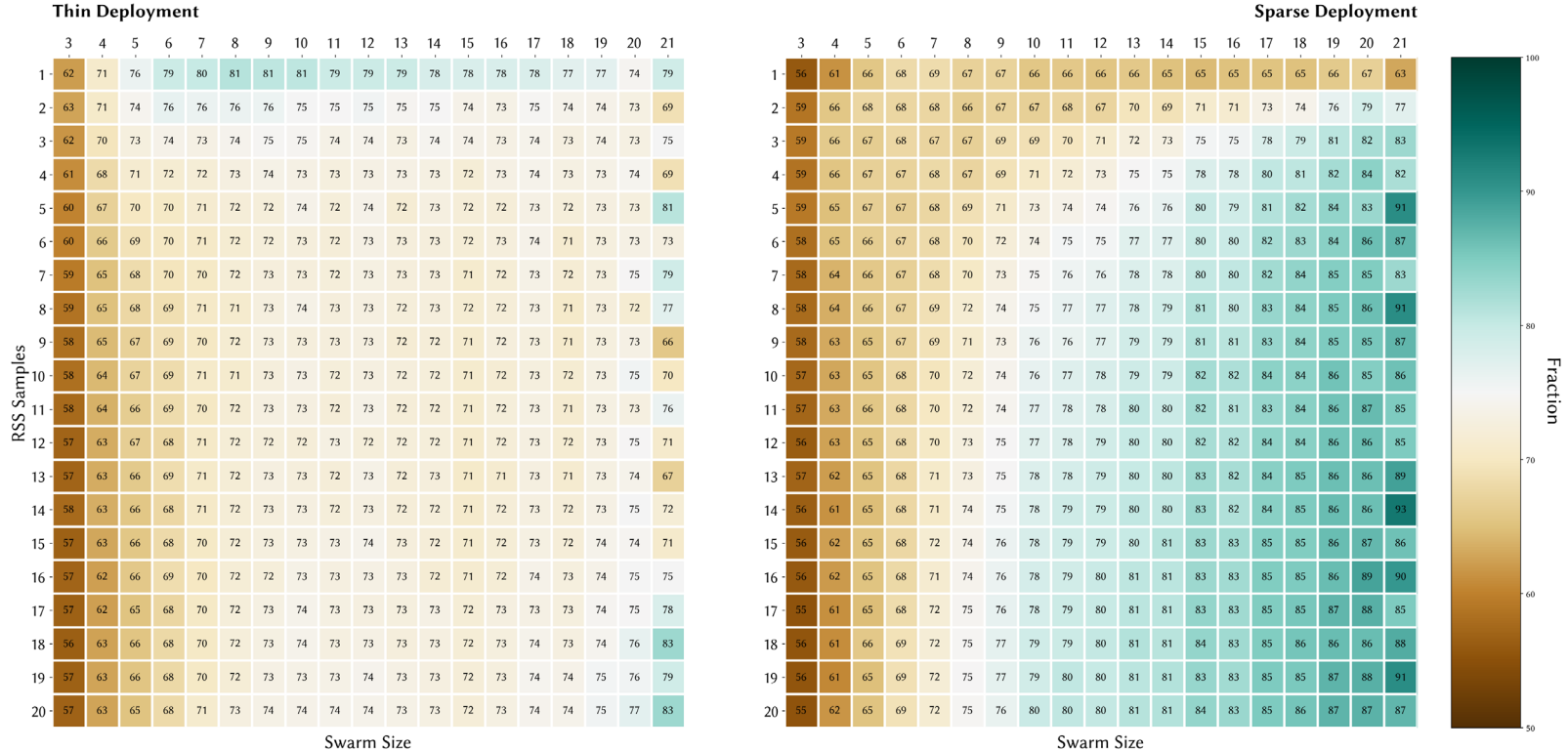


CDF of errors for Thin Deployment



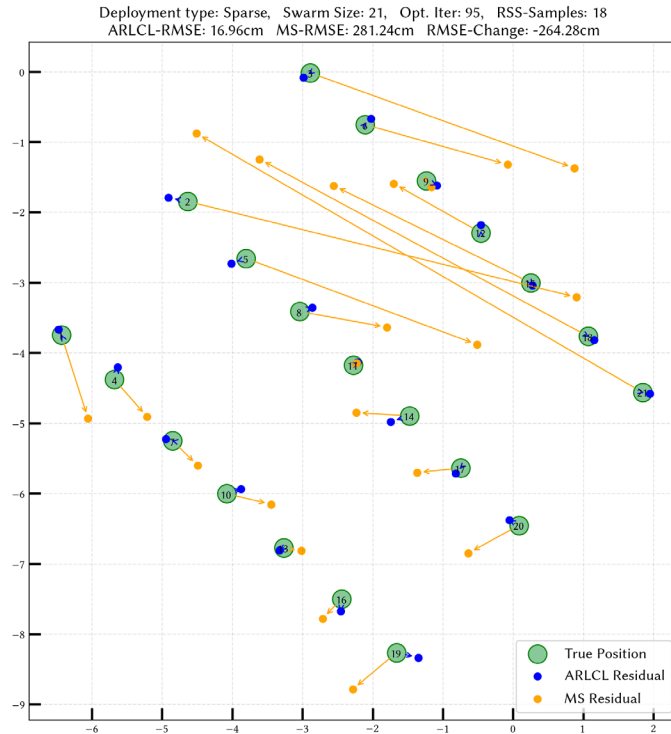
# Results

## Fraction of improved cases



# Results

## Estimation residuals and trajectories (best ARLCL win for Size:21)





# Results

## Conclusions

- Positioning error for both **ARLCL** and **MS** is correlated to both **Swarm Size** and **Sample Size**
- **Sparse** deployments are more **prone to signal noise**
- Bellow **85<sup>th</sup> percentile**, **ARLCL** introduces an overall **improvement** (same performance above that)
- **ARLCL's** gain is also correlated to both **Swarm Size** and **Sample Size**
- **ARLCL's** gain depends also on the Swarm Shape (more gain at **Thin/Dense** scenarios)

# Results

## Future work

- Assess more swarm deployment scenarios  
(of different densities/shapes/with in-between obstacles/etc.)
- Assess common ranging models under different environments
- Assess other ranging technologies (UWB/WiFi)
- Fuse other types of signals into the localization process (Inertial data)
- Take it from offline to online positioning

# Thank you for your time!

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