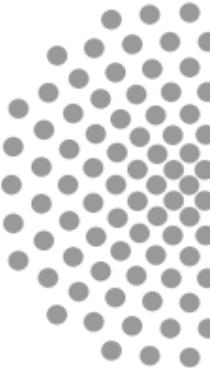


# Augmenting Channel Charting with Classical Wireless Source Localization Techniques



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Stephan ten Brink

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Asilomar Conference  
November 1<sup>st</sup>, 2023



**University of Stuttgart**  
Institute of Telecommunications  
Prof. Dr. Ing. Stephan ten Brink



## Outline

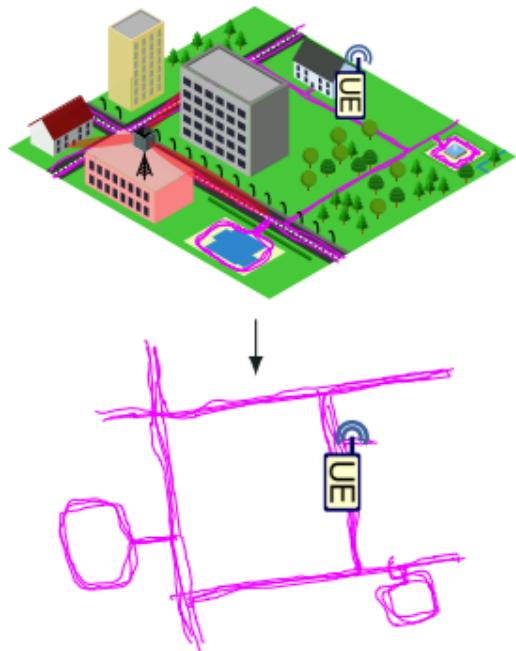
- ① Channel Charting for Localization
- ② Dataset and Problem Formulation
- ③ Classical Source Localization Techniques
- ④ Channel Charting
- ⑤ Combining Channel Charting and Classical Methods
- ⑥ Outlook and Conclusion

## Agenda

- ① Channel Charting for Localization
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## Objective of Channel Charting [Studer et al., 2018]



**Channel Charting** is a **dimensionality reduction** technique that learns a mapping from high-dimensional **channel state information (CSI)** to a low-dimensional space, called **Channel Chart (CC)**, purely from data available at the base station.

- The mapping is called the **forward charting function**, usually  $D = 2$  or  $D = 3$ :

$$C_{\Theta} : \mathbb{C}^{B \times M \times N_{\text{sub}}} \rightarrow \mathbb{R}^D$$

- Channel Charting is self-supervised



## What is a Channel Chart?

A channel chart is a *map* and  $C_{\Theta}$  localizes the UE on the map:

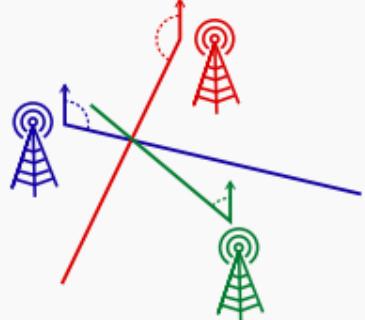
- Maps depict (spatial) relationships
- Different maps preserve different properties, serve different purposes
- Channel Charts may be used for:
  - Handover prediction
  - UE clustering, pilot allocation
  - Channel prediction
  - **Absolute Localization (Our Focus!)**
  - ...
- Valid criticism: Classical techniques?



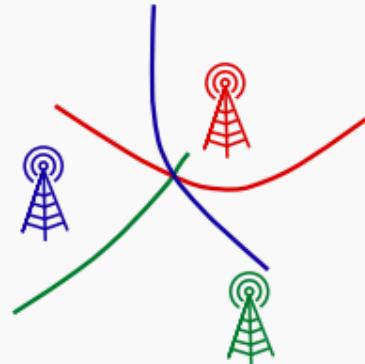
TfL Tube Map, OpenTopoMap



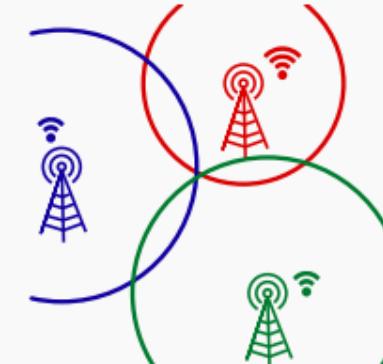
## Alternative Source Localization Techniques



## AoA-based triangulation



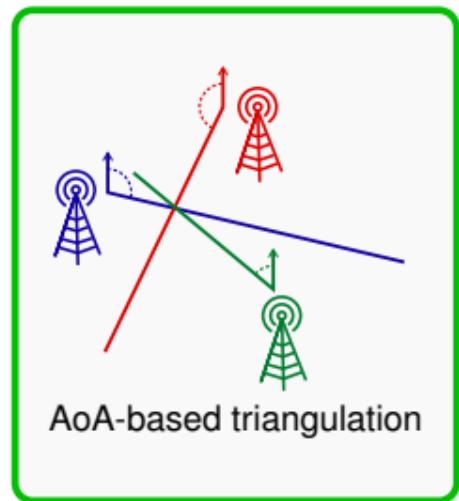
## ToA/TDoA-based multilateration



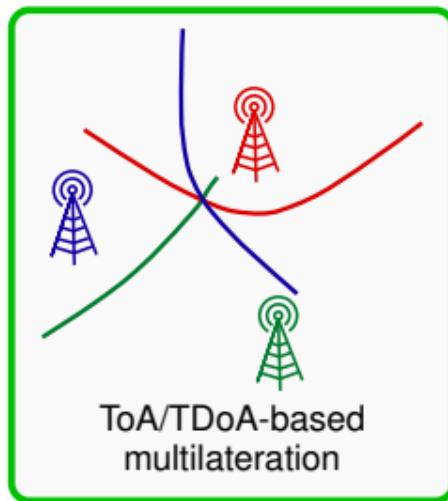
## Power-based localization



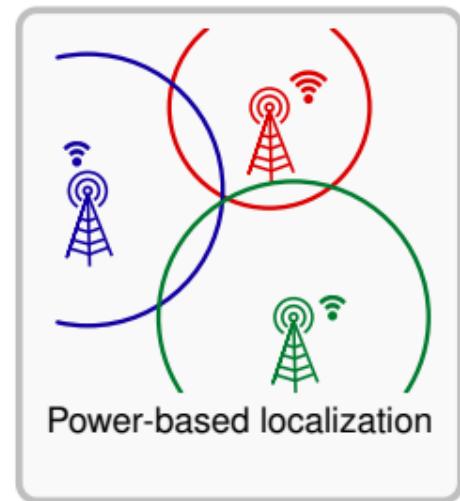
## Alternative Source Localization Techniques



## AoA-based triangulation



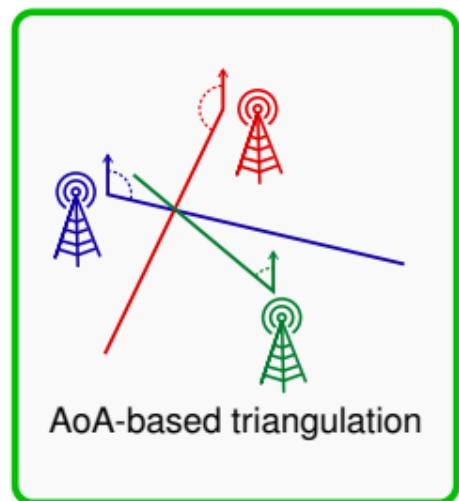
## ToA/TDoA-based multilateration



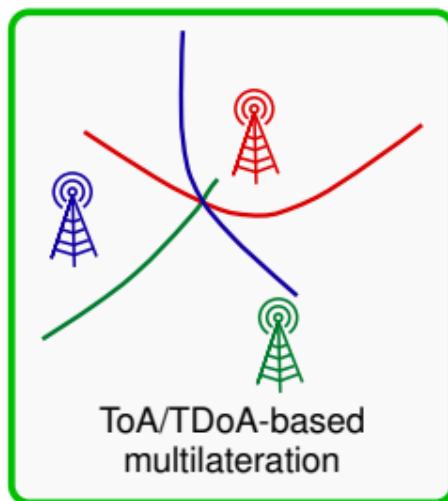
## Power-based localization

→ How do these techniques compare to Channel Charting?

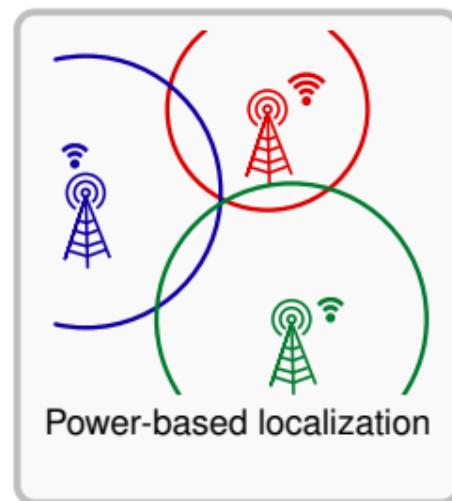
## Alternative Source Localization Techniques



## AoA-based triangulation



## ToA/TDoA-based multilateration



Power-based localization

- How do these techniques compare to Channel Charting?
  - Can we combine classical techniques and Channel Charting?



## **State of the Art: Channel Charting for Localization**

- “Absolute positioning with unsupervised multipoint channel charting for 5G networks” [Pihlajasalo et al., 2020]
    - Estimates position of base stations (BSs) in channel chart using powers.
    - Compares real BS positions to BS positions in chart.
    - Computes optimal affine transform from CC to real-world coordinates.  
Training and affine transformation are *separate* steps.
  - “Channel Charting in Real-World Coordinates” [Taner et al., 2023]
    - Based on differences in received power
    - Interesting approach: “bilateration loss”
    - Demonstrated in simulation. Did not work well with our measurements (non-omnidirectional antennas, too few antenna sites).
  - Previous work: Simulation-based (no measurements), using only power information, bad performance on our measurements

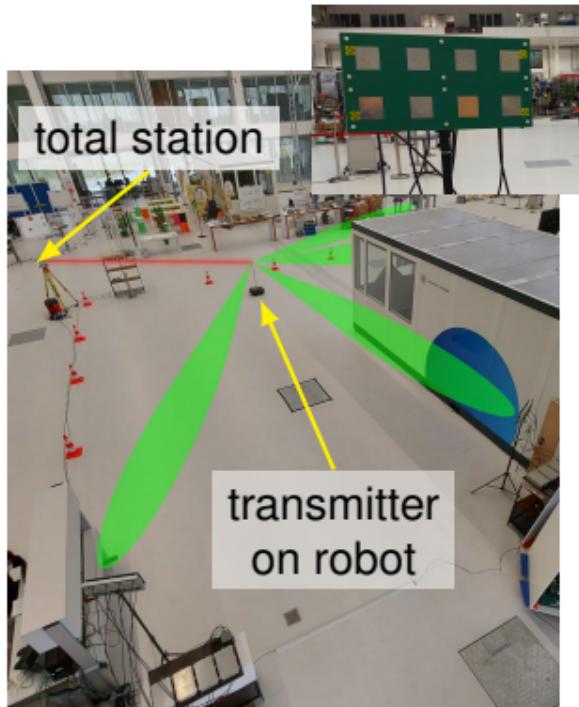


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# CSI Dataset: Distributed mMIMO in Factory



- DICHASUS (Distributed Channel SUniversity of Stuttgart):  
<https://dichasus.inue.uni-stuttgart.de>
  - Single transmitter on robot, highly accurate reference positions
  - $B = 4$  antenna arrays, with  $M = 2 \times 4$  phase-synchronous antennas each (32 antennas total), OFDM,  $N_{\text{sub}} = 1024$  subcarriers
  - 50MHz bandwidth,  $f_c = 1.27$  GHz carrier frequency
  - `dichasus-cf0x`, publicly available <sup>a</sup>

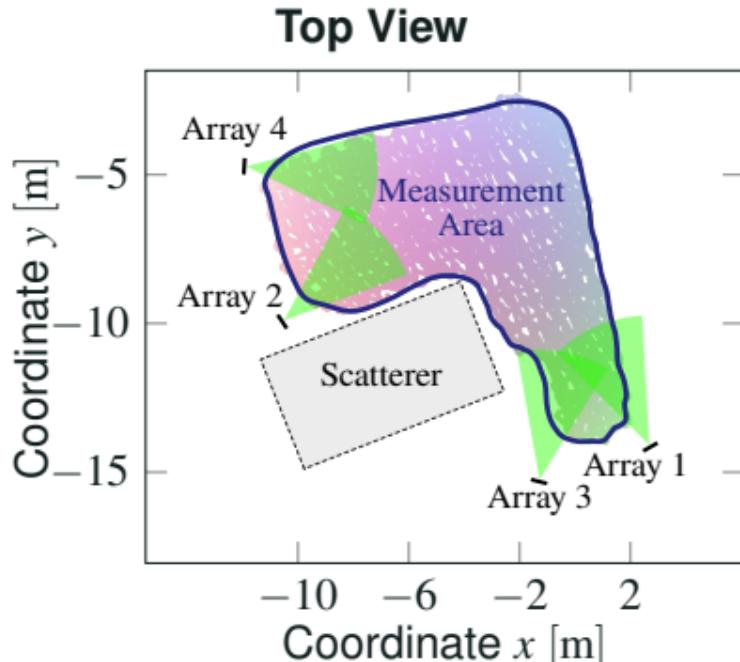
<https://dichasus.inue.uni-stuttgart.de/datasets/data/dichasus-cf0x/>

# CSI Dataset: Distributed mMIMO in Factory

- Subset of  $L = 20997$  measurements (“datapoints”)
  - Antenna array positions and normal vectors:  $\mathbf{y}_b, \mathbf{n}_b \in \mathbb{R}^3$ ,  $b \in \{1, \dots, B\}$
  - Size of area bounding box:  
Around  $13\text{m} \times 13\text{m}$

Dataset:  $S = \left\{ (\mathbf{H}^{(l)}, \mathbf{x}^{(l)}, t^{(l)}) \right\}_{l=1, \dots, L}$

with CSI  $\mathbf{H}^{(l)} \in \mathbb{C}^{B \times M \times N_{\text{sub}}}$ , position  $\mathbf{x}^{(l)} \in \mathbb{R}^3$ , timestamp  $t^{(l)}$ .





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## ToA-Based Multilateration - Theory

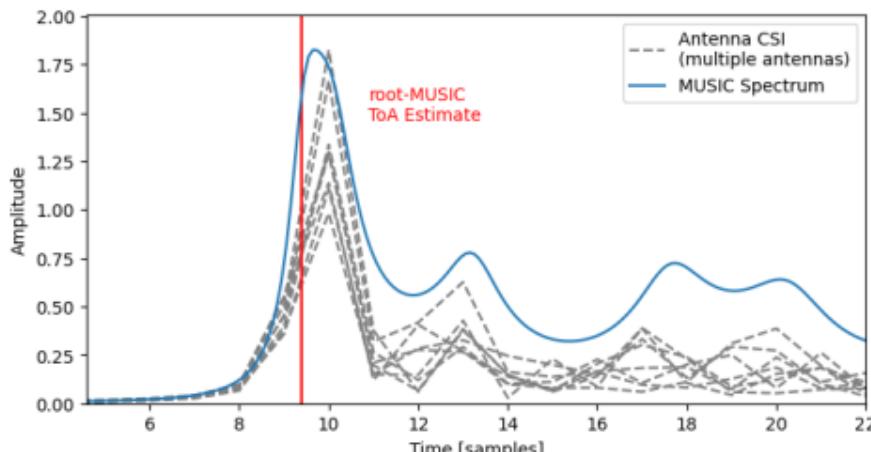
- 1) Estimate ToA
  - 2) Define Likelihood
  - 3) Maximize Likelihood



## ToA-Based Multilateration - Theory

### 1) Estimate ToA

- Based on root-MUSIC super-resolution [Li and Pahlavan, 2004]
- Time of transmission unknown



### Outcome:

- ToA estimates  $\hat{\tau}_b$
- Array-specific,  
 $b \in \{1, \dots, B\}$



## ToA-Based Multilateration - Theory

## 1) Estimate ToA

## 2) Define Likelihood

### 3) Maximize Likelihood

- Likelihood function based on normal distribution:

$$L_{\text{ToA}}(\mathbf{x}, \tau_{\text{TX}}) = \prod_{b=1}^B \frac{1}{\sqrt{2\pi}\sigma} \exp \left( -\frac{1}{2} \left( \frac{\frac{1}{c_0} \|\mathbf{x} - \mathbf{y}_b\|_2 - \tau_b + \tau_{\text{TX}}}{\sigma} \right)^2 \right)$$

- Variance  $\sigma^2$  chosen based on observed RMS delay spread (heuristic)

## ToA-Based Multilateration - Theory

## 1) Estimate ToA

## 2) Define Likelihood

### 3) Maximize Likelihood

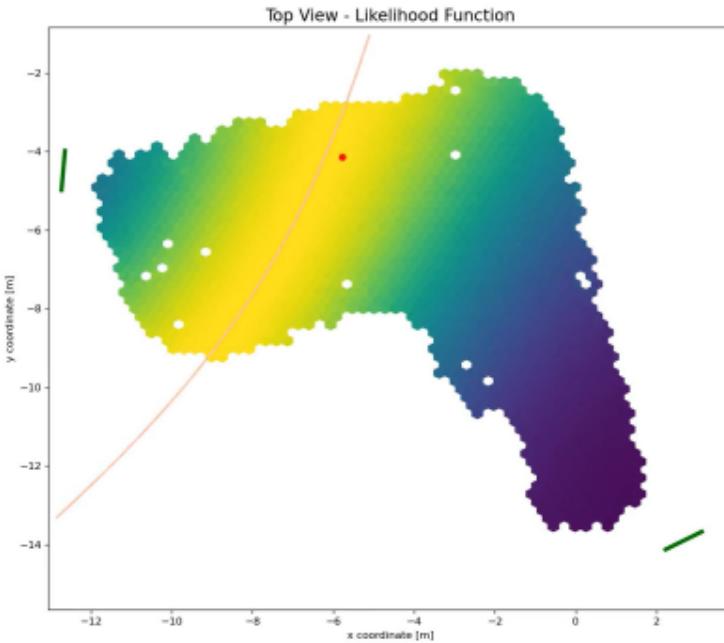
- Maximum likelihood estimation, i.e.:

$$(\hat{\mathbf{x}}, \hat{\tau}_{\text{TX}}) = \arg \max_{(\mathbf{x}, \tau_{\text{TX}})} L_{\text{ToA}}(\mathbf{x}, \tau_{\text{TX}})$$

- Time of transmission  $\tau_{\text{TX}}$  as nuisance parameter
  - Implementation: SciPy's BFGS (room for improvement!)

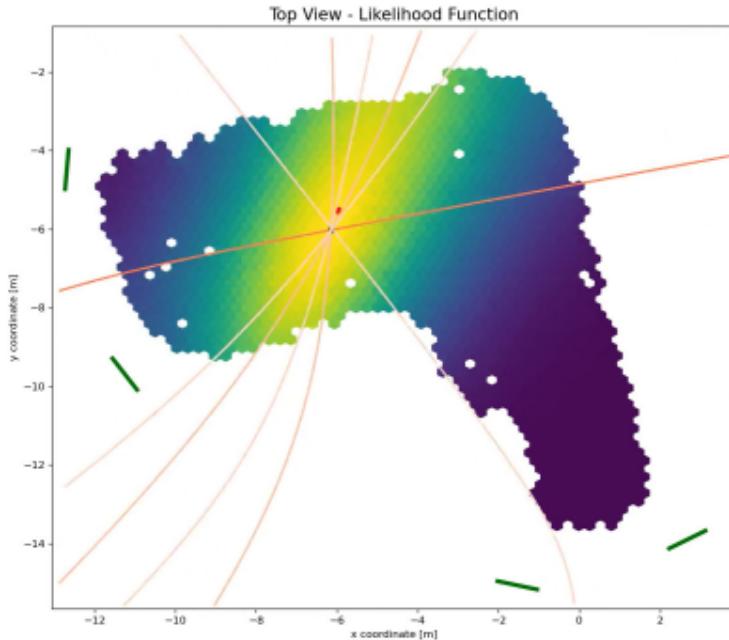


## ToA / Multilateration - Visualization



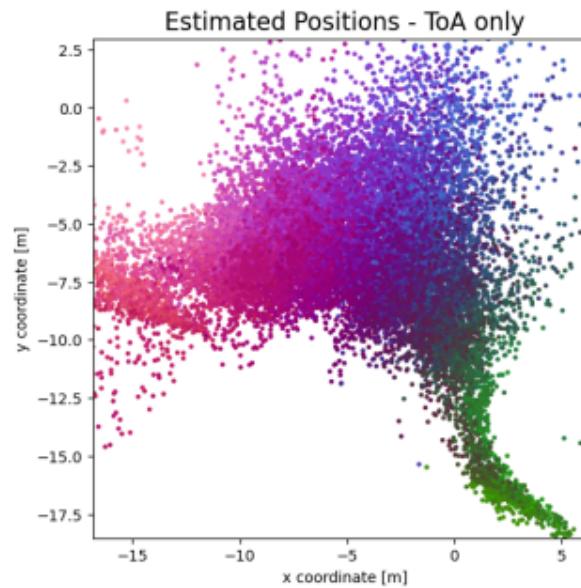
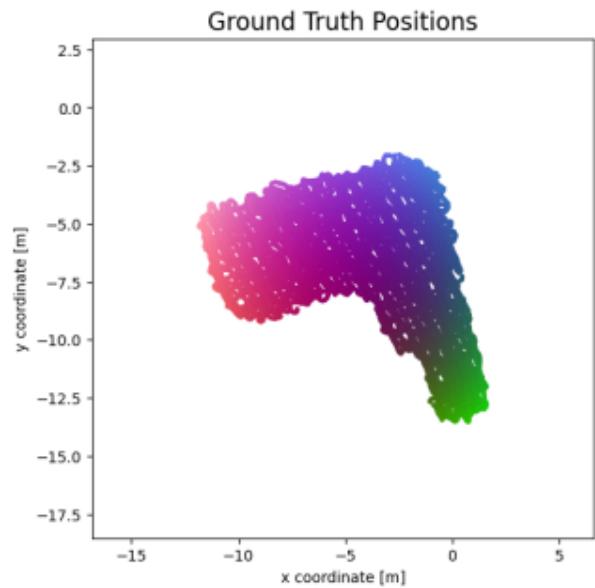


## ToA / Multilateration - Visualization



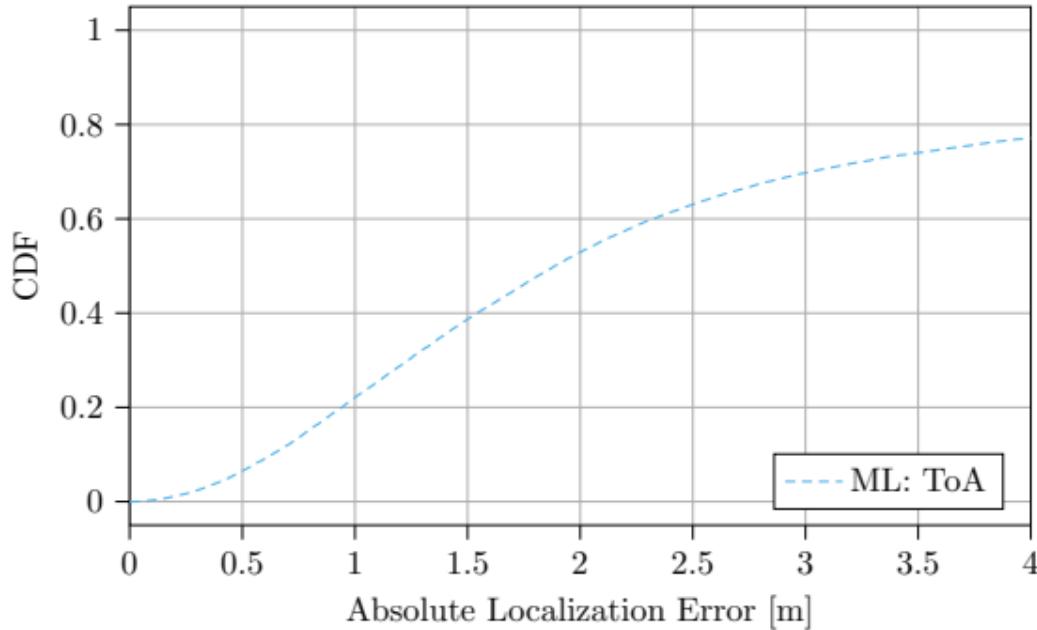


## ToA / Multilateration - Results





## ToA / Multilateration - Results





## AoA-Based Triangulation - Theory

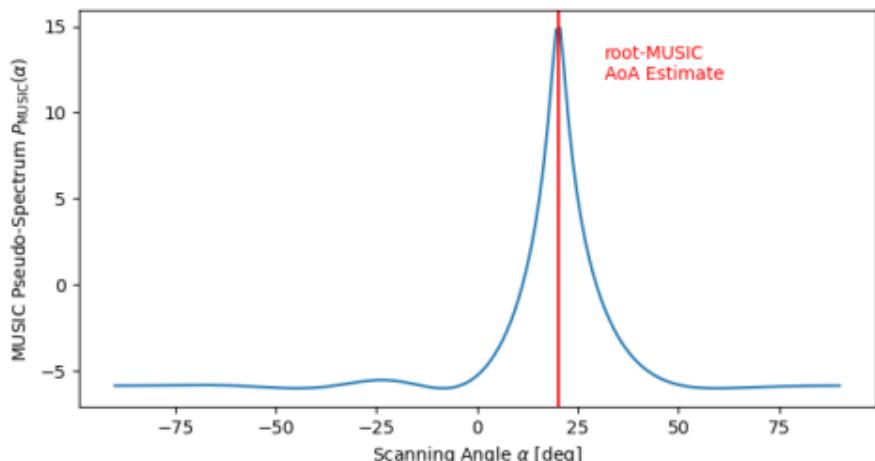
- 1) Estimate AoA
  - 2) Define Likelihood
  - 3) Maximize Likelihood
-



## AoA-Based Triangulation - Theory

### 1) Estimate AoA

- Also based on root-MUSIC super-resolution
- Uses ToA estimate to extract LoS component



### Outcome:

- AoA estimates  $\hat{\alpha}_b$
- Array-specific,  
 $b \in \{1, \dots, B\}$



## AoA-Based Triangulation - Theory

1) Estimate AoA

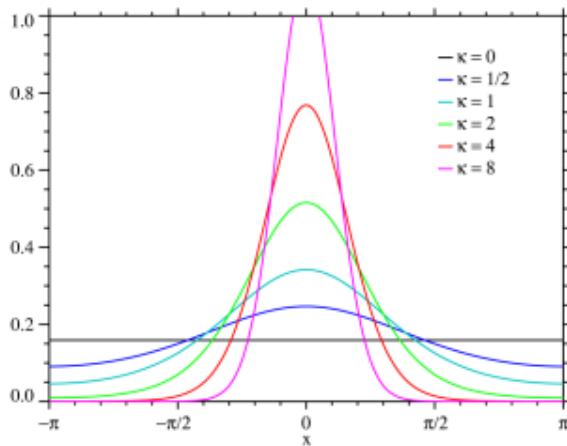
2) Define Likelihood

3) Maximize Likelihood

- We assume a *wrapped normal distribution* for the distribution of AoA estimation errors
- Good approximation: *von Mises distribution*

$$L_{\text{AoA}}(\mathbf{x}) = \prod_{b=1}^B \frac{\exp(\kappa \cos(\angle(\mathbf{x} - \mathbf{y}_b, \mathbf{n}_b) - \alpha_b))}{2\pi I_0(\kappa)}$$

- Concentration parameter  $\kappa$



von Mises PDF [Wikimedia, 2021]



## AoA-Based Triangulation - Theory

1) Estimate AoA

2) Define Likelihood

3) Maximize Likelihood

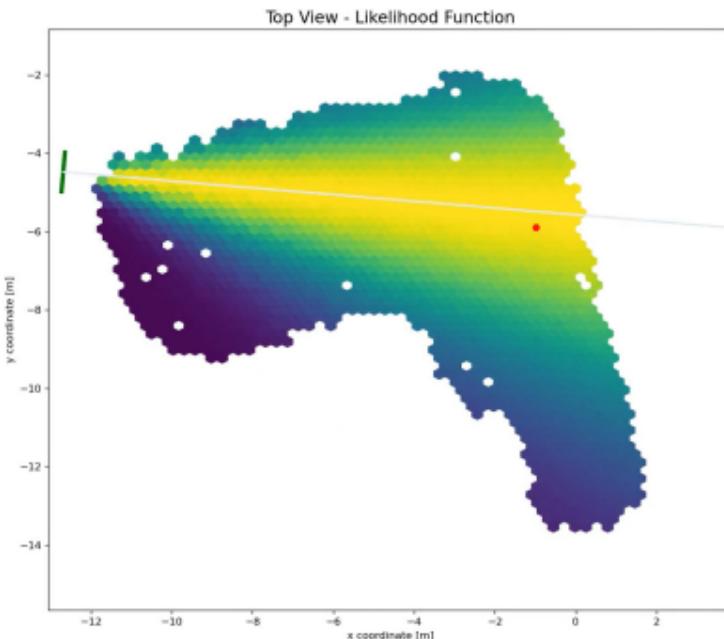
- Maximum likelihood estimation, i.e.:

$$\hat{\mathbf{x}} = \arg \max_{\mathbf{x}} L_{\text{AoA}}(\mathbf{x})$$

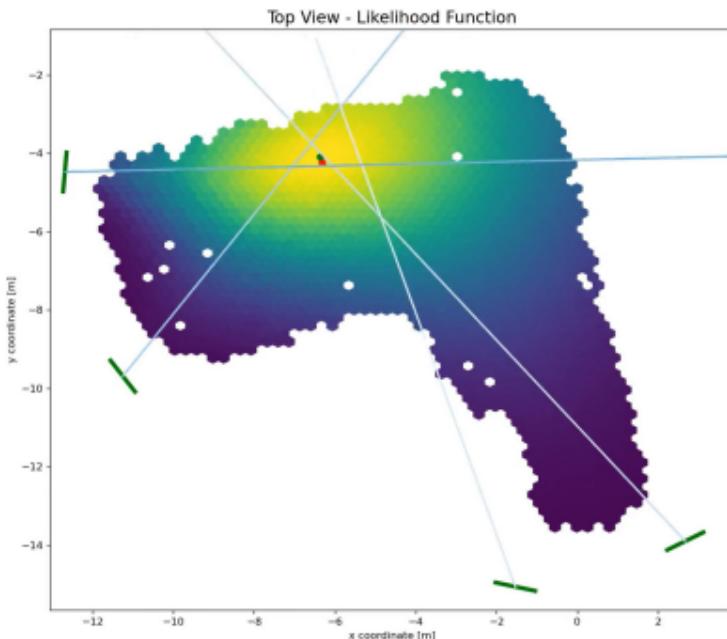
- Implementation: SciPy's BFGS (room for improvement!)



## AoA-Based Triangulation - Visualization

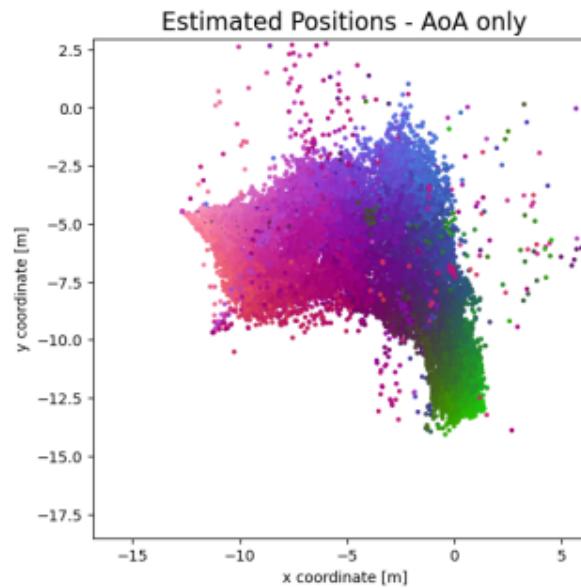
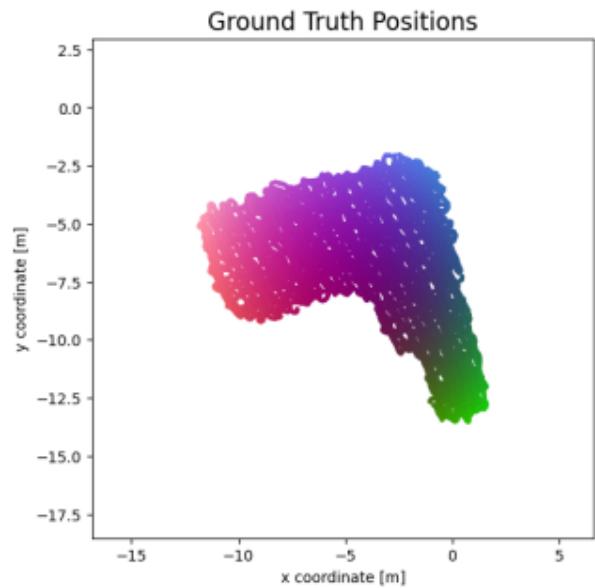


## AoA-Based Triangulation - Visualization

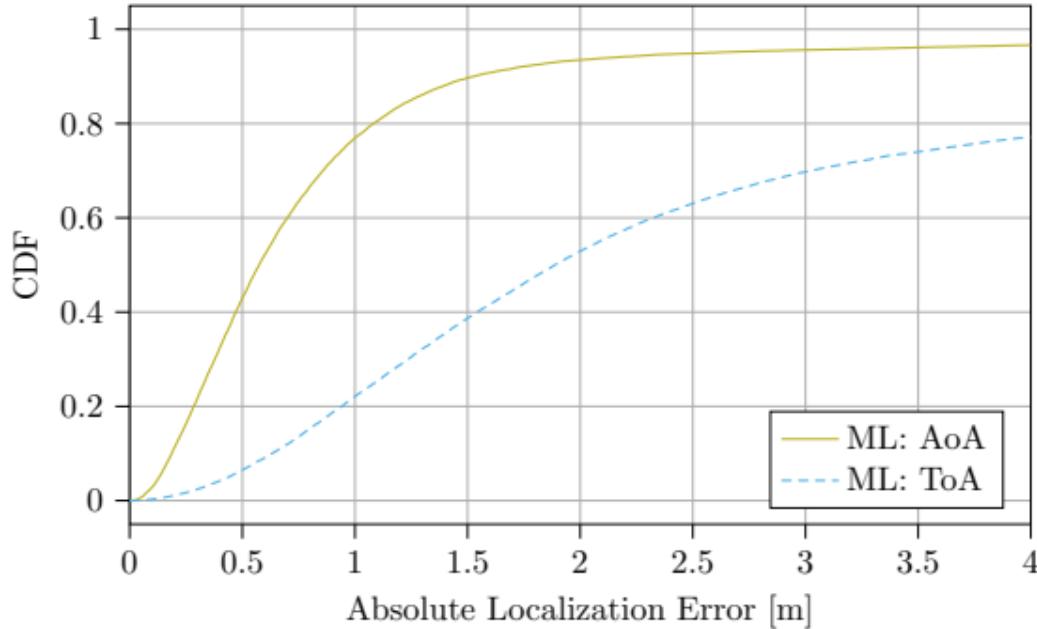




## AoA-Based Triangulation - Results



## AoA-Based Triangulation - Results





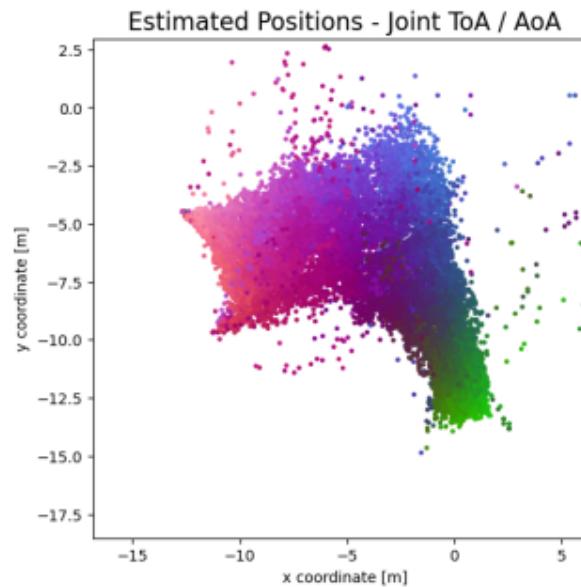
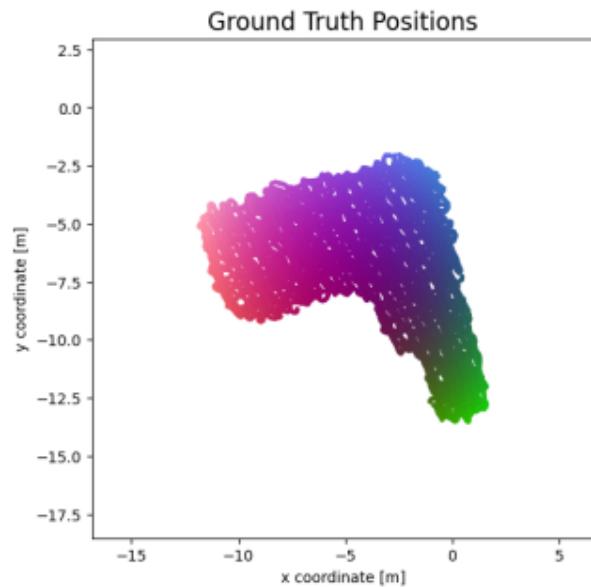
## ToA / AoA Joint Localization - Theory and Results

**Idea:** Assume ToA / AoA estimation errors independent, maximize joint likelihood function:

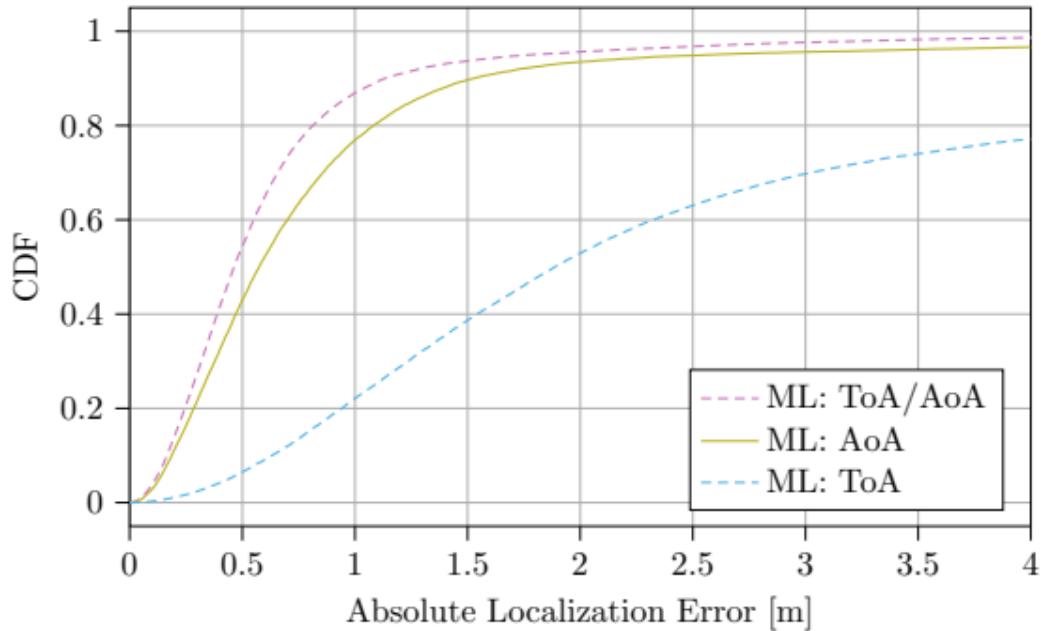
$$\begin{aligned}(\hat{\mathbf{x}}, \hat{\tau}_{\text{TX}}) &= \arg \max_{(\mathbf{x}, \tau_{\text{TX}})} L_{\text{joint}}(\mathbf{x}, \tau_{\text{TX}}) \\&= \arg \max_{(\mathbf{x}, \tau_{\text{TX}})} L_{\text{AoA}}(\mathbf{x}) \cdot L_{\text{ToA}}(\mathbf{x}, \tau_{\text{TX}})\end{aligned}$$



## ToA / AoA Joint Localization - Theory and Results



## ToA / AoA Joint Localization - Theory and Results





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## Channel State Information

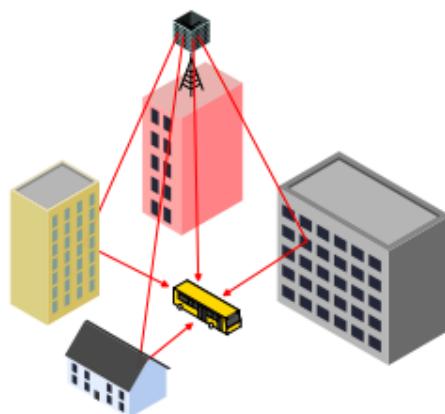


Figure: Multipath propagation

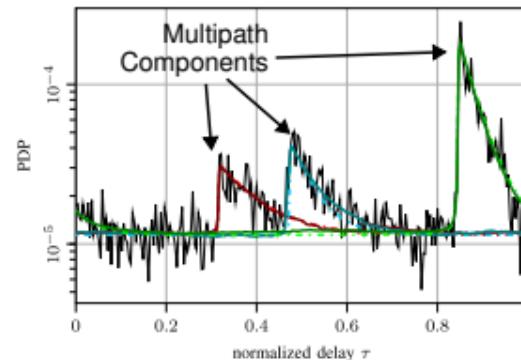
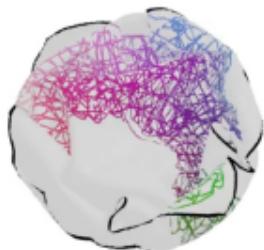
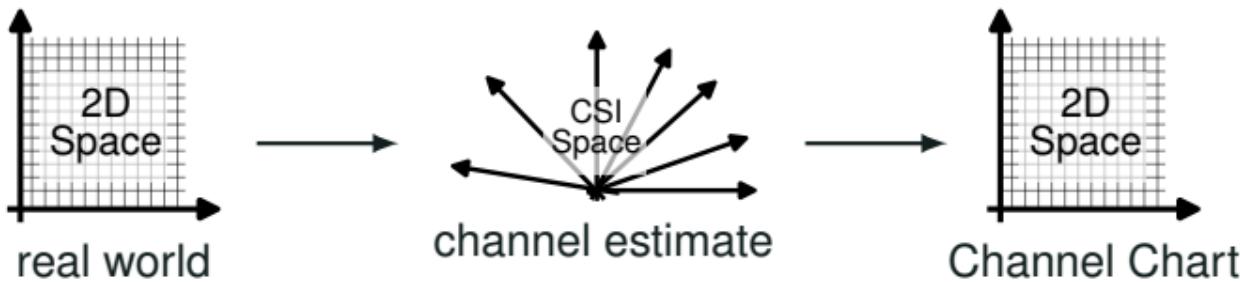


Figure: Power Delay Profile (PDP) of a synthetic channel, from [Schieler et al., 2022]

- CSI: Impulse response, multipath, ... in various representations
- Here: CSI = OFDM channel coefficient estimates



## From CSI to Channel Chart

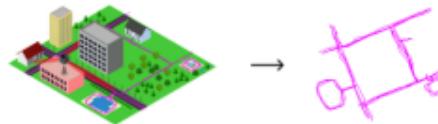


- The physical environment maps CSI onto a high-dimensional manifold
- UEs are mostly located in 2D space (surface)
- Can we un-crumple the manifold into a map using similarity relationships?

## Our Channel Charting Approach

- See paper [Stephan et al., 2023]
  - Source code: Tutorial "Dissimilarity Metric-Based Channel Charting" on our Website

## What is Channel Charting?



Thanks to global-navigation-satellite systems, your phone can tell you your location and reliably guide you to your destination. (Well, except if you are indoors or in an urban canyon of course, then you are on your own.) And, sure it will drain your battery a bit faster. It will also take a few moments until your phone has picked up signals from sufficiently many satellites to localize you. Is this really the best technology we can do?

We believe that, by leveraging future machine learning (ML) deployments in 5G and beyond in a process known as "Delayed Channel", there is still room for enhancing quality-of-service guarantees. Massive MIMO is a key technology for increasing the spectral efficiency of wireless communication systems through spatial multiplexing and will likely be deployed in the form of small cell base stations. In addition, massive MIMO can be used to support ultra-dense networks (UDN) at the edge of the network, where the base stations are located close to the users. This will increase the density of the network and reduce the distance between the base stations and the users, which will improve the quality of service. Delayed Channel is a technique that can be used to enhance the performance of massive MIMO. It allows for the transmission of data to be delayed until after the reception of data from the channel. This can be done by using a buffer or a queue to store the data before it is transmitted. Delayed Channel is also useful for improving the reliability of the system. If a transmission fails, the data can be retransmitted without having to wait for the next transmission opportunity. This can be done by using a buffer or a queue to store the data before it is transmitted. Delayed Channel is also useful for improving the reliability of the system. If a transmission fails, the data can be retransmitted without having to wait for the next transmission opportunity. This can be done by using a buffer or a queue to store the data before it is transmitted.

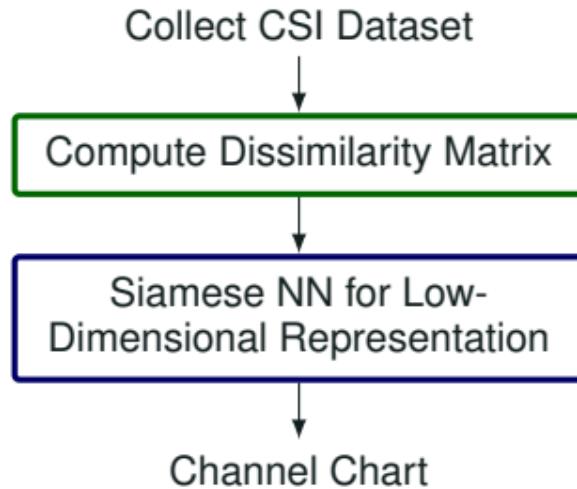
'While fixed and mobile-reachable personnel navigation will be the most visible advantage for end-users, asset tracking and utility access networks (RAN) management tools will benefit even more significantly. Asset tracking, because enabling GRSS-14, GPS receivers into trackers is often unreliable. A GPS receiver is more expensive than just a radio-to-radio modulator; it doesn't handle noise well and needs a lot of energy and hence does not last as long for battery life. Longevity especially if the device is usually in sleep mode, and needs up to 8 minutes to obtain an accurate position estimate after waking up before going back to sleep. The mobile network (RAN) will also benefit significantly from the availability of location information at the base station. For example, knowing location and velocity of a user will allow the base station to predict the wireless channel into the future. In addition, the network will be able to slice base stations between locations of their users according to user needs.'

Online Tutorial

<https://dichasus.inue.uni-stuttgart.de/tutorials>



# Siamese NN Channel Charting in a Nutshell

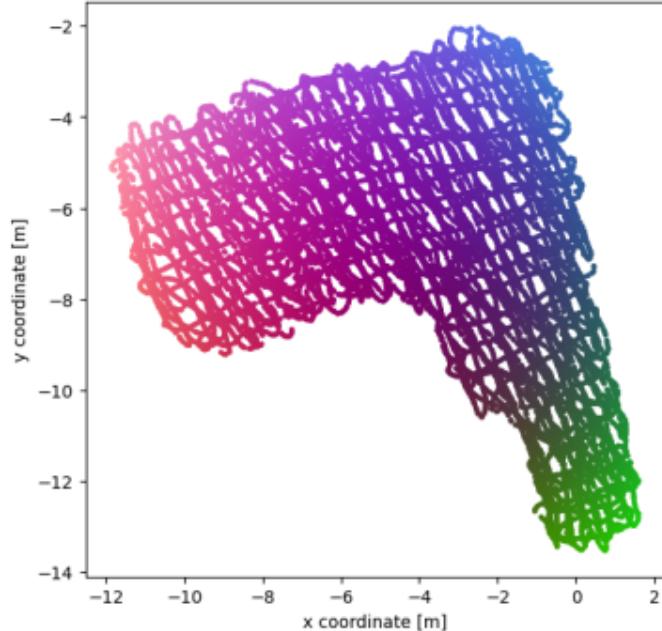


- Compute dissimilarity  $d_{i,j}$  between datapoints  $i$  and  $j$ , from
    - CSI (angle delay profile dissimilarity)
    - absolute timestamp difference
  - Use Siamese loss function with neural network to learn locations  $\mathbf{z}^{(i)}, \mathbf{z}^{(j)} \in \mathbb{R}^2$  of datapoints in Channel Chart:

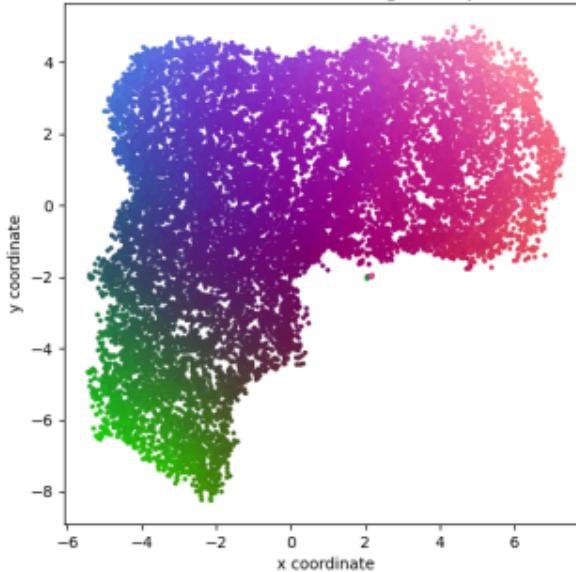
$$L_{\text{Siam}} = \sum_{i,j} d_{i,j} - \|\mathbf{z}^{(i)} - \mathbf{z}^{(j)}\|_2$$

## Channel Chart Training

## Ground Truth Positions



Channel Chart Training - Step 079

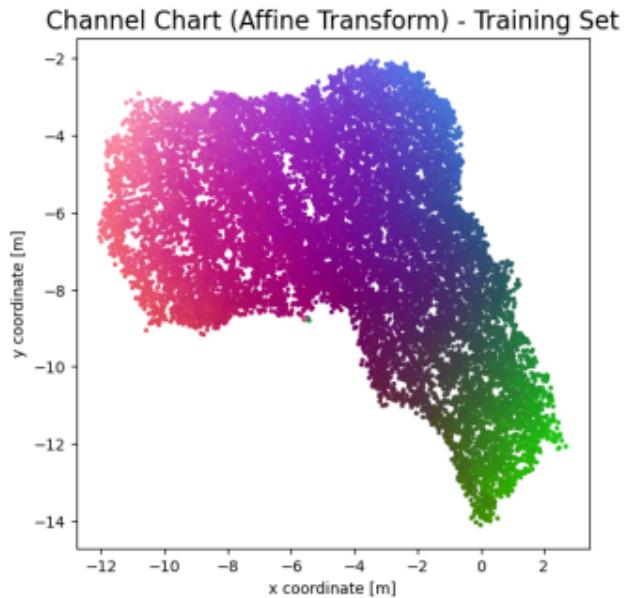
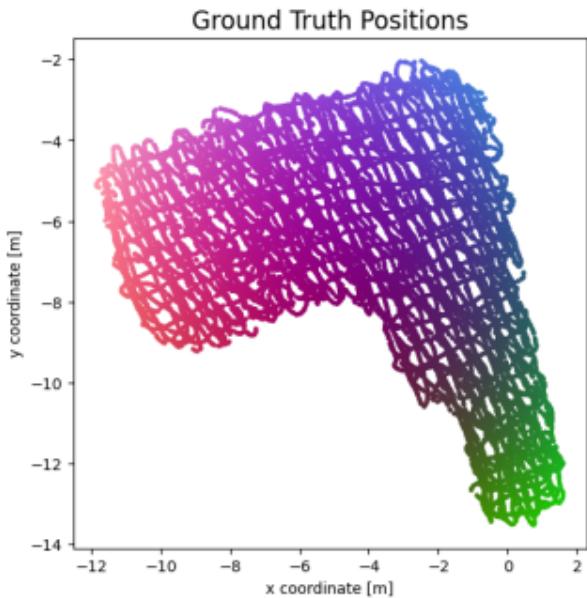


## CC-based Localization

- **Fundamental Problem:** Arbitrary affine transform between *channel chart coordinates* and *physical coordinates*
  - **Idea** [Pihlajasalo et al., 2020]: Use position estimates  $\hat{\mathbf{x}}^{(l)}$  from classical localization techniques to estimate affine transform  $T_{\text{classical}}(\mathbf{z}) = \mathbf{Az} + \mathbf{b}$  of CC locations  $\mathbf{z}^{(l)}$ , least squares solution:

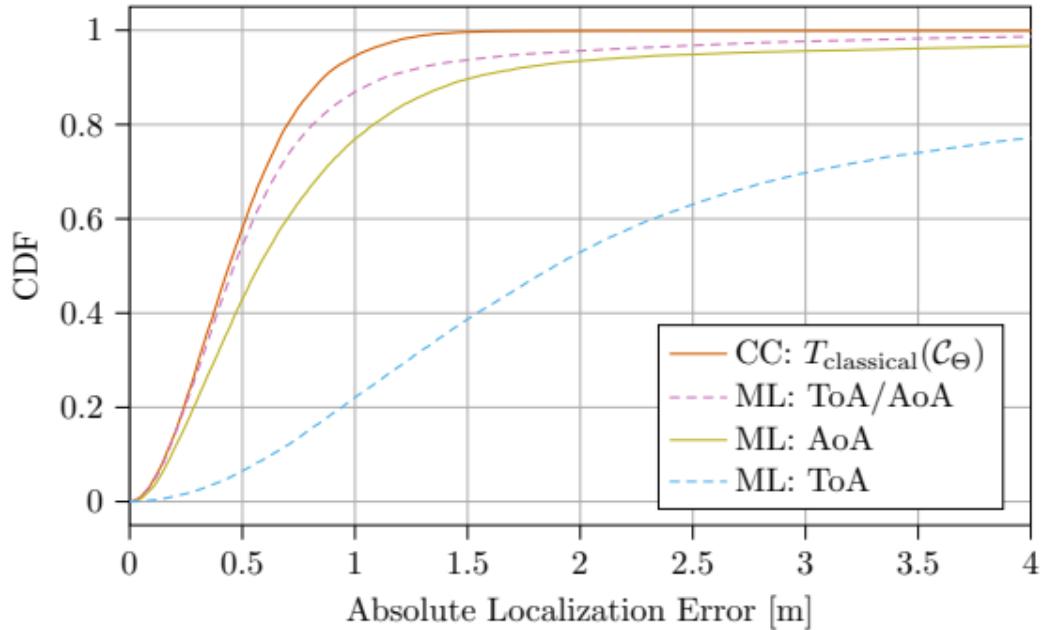
$$(\hat{\mathbf{A}}, \hat{\mathbf{b}}) = \arg \min_{(\mathbf{A}, \mathbf{b})} \sum_{l=1}^L \|\mathbf{A}\mathbf{z}^{(l)} + \mathbf{b} - \hat{\mathbf{x}}^{(l)}\|_2^2$$

## CC-based Localization - Results





## CC-based Localization - Results





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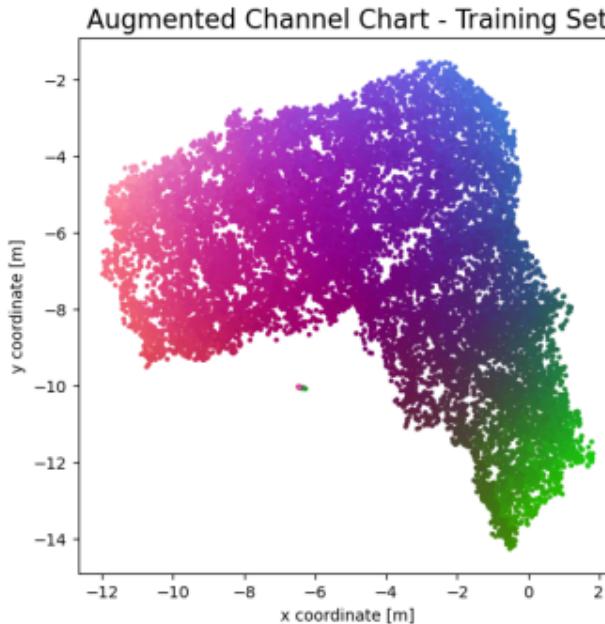
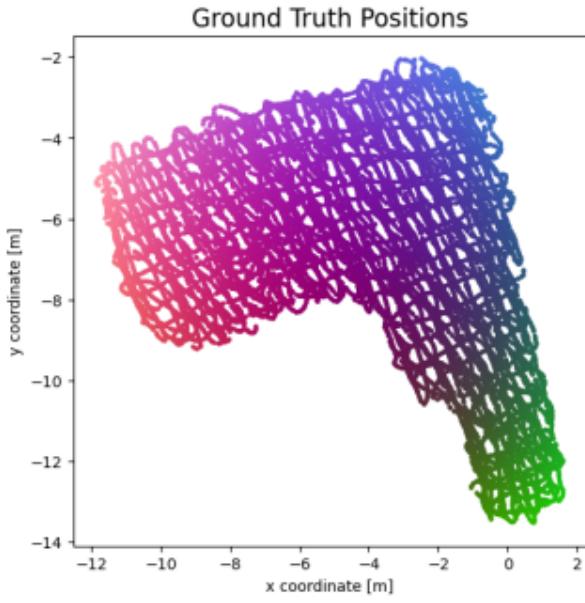
## Augmented Channel Charting - Combined Loss Function

- **Idea:** Use AoA / ToA-derived information already during CC training
  - Siamese loss + classical likelihood combined:

$$L_{\text{combined}} = \sum_{i,j} (1 - \lambda)(d_{i,j} - \|\mathbf{z}^{(i)} - \mathbf{z}^{(j)}\|_2) - \lambda(L_{\text{joint}}(\mathbf{z}^{(i)}) + L_{\text{joint}}(\mathbf{z}^{(j)}))$$

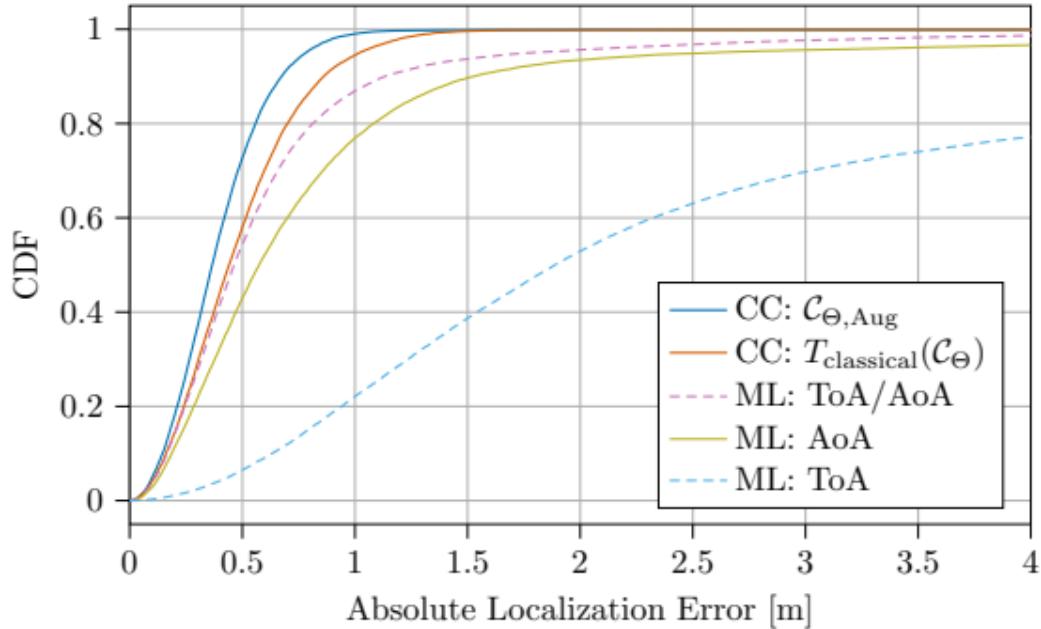
- Hyperparameter: Weighting factor  $\lambda$ , adjusted over training sessions

## Augmented Channel Charting - Results





## Augmented Channel Charting - Results





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## Summary - Performance Overview

	<b>MAE</b> ↓ [2]	<b>DRMS</b> ↓ [2]	<b>CEP</b> ↓ [2]	<b>R95</b> ↓ [2]	<b>KS</b> ↓ [2]	<b>CT/TW</b> ↑ [2]
ML: ToA	2.314 m	3.090 m	1.715 m	6.298 m	0.980	0.871/0.933
ML: AoA	0.909 m	1.643 m	0.574 m	2.563 m	0.236	0.932/0.936
ML: ToA / AoA	0.676 m	1.228 m	0.462 m	1.763 m	0.214	0.965/0.970
CC: $T_{\text{classical}}(C_\Theta)$	0.490 m	0.584 m	0.441 m	1.026 m	0.071	<b>0.996/0.996</b>
CC: $C_{\Theta,\text{Aug}}$	<b>0.401 m</b>	<b>0.483 m</b>	<b>0.369 m</b>	<b>0.789 m</b>	<b>0.070</b>	0.995/0.995

- Successful *absolute* CC-based localization on real-world data
  - “*Classical augments CC*” or “*CC augments classical*”
  - **Source code available online** [1]

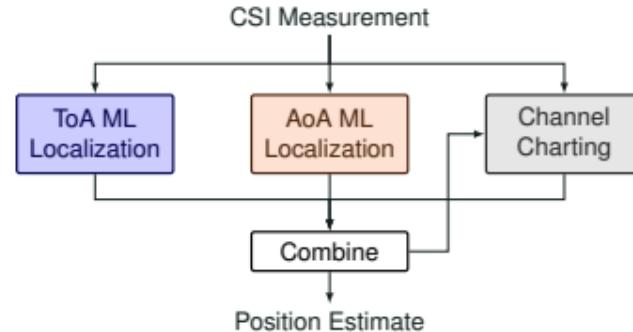
[1] <https://github.com/Jeija/ToA-AoA-Augmented-ChannelCharting>

<sup>[2]</sup>MAE = mean absolute error, DRMS = distance root mean squared, CEP = circular error probable, R95 = 95<sup>th</sup> error percentile, KS = Kruskal Stress, CT/TW = Continuity / Trustworthiness



## Outlook and Possibilities

Common Situation: Partly LoS, partly NLoS



- Suggestion: Use ensemble of experts
- Our vision: **Demonstrate real-time Channel Charting** for indoor localization



# Thank you for your attention! Questions?



**Source code for this work:**

<https://github.com/Jeija/ToA-AoA-Augmented-ChannelCharting/>

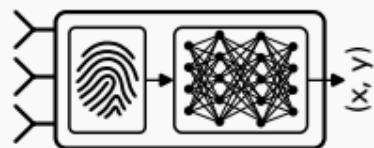


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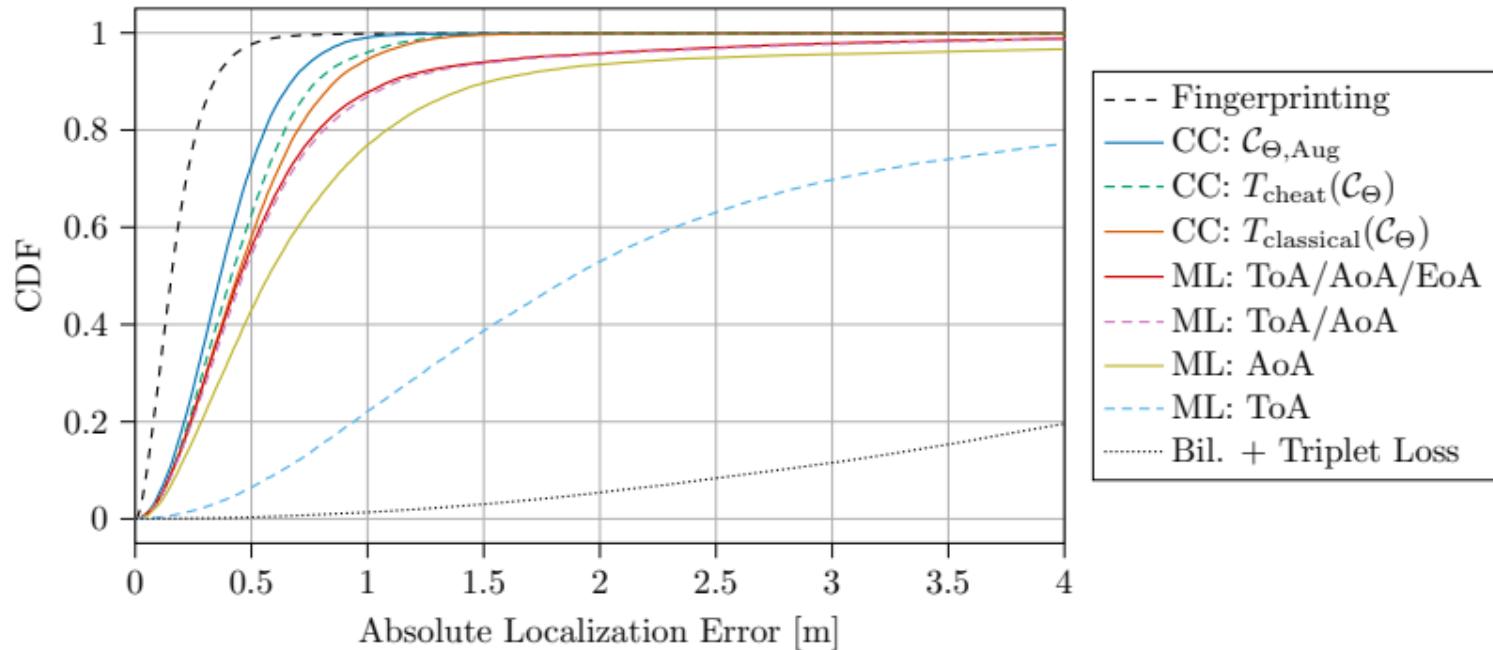
## Other Baselines



Supervised Learning: CSI  
fingerprinting

- Perform Channel Charting:  $C_\Theta$
- Learn affine transform from “ground truth” positions ( $\rightarrow$  cheating):  $T_{\text{cheat}}$

Triplet Loss  
+  
Bilateration Loss  
[Taner et al., 2023]





Channel Chart - Bilateration + Triplet Loss

