Augmenting Channel Charting with Classical Wireless Source Localization Techniques

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University of Stuttgart
Institute of Telecommunications
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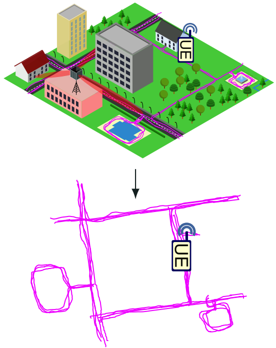
Outline

Agenda

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 **Cannel Chart (CC)**, purely from data available at the base station.

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

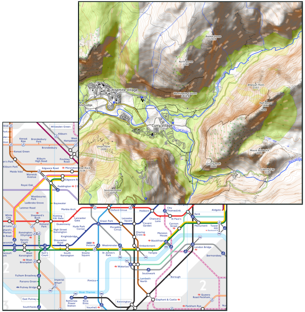
$$C_\Theta : \mathbb{C}^{B \times M \times N_{\mathrm{sub}}} \rightarrow \mathbb{R}^D$$

- Channel Charting is self-supervised

What is a Channel Chart?

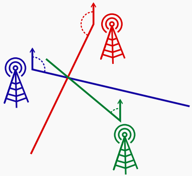
A channel chart is a *map* and C_Θ localizes the UE on the map:

- 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?

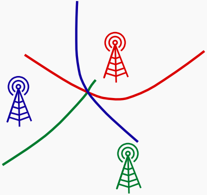


TfL Tube Map, OpenTopoMap

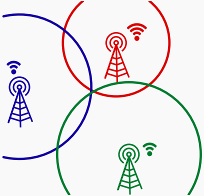
Alternative Source Localization Techniques



AoA-based triangulation

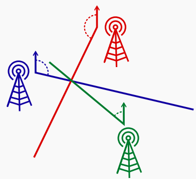


ToA/TDoA-based multilateration



Power-based localization

Alternative Source Localization Techniques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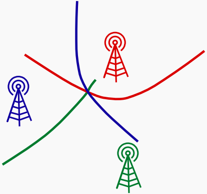
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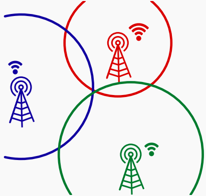
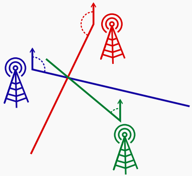

Power-based localization

→ How do these techniques compare to Channel Charting?

Alternative Source Localization Techniques



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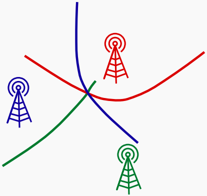

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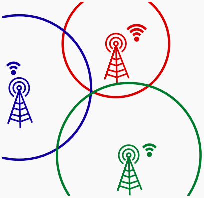


Power-based localization

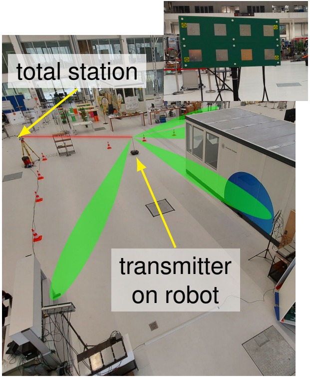
→ How do these techniques compare to Channel Charting?
→ Can we combine classical techniques and Channel Charting?

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

Agenda

CSI Dataset: Distributed mMIMO in Factory



- DICHASUS (Distributed Channel Sounder by University 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, $N_{\mathrm{sub}} = 1024$ subcarriers
- $50\,\mathrm{MHz}$ bandwidth, $f_c = 1.27\,\mathrm{GHz}$ carrier frequency
- `dichasus-cf0x`, publicly available[a]

[a] `https://dichasus.inue.uni-stuttgart.de/datasets/data/dichasus-cf0x/`

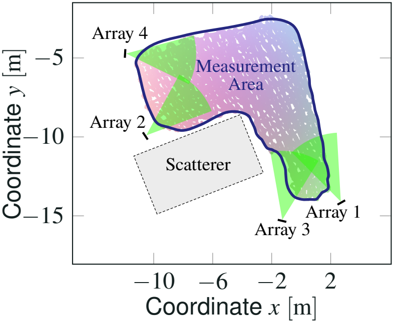
CSI Dataset: Distributed mMIMO in Factory

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

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

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

Top View



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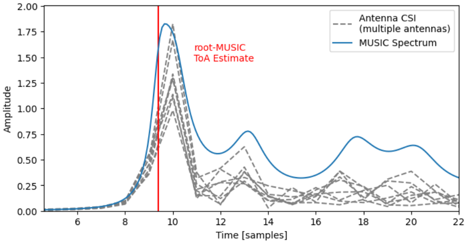
ToA-Based Multilateration - Theory

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

ToA-Based Multilateration - Theory

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

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



Outcome:

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

ToA-Based Multilateration - Theory

1) Estimate ToA | **2) Define Likelihood** | 3) Maximize Likelihood

- Likelihood function based on normal distribution:

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

- Variance σ^2 chosen based on observed RMS delay spread (heuristic)

ToA-Based Multilateration - Theory

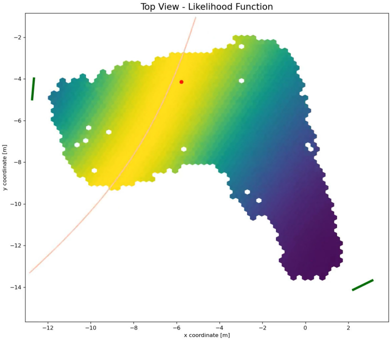
1) Estimate ToA | 2) Define Likelihood | 3) Maximize Likelihood

- Maximimum likelihood estimation, i.e.:

$$(\hat{\mathbf{x}}, \hat{\tau}_{\mathrm{TX}}) = \underset{(\mathbf{x}, \tau_{\mathrm{TX}})}{\arg\max}\, L_{\mathrm{ToA}}(\mathbf{x}, \tau_{\mathrm{TX}})$$

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

ToA / Multilateration - Visualization



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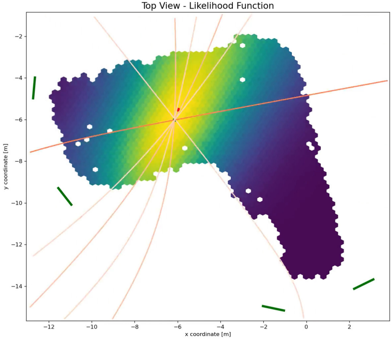
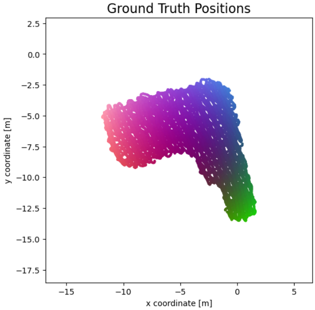
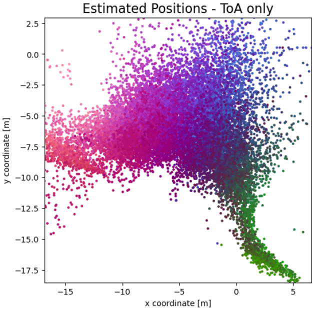


ToA / Multilateration - Results





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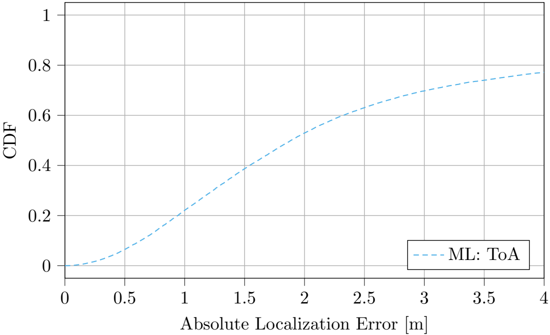


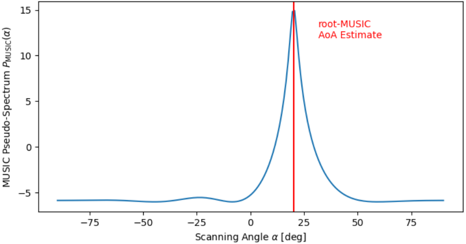
AoA-Based Triangulation - Theory

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

AoA-Based Triangulation - Theory

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

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



Outcome:

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

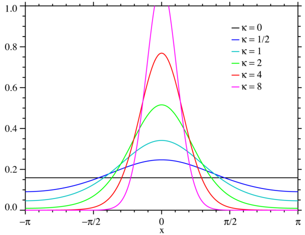
AoA-Based Triangulation - Theory

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

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

- Concentration parameter κ



von Mises PDF [Wikimedia, 2021]

AoA-Based Triangulation - Theory

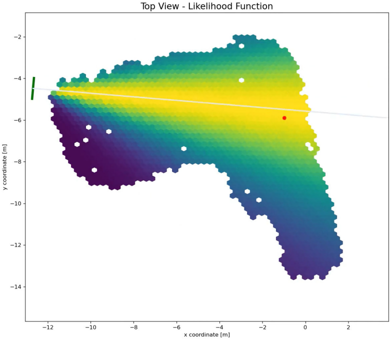
1) Estimate AoA 2) Define Likelihood **3) Maximize Likelihood**

- Maximimum likelihood estimation, i.e.:

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

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

AoA-Based Triangulation - Visualization



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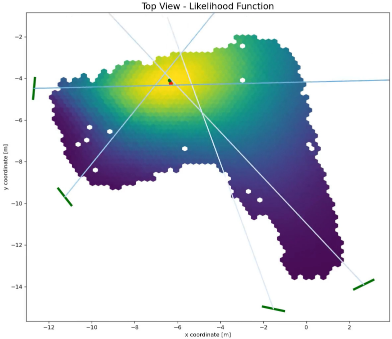

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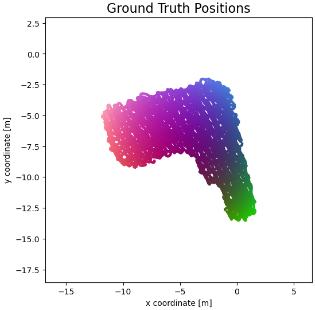
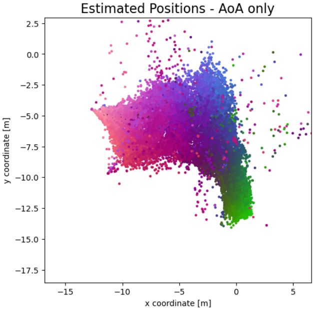
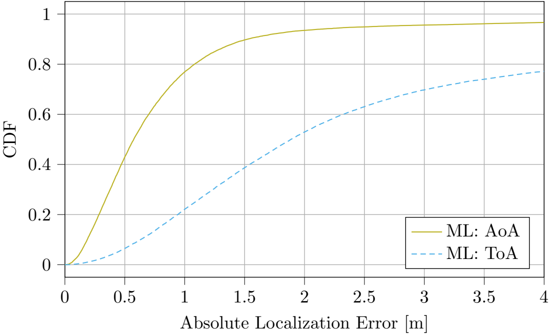




AoA-Based Triangulation - Results

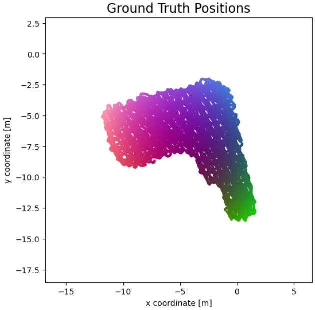


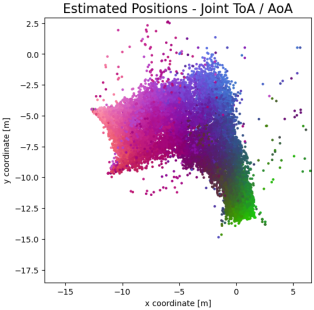
ToA / AoA Joint Localization - Theory and Results

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

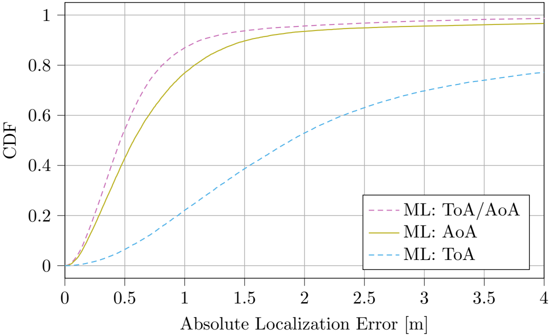
$$\begin{aligned}(\hat{\mathbf{x}}, \hat{\tau}_\mathrm{TX}) &= \underset{(\mathbf{x}, \tau_\mathrm{TX})}{\arg\max}\, L_\mathrm{joint}(\mathbf{x}, \tau_\mathrm{TX}) \\ &= \underset{(\mathbf{x}, \tau_\mathrm{TX})}{\arg\max}\, L_\mathrm{AoA}(\mathbf{x}) \cdot L_\mathrm{ToA}(\mathbf{x}, \tau_\mathrm{TX})\end{aligned}$$

ToA / AoA Joint Localization - Theory and Results





ToA / AoA Joint Localization - Theory and Results



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

Channel State Information

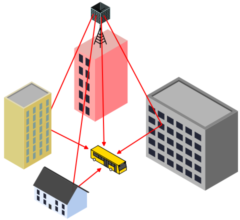


Figure: Multipath propagation

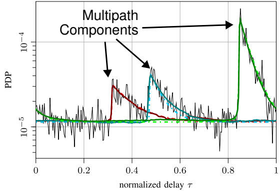
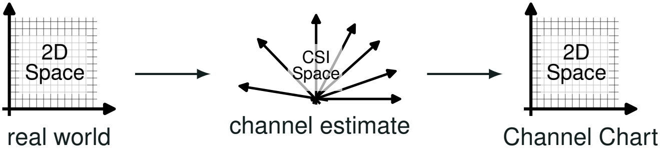
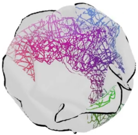


Figure: Power Delay Profile (PDP) of a synthetic channel, from [Schieler et al., 2022]

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

From CSI to Channel Chart

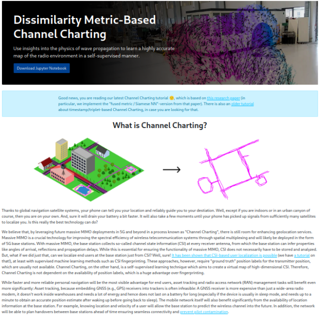




- The physical environment maps CSI onto a high-dimensional manifold
- UEs are mostly located in 2D space (surface)
- Can we un-crumple the manifold into a map using similarity relationships?

Our Channel Charting Approach

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



Online Tutorial

`https://dichasus.inue.uni-stuttgart.de/tutorials`

Siamese NN Channel Charting in a Nutshell

Collect CSI Dataset

↓

Compute Dissimilarity Matrix

↓

Siamese NN for Low-Dimensional Representation

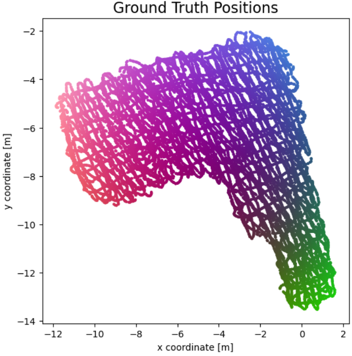
↓

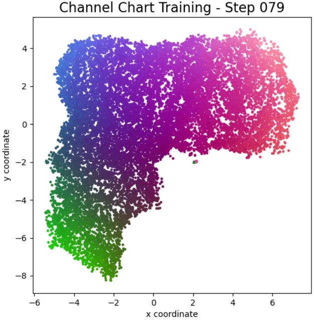
Channel Chart

- 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



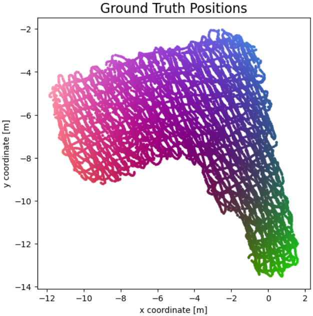


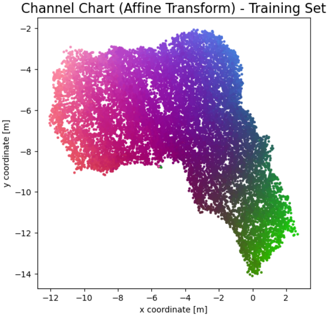
CC-based Localization

- **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 $T_{\text{classical}}(\mathbf{z}) = \mathbf{A}\mathbf{z} + \mathbf{b}$ of CC locations $\mathbf{z}^{(l)}$, least squares solution:

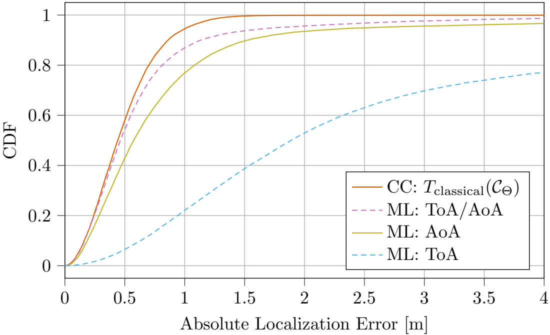
$$(\hat{\mathbf{A}}, \hat{\mathbf{b}}) = \underset{(\mathbf{A},\mathbf{b})}{\arg\min} \sum_{l=1}^{L} \|\mathbf{A}\mathbf{z}^{(l)} + \mathbf{b} - \hat{\mathbf{x}}^{(l)}\|_2^2$$

CC-based Localization - Results





CC-based Localization - Results



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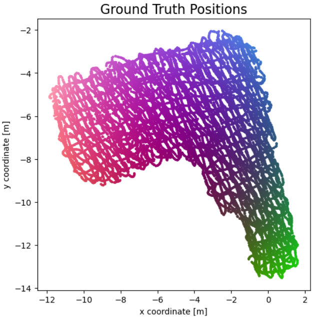
Augmented Channel Charting - Combined Loss Function

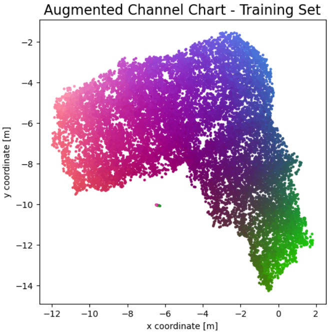
- **Idea**: Use AoA / ToA-derived information already during CC training
- Siamese loss + classical likelihood combined:

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

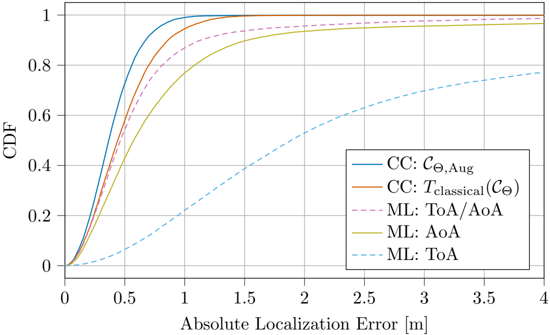
- Hyperparameter: Weighting factor λ, adjusted over training sessions

Augmented Channel Charting - Results





Augmented Channel Charting - Results



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Summary - Performance Overview

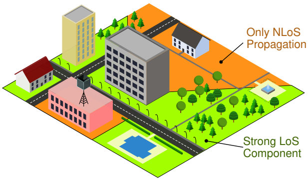
	MAE ↓[2]	DRMS ↓[2]	CEP ↓[2]	R95 ↓[2]	KS ↓[2]	CT/TW ↑[2]
ML: ToA	2.314 m	3.090 m	1.715 m	6.298 m	0.980	0.871/0.933
ML: AoA	0.909 m	1.643 m	0.574 m	2.563 m	0.236	0.932/0.936
ML: ToA / AoA	0.676 m	1.228 m	0.462 m	1.763 m	0.214	0.965/0.970
CC: $T_{\text{classical}}(C_\Theta)$	0.490 m	0.584 m	0.441 m	1.026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

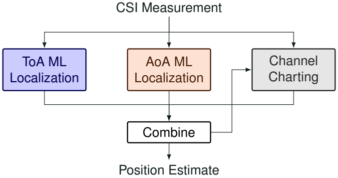
- Successful *absolute* CC-based localization on real-world data
- "*Classical augments CC*" or "*CC augments classical*"
- **Source code available online** [1]

[1] `https://github.com/Jeija/ToA-AoA-Augmented-ChannelCharting`
[2] MAE = mean absolute error, DRMS = distance root mean squared, CEP = circular error probable, R95 = 95$^{\text{th}}$ 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

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Thank you for your attention! Questions?

Source code for this work:

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

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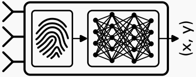
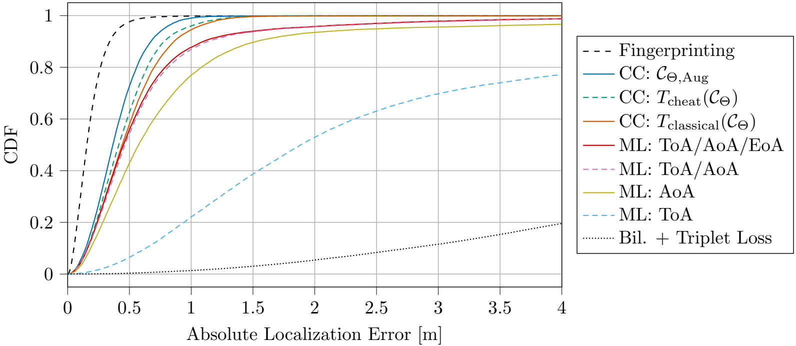
Other Baselines

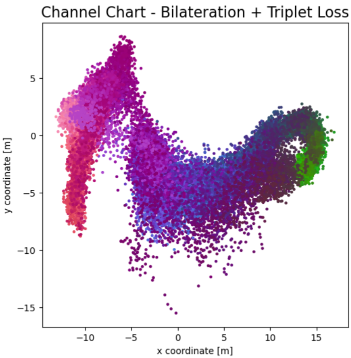


Supervised Learning: CSI fingerprinting

- Perform Channel Charting: C_Θ
- Learn affine transform from “ground truth” positions ($\rightarrow$ cheating): T_cheat

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


CDF
1
0.8
0.6
0.4
0.2
0
0 0.5 1 1.5 2 2.5 3 3.5 4
Absolute Localization Error [m]
Fingerprinting
CC: $\mathcal{C}_{\Theta,\mathrm{Aug}}$
CC: $T_{\mathrm{cheat}}(\mathcal{C}_\Theta)$
CC: $T_{\mathrm{classical}}(\mathcal{C}_\Theta)$
ML: ToA/AoA/EoA
ML: ToA/AoA
ML: AoA
ML: ToA
Bil. + Triplet Loss


Channel Chart - Bilateration + Triplet Loss
y coordinate [m]
x coordinate [m]
5
0
−5
−10
−15
−10
−5
0
5
10
15