Channel Charting-Based Channel Prediction on Real-World Distributed Massive MIMO CSI

Phillip Stephan, Florian Euchner,
Stephan ten Brink

Institute of Telecommunications, University of Stuttgart

IEEE WCNC (TR3-16: MIMO II)
March 26th, 2025

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

Outline

Agenda

Channel Prediction - Motivation

- **Distributed Massive MIMO:** spatially distributed BS antennas
- **Timely CSI** crucial for reliable wireless communication
- **Channel aging** due to UE mobility
- **Solution 1:** Increase frequency of CSI estimation
- **Solution 2:** Channel Prediction

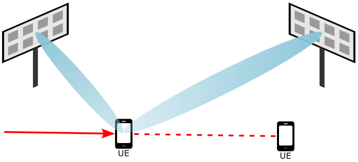
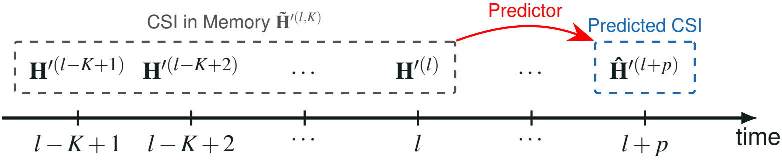


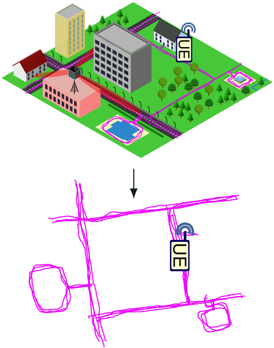
Figure: Channel aging

Objective of Channel Prediction

- At time instant l, predict future CSI $\hat{\mathbf{H}}'^{(l+p)}$ from most recent CSI samples in memory $\tilde{\mathbf{H}}'^{(l,K)}$
  - Prediction horizon p
  - Memory size K
- Maximize sum rate for $\hat{\mathbf{H}}'^{(l+p)}$ and the true CSI $\mathbf{H}'^{(l+p)}$



Idea: Predict CSI Through Channel Chart [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 $D = 3$:

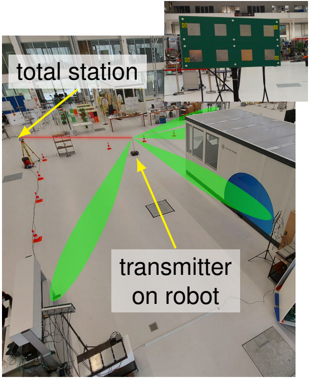
$$C_\Theta : \mathbb{C}^{B \times M \times N_{\text{sub}}} \to \mathbb{R}^D$$

- **Channel Charting is self-supervised!**

Agenda

1. Introduction
2. CSI Dataset
3. Channel Charting-Based Channel Prediction
4. Experimental Results and Outlook

CSI Dataset: Distributed mMIMO in Factory



- DICHASUS (Distributed Channel Sounder by University of Stuttgart) [Euchner et al., 2021]
- Single transmitter on robot, highly accurate reference positions, velocity $\approx 0.3\,\mathrm{m\,s^{-1}}$
- $B = 4$ antenna arrays, with $M = 2 \times 4$ phase-synchronous antennas each (32 antennas total), $N_{\mathrm{sub}} = 1024$ OFDM 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

- Size of area bounding box:
  Around $13\,\mathrm{m} \times 13\,\mathrm{m}$

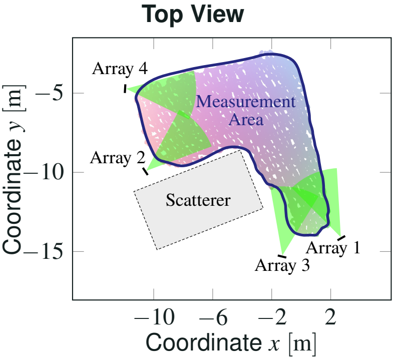
- Training Dataset ($L = 20827$):

$$\mathcal{D}_{\mathrm{train}} = \left\{ \left(\mathbf{H}^{(l)}, \mathbf{x}^{(l)}, t^{(l)} \right) \right\}_{l=1,\dots,L}$$

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

- Prediction Dataset ($L' = 20841$):

$$\mathcal{D}_{\mathrm{pred}} = \left\{ \left(\mathbf{H}'^{(l)}, \mathbf{x}'^{(l)}, t'^{(l)} \right) \right\}_{l=1,\dots,L'}.$$



Agenda

Step 1: Learn Channel Chart on Training Set

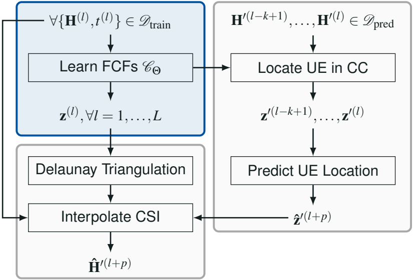
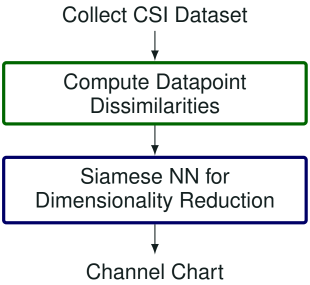
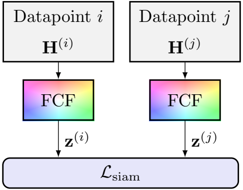


Figure: The three major steps of Channel Charting-based channel prediction.

Figure: Learned Channel Chart

Learn Channel Chart with Siamese Neural Network





$$\mathscr{L}_{\text{siam}} = \frac{1}{L^2} \sum_{i,j} \frac{\left(\left\| \mathbf{z}^{(i)} - \mathbf{z}^{(j)} \right\| - \Delta_{\text{geo},i,j} \right)^2}{\Delta_{\text{geo},i,j}}$$

with CC locations $\mathbf{z}^{(l)} \in \mathbb{R}^2$, $l = 1, \ldots, |\mathscr{S}|$.

Step 2: Predict UE Position within Channel Chart

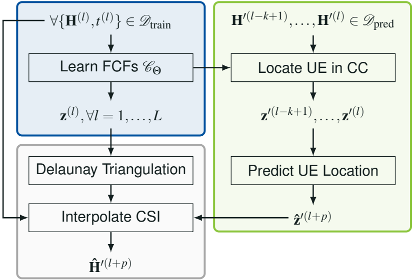


Figure: The three major steps of Channel Charting-based channel prediction.

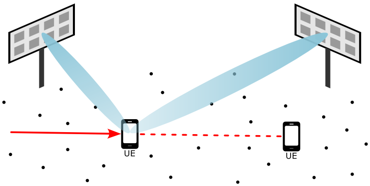


Figure: Predict UE position $\hat{\mathbf{z}}'^{(l+p)}$

Step 3: Delaunay Triangulation and CSI Interpolation

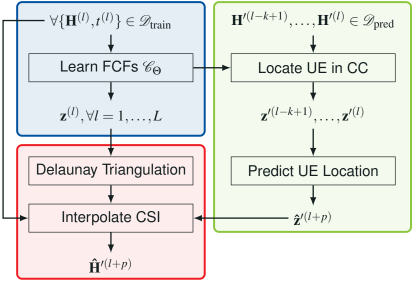


Figure: The three major steps of Channel Charting-based channel prediction.

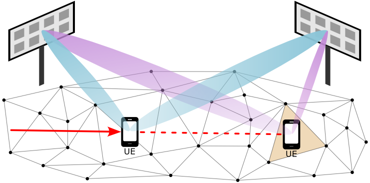


Figure: Estimate CSI at $\hat{\mathbf{z}}'^{(l+p)}$

CSI Interpolation ("CC-interp")

- triangle formed by three known channel chart positions $\mathbf{z}^{(\Delta 1)}, \mathbf{z}^{(\Delta 2)}, \mathbf{z}^{(\Delta 3)}$
- Weight vector $\mathbf{c} \in \mathbb{R}^3$ with $\sum_i c_i = 1$
- Linear interpolation:

$$\hat{\mathbf{H}}'^{(l+p)} = \frac{1}{3} \sum_{i=1}^{3} c_i \cdot \mathbf{H}^{(\Delta i)}$$

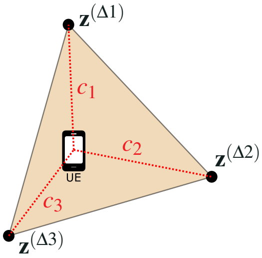


Figure: CSI Interpolation

Alternative: Nearest Neighbor (”CC-NN”)

- Index of nearest neighbor in channel chart

$$i_{\mathrm{NN}} = \arg\min_{i} \|\mathbf{z}^{(i)} - \hat{\mathbf{z}}'^{(l+p)}\|$$

- Select respective CSI as estimated channel

$$\hat{\mathbf{H}}'^{(l+p)} = \mathbf{H}^{(i_{\mathrm{NN}})}$$

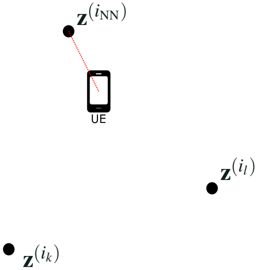


Figure: Nearest Neighbor

Agenda

Channel Charting - Results

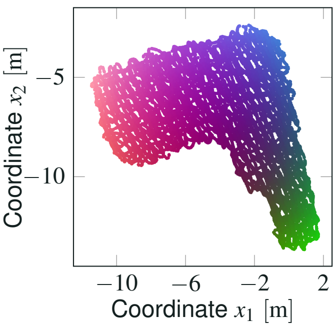


Figure: Ground Truth Positions

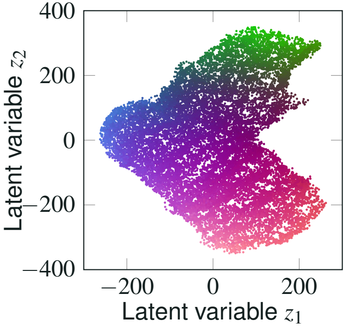


Figure: Channel Chart

Sum Rate at Channel Chart Position

- Best array selected at each datapoint for DL communication
- Sum rate generally higher at positions closer to the arrays

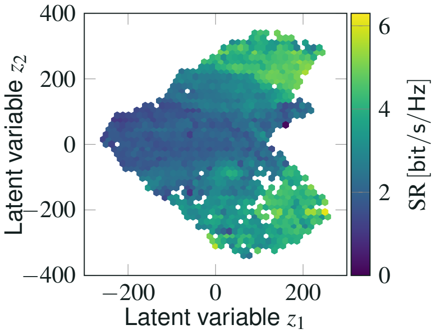


Figure: Sum rate at channel chart position

Sum Rate vs. Prediction Horizon

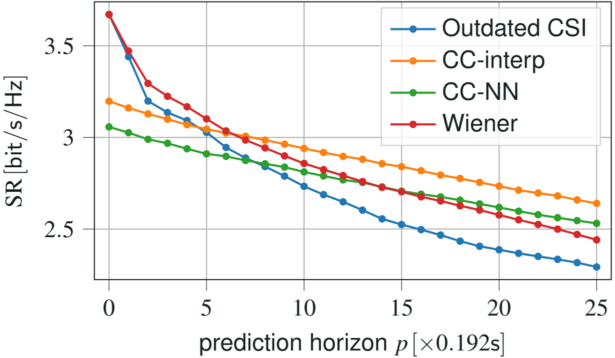


Figure: Average sum rate vs. prediction horizon p.

Outlook

- Improved channel charting algorithms
  $\rightarrow$ better channel prediction performance
- Extend approach to DL communication with all BS arrays
  - predict phase differences between arrays to prevent destructive interference at UE

Thank you for your attention! Questions?

Source Code (GitHub)

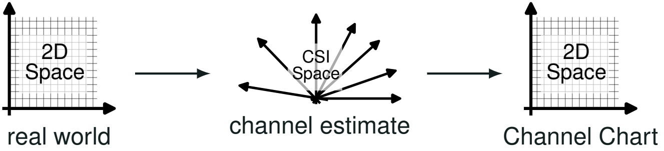
References

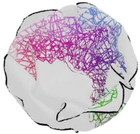
[Euchner et al., 2021] Euchner, F., Gauger, M., Dörner, S., and ten Brink, S. (2021).
A Distributed Massive MIMO Channel Sounder for "Big CSI Data"-driven Machine Learning.
In *WSA 2021; 25th International ITG Workshop on Smart Antennas*.

[Stephan et al., 2024] Stephan, P., Euchner, F., and Brink, S. t. (2024).
Angle-delay profile-based and timestamp-aided dissimilarity metrics for channel charting.
IEEE Transactions on Communications, 72(9):5611–5625.

[Studer et al., 2018] Studer, C., Medjkouh, S., Gonultaş, E., Goldstein, T., and Tirkkonen, O. (2018).
Channel charting: Locating users within the radio environment using channel state information.
IEEE Access, 6:47682–47698.

From CSI to Channel Chart



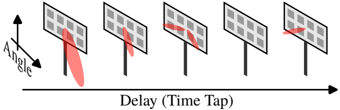


- The high-dimensional CSI is mainly dependent on the physical UE location
- UEs are mostly located in 2D space (surface)
- Can we un-crumple the high-dimensional CSI space into a 2D map using similarity relationships?

Dissimilarity Metrics [Stephan et al., 2024]

1. Angle-Delay-Profile Δ_{ADP}

- Same power from same angle at same delay $\rightarrow$ similar location



- Uses *time-domain* CSI $\mathbf{H} \in \mathbb{C}^{B \times M \times T}$:

$$\Delta_{\mathrm{ADP},i,j} = \sum_{b=1}^{B} \sum_{\tau=1}^{T} \left(1 - \frac{\left| \sum_{m=1}^{M} \left(\mathbf{H}_{b,m,\tau}^{(i)} \right)^{*} \mathbf{H}_{b,m,\tau}^{(j)} \right|^2}{\left(\sum_{m=1}^{M} \left| \mathbf{H}_{b,m,\tau}^{(i)} \right|^2 \right) \left(\sum_{m=1}^{M} \left| \mathbf{H}_{b,m,\tau}^{(j)} \right|^2 \right)} \right)$$

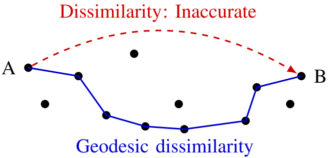
2. Timestamps Δ_{time}

- Use time difference as dissimilarity

$$\Delta_{\mathrm{time},i,j} = \left| t^{(i)} - t^{(j)} \right|$$

3. Geodesic Dissimilarities Δ_{geo}

- shortest path algorithm



Array Selection Strategy

- predicted UL CSI tensor $\hat{\mathbf{H}}'^{(l+p)} \in \mathbb{C}^{B \times M \times N_{\text{sub}}}$
  - B BS antenna arrays
  - M antennas per array
  - N_{sub} subcarriers
- Only the array with the best predicted channel is used for DL communication

$$\hat{b}^{(l+p)} = \arg\max_{b} \sum_{n}^{N_{\text{sub}}} \left| \left(\hat{\mathbf{H}}'^{(l+p)}_{b:n} \right)^{\mathrm{H}} \left(\hat{\mathbf{H}}'^{(l+p)}_{b:n} \right) \right| .$$

This strategy is applied for all considered prediction methods.

Sum Rate

- Compute sum rate based on received DL power
- Assumptions:
  - TX power equally allocated to all subcarriers
  - constant noise power $N_0 = \mathbb{E}[P/\mu]$ (average SNR $\mu = 100$)
- Power at array b and subcarrier n

$$P_{bn}^{(l+p)} = \frac{\left| \left(\mathbf{H}'^{(l+p)}_{b:n}\right)^{\mathrm{H}} \left(\hat{\mathbf{H}}'^{(l+p)}_{b:n}\right) \right|^2}{N_{\mathrm{sub}} \cdot \left\| \hat{\mathbf{H}}'^{(l+p)}_{b:n} \right\|^2}.$$

- Sum rate at array b

$$\mathrm{SR}_b^{(l+p)} = \frac{1}{N_{\mathrm{sub}}} \sum_{n=1}^{N_{\mathrm{sub}}} \log_2\left(1 + \frac{1}{N_0} \cdot P_{bn}^{(l+p)}\right).$$