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Leveraging the Doppler Effect for Channel Charting

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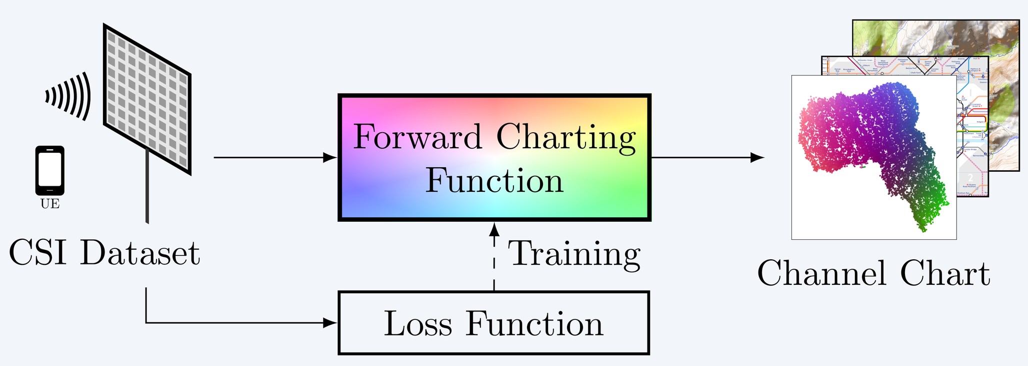
Abstract (Shortened)

Channel Charting is a dimensionality reduction technique that reconstructs a map of the radio environment from similarity relationships found in channel state information. Distances in the channel chart are often computed based on some dissimilarity metric, which can be derived from angular-domain information, channel impulse responses or measured phase differences. Using such information implicitly makes strong assumptions about the level of phase and time synchronization between base station antennas. Many practical systems, however, may not provide phase and time synchronization and single-antenna base stations may not even have angular-domain information. We propose a Doppler effect-based loss function for Channel Charting that only requires frequency synchronization between spatially distributed antennas, which is a much weaker assumption. We use a dataset measured in an indoor environment to demonstrate that the proposed method outperforms other state-of-the-art methods under the given limitations.

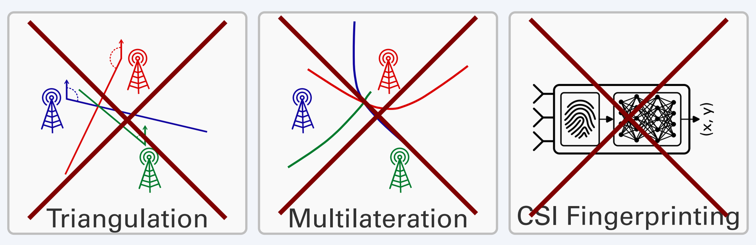
Introduction to Channel Charting



Channel Charting [1] is a *dimensionality reduction* technique that learns the **Forward Charting Function (FCF)**

$$\mathcal{C}_\Theta : \mathbb{C}^M \to \mathbb{R}^{D'},\ M \gg D',$$

which is a mapping from high-dimensional (M) channel state information (CSI) to a low-dimensional space (usually $D' = 2$ or 3), called channel chart, learned purely from data available at the base station (BS). The channel chart is a *map* of the radio environment whose appearance varies greatly with the considered use case (e.g., localization, pilot assignment, handover optimization).

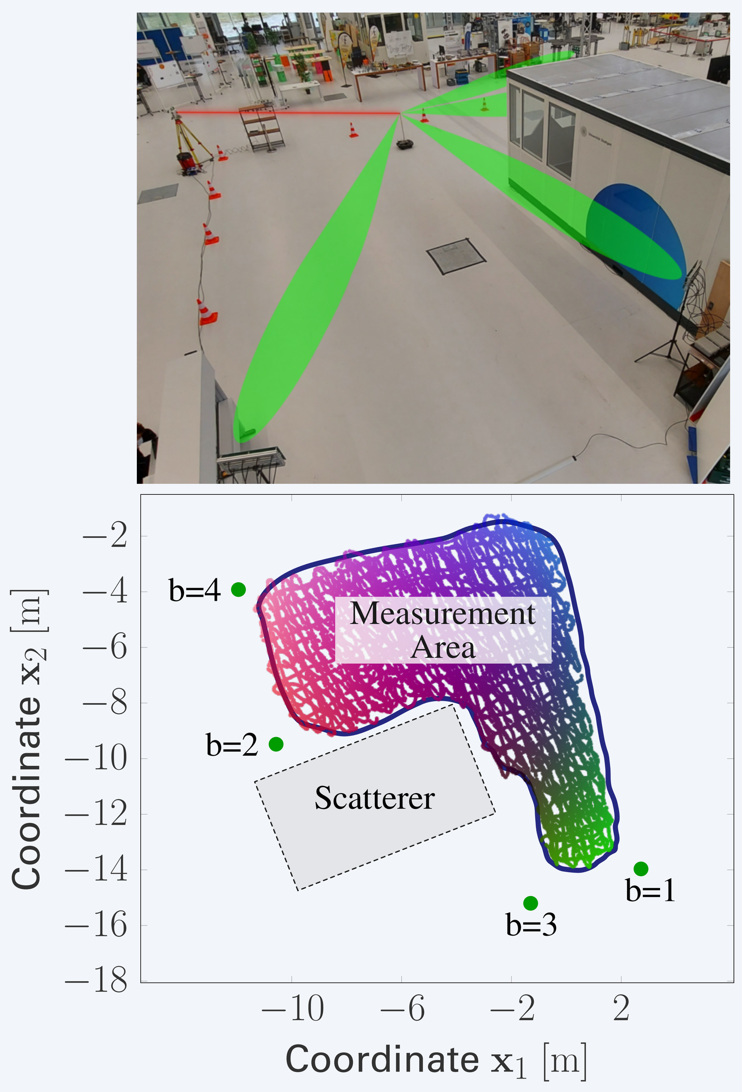


Channel Charting is primarily *data-based*, not model-based, but model-based observations (e.g. angle / time of arrival) can be taken into account. In contrast to CSI fingerprinting, Channel Charting *does not need labeled training data*.

Measured CSI Dataset

The dataset (*dichasus-cf0x*) was measured by DICHASUS, our "big data" distributed massive MIMO channel sounder [2]:

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



Carrier Frequency
1.272 GHz
Bandwidth
50 MHz
Datapoints
$|\mathcal{S}_\mathrm{train}| = 20851$,
$|\mathcal{S}_\mathrm{test}| = 20851$
Mean UE Speed
$\sim 0.25\,\mathrm{m/s}$
Antennas
Single dipole for UE, single patch antenna for each of the $B = 4$ BSs
Area
L-shaped and bounded by $\sim 13\,\mathrm{m} \times 13\,\mathrm{m}$ square

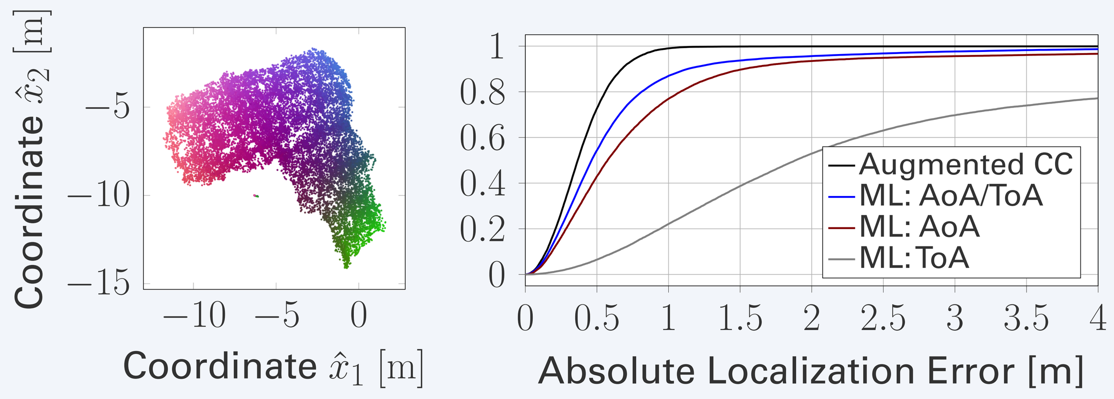
$$\text{Dataset}: \mathcal{S} = \{(\mathbf{H}(t), \mathbf{x}(t), t, \mathbf{f}(t))\}_{t\in\mathcal{T}}$$

with CSI $\mathbf{H}(t) \in \mathbb{C}^{B\times N_\mathrm{sub}}$, positions $\mathbf{x}(t) \in \mathbb{R}^3$ (only for evaluation!), timestamps $t \in \mathcal{T}$ and frequency measurements $\mathbf{f}(t) \in \mathbb{R}^B$.

Note: The original dataset contains frequency-, time- and phase-synchronized CSI from 4 arrays with 2×4 antennas each. For the proposed method, we only use data from one antenna per array and artificially randomize phases and time shifts in $\mathbf{H}(t)$.

Scenario and Problem Statement

Channel Charting = Solved Problem?



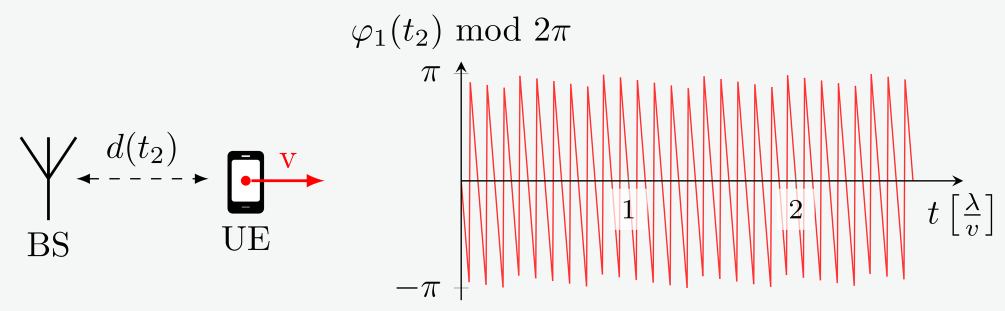
Channel Charting with four synchronized 2×4 antenna arrays

With many antennas and time and / or phase synchronization, CC delivers excellent localization performance (but classical techniques also come close), see e.g. [3] (figure above). But what if:

- There are only few, single-antenna BSs
- There is no time and phase synchronization, only frequency synchronization (= fixed phase offsets over short intervals)

Time / angle of arrival estimation are now impossible. CSI fingerprinting will work (characertistic power delay profiles), but requires labels. How to learn a channel chart?

Doppler Effect for Localization: Classical Approach



Changing the propagation path length between UE and BS leads to a shift in the received signal phase. Continuous movement leads to a perceived frequency change known as **Doppler shift**. In practice, the Doppler shift is dwarfed by the carrier frequency offset (CFO) between BS and UE. For time $t = t_1, t_2$, we note

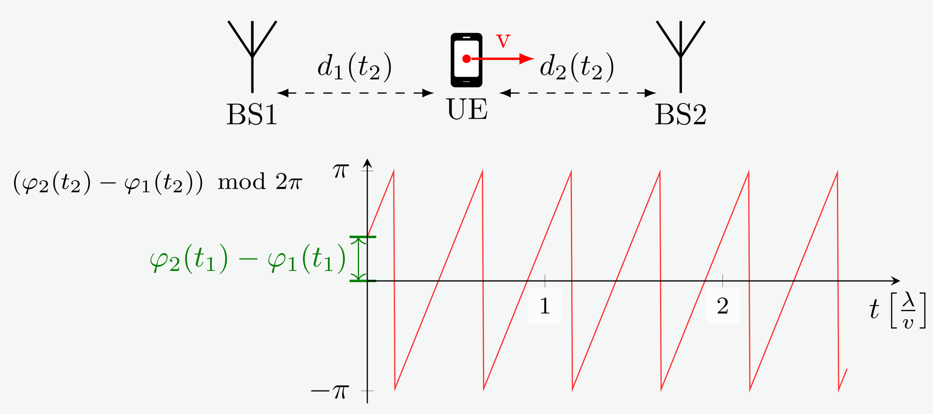
$$\varphi_b(t_2) = \varphi_b(t_1) + \varphi_\mathrm{CFO}(t_2) + \varphi_{\mathrm{Dop},b}(t_2) \quad \text{with} \tag{1}$$

$\varphi_b(t)$ … measured received phase for BS b,
$\varphi_\mathrm{CFO}(t)$ … CFO-induced phase change (same for all BSs),
$\varphi_{\mathrm{Dop},b}(t)$ … movement-induced phase shift for BS b, can be expressed as a function of $\mathbf{x}, \mathbf{v} \in \mathbb{R}^{D'}$ and b.

Considering a moving UE with D' unknown location and velocity dimensions $\mathbf{x}, \mathbf{v} \in \mathbb{R}^D$ and unknown $\varphi_\mathrm{CFO}(t)$, observations $(\varphi_b(t_2), \varphi_b(t_1))$ from at least $2D'+1$ BSs are needed to find all unknowns $\mathbf{x}, \mathbf{v}, \varphi_\mathrm{CFO}(t)$ in a classical way (system of equations) [4].

Problem: Classical Doppler Effect-based localization needs many $(2D'+1)$ BSs and can only localize moving UEs.

Doppler Effect as Channel Charting Loss



Channel Charting can make use of similarity relationships in measured CSI to perform localization with fewer than $2D'+1$ BSs and, once the FCF is trained, can also localize non-moving UEs.

Idea: By considering phase *differences* between two BSs b_1, b_2, eliminate unknowns in Eq. (1) to make it usable as loss function.

Let $d_b(t)$ denote the distance between UE and BS b at time t. After some mathematical manipulations and with abbreviations

$$\Delta\varphi_{b_1,b_2}(t_1,t_2) = (\varphi_{b_2}(t_2) - \varphi_{b_1}(t_2)) - (\varphi_{b_2}(t_1) - \varphi_{b_1}(t_1)) \text{ and}$$
$$\Delta d_{b_1,b_2}(t_1,t_2) = (d_{b_2}(t_2) - d_{b_1}(t_2)) - (d_{b_2}(t_1) - d_{b_1}(t_1)),$$

we find a log-likelihood loss function

$$\mathcal{L}(t_1,t_2) = \sum_{b_1=1}^{B}\sum_{b_2=1}^{B}\left(\frac{\Delta\varphi_{b_1,b_2}(t_1,t_2) - \frac{2\pi}{\lambda}\Delta d_{b_1,b_2}(t_1,t_2)}{\sigma_{b_1,b_2}(t_1,t_2)}\right)^2. \tag{2}$$

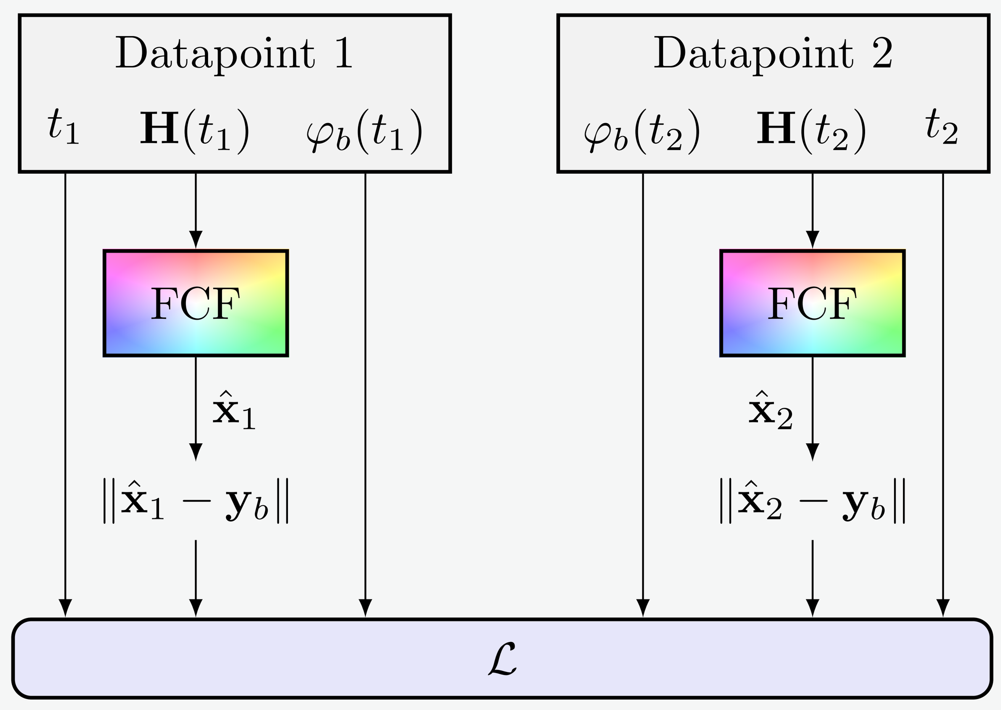
The uncertainty parameter $\sigma_{b_1,b_2}(t_1,t_2)$ in Eq. (2) is estimated based on the observed delay spread using a heuristic. The observed phases $\varphi_b(t)$ can be computed from observed instantaneous frequencies $f_b(\tau)$ by integration:

$$\varphi_b(t) = \int_0^t 2\pi f_b(\tau)\,\mathrm{d}\tau$$

If instantaneous phase information is available in $\mathbf{H}(t)$, $\varphi_b(t)$ can be compared against measured phases. $\varphi_b(t)$ is the *unwrapped* phase shift, i.e., it can be outside $[0, 2\pi)$.

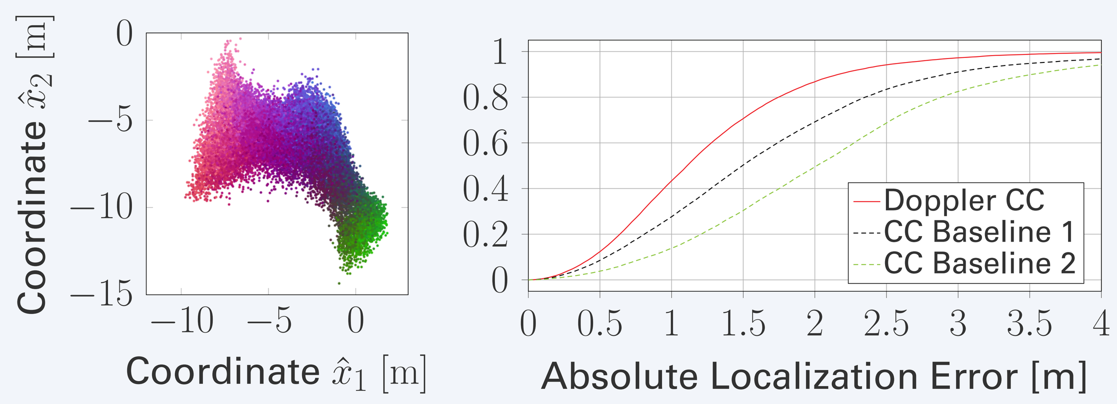
Forward Charting Function Training

The FCF is trained in a **Siamese Neural Network** [5] configuration, i.e., the FCF learns to place datapoints in the channel chart such that expected phase changes for the predicted location (based on the Doppler effect) match actually measured phase shifts.



The FCF is implemented as a neural network with 6 dense layers and a total of less than 2000 neurons.

Evaluation on Training and Test Set



Doppler Effect-based Channel Charting with 4 BS antennas only synchronized in frequency

Doppler effect-based Channel Charting outperforms the baselines [6, 7] (see paper) and provides a channel chart in the global coordinate frame. Note that the baselines do not provide the chart in the global coordinate frame and are evaluated after an optimal affine transform, i.e., the baselines are given an unrealistic advantage.

	Dataset	MAE ↓	DRMS ↓	CEP ↓	R95 ↓
Doppler CC	$\mathcal{S}_\mathrm{train}$	**1.235 m**	**1.431 m**	**1.108 m**	**2.607 m**
Baseline 1	$\mathcal{S}_\mathrm{train}$	1.653 m	1.923 m	1.495 m	3.541 m
Baseline 2	$\mathcal{S}_\mathrm{train}$	2.103 m	2.345 m	2.014 m	4.112 m
Doppler CC	$\mathcal{S}_\mathrm{test}$	1.346 m	1.540 m	1.227 m	2.757 m

Conclusion and Outlook

- Channel Charting is viable for systems with single-antenna or few-antenna BSs without time synchronization and enables localization in the global coordinate frame.
- The Doppler effect-based loss function may be combined with other CC losses to further improve performance.
- Observations should be verified with other datasets, from different environments.

References

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