Network-side Localization via Semi-Supervised Multi-point Channel Charting (SS-MPCC)

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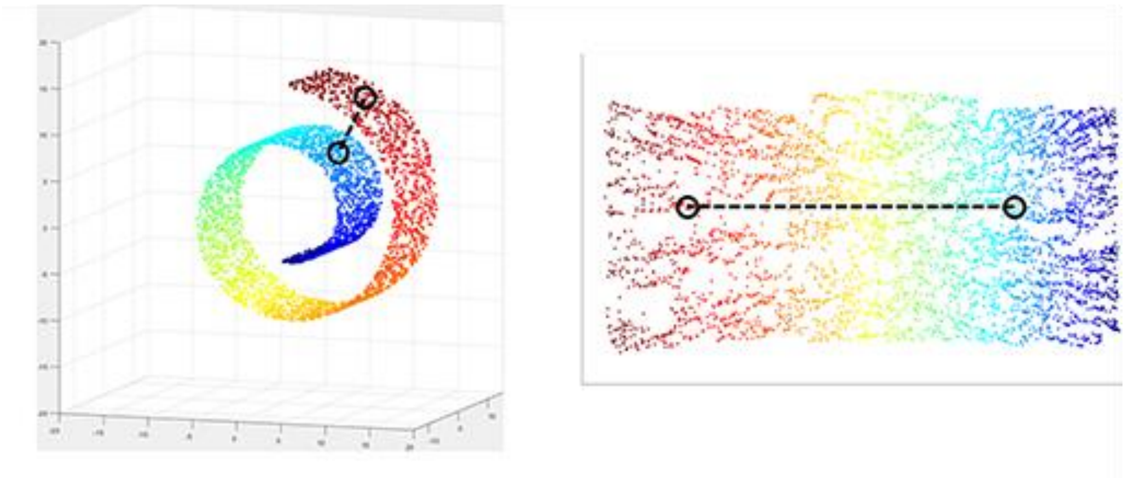
Motivation

- **Mobile location information acquisition** is fundamental in building smart cites and intelligent transportation systems
- Seamless high-precision localization, especially on the network side, is a challenging problem in **GPS-denied** environments
- High-resolution sensing functions are envisioned to be integrated in future 6G RANs, which opens up new opportunities for **high-precision positioning and tracking**

Channel Charting (CC) Principle

- **High-dimensional** Channel State Information (**CSI**) strongly dependents on UE position, which is **low-dimensional**
- **In CC**, **Manifold learning** methods are applied to map CSI data to a channel chart where nearby points correspond to nearby locations in geographical space



State of the art

- Current **network-side NR positioning** techniques require rigorous calibration or accurate synchronization among network elements
- Conventional **fingerprinting** methods require a large number of densely-sampled measurements, which scales poorly to large areas and renders automation to dynamic environments challenging
- **Absolute position information** is not available in conventional CC
- CSI at **a single BS** is considered in conventional CC

Semi-Supervised Multi-point Channel Charting (SS-MPCC)

- A new framework for large-scale network-side cellular localization
- Based on CSI samples from spatio-temporal mobile locations, a few labeled CSI samples with location information, and side information（RSRP, timestamp）
- Accurate synchronization among multiple BSs is not required

SS-MPCC Framework

STEPs:

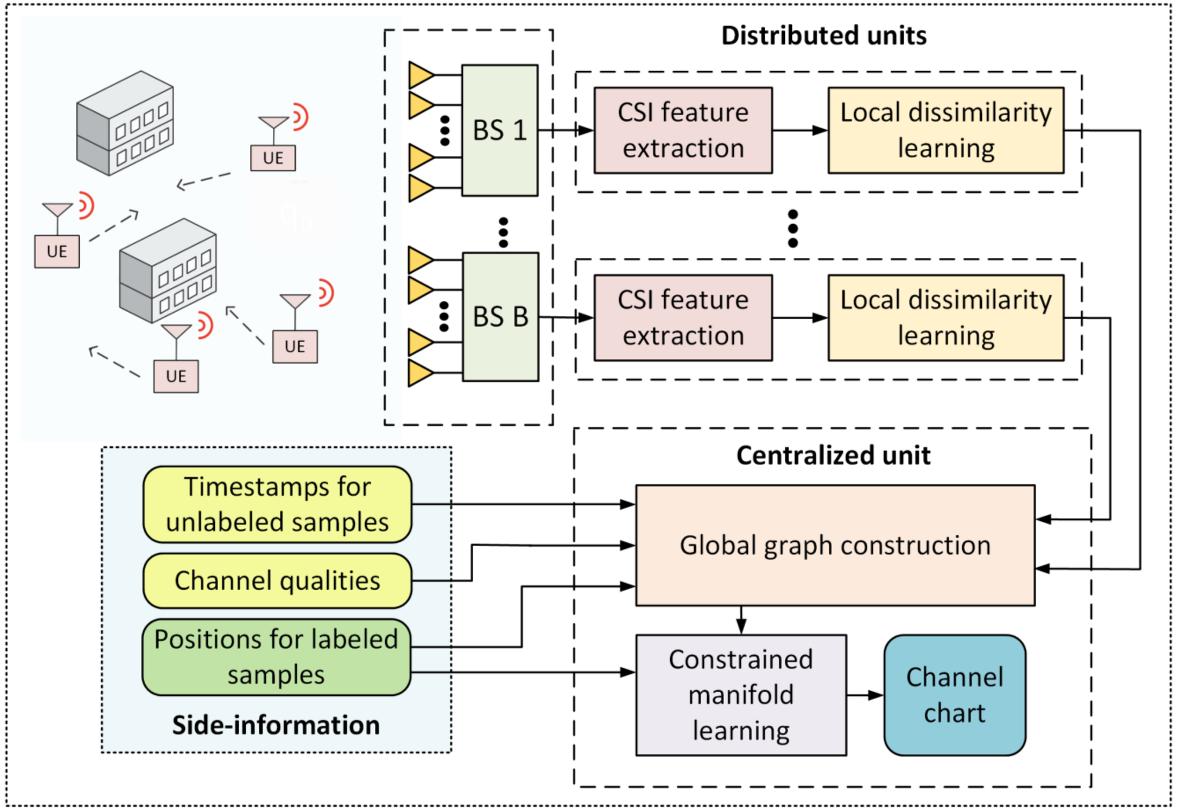
① CSI and side-information collection

② CSI feature extraction

③ Local CSI dissimilarity learning

④ Global graph construction

⑤ Constrained manifold learning



CSI and side-information collection

One CSI sample:

$$\mathbf{h}_{t,f} = \sum_{l=1}^{P} \alpha_{t,f}^{(l)} \mathbf{s}(\phi_t^{(l)}) + \mathbf{n} \Rightarrow \mathbf{C} = \mathbb{E}_f \left[\mathbf{h}_{t,f} \mathbf{h}_{t,f}^{\mathrm{H}} \right]$$

Labeled CSI date set:

$$\mathcal{L}^{(b)} = \{\mathbf{C}_1^{(b)}, \ldots, \mathbf{C}_L^{(b)}\} \text{ with } \mathbf{P} = [\mathbf{p}_1, \ldots, \mathbf{p}_L]$$

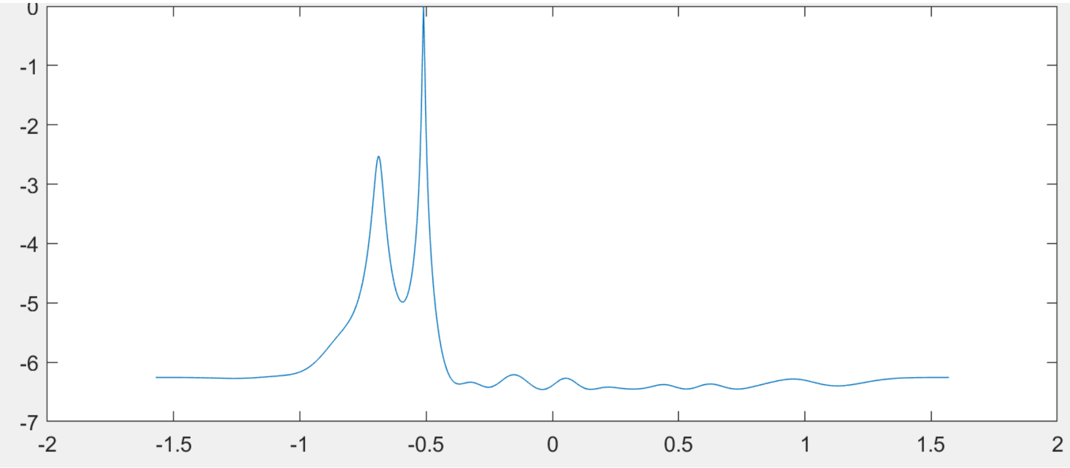
Unlabeled CSI date set:

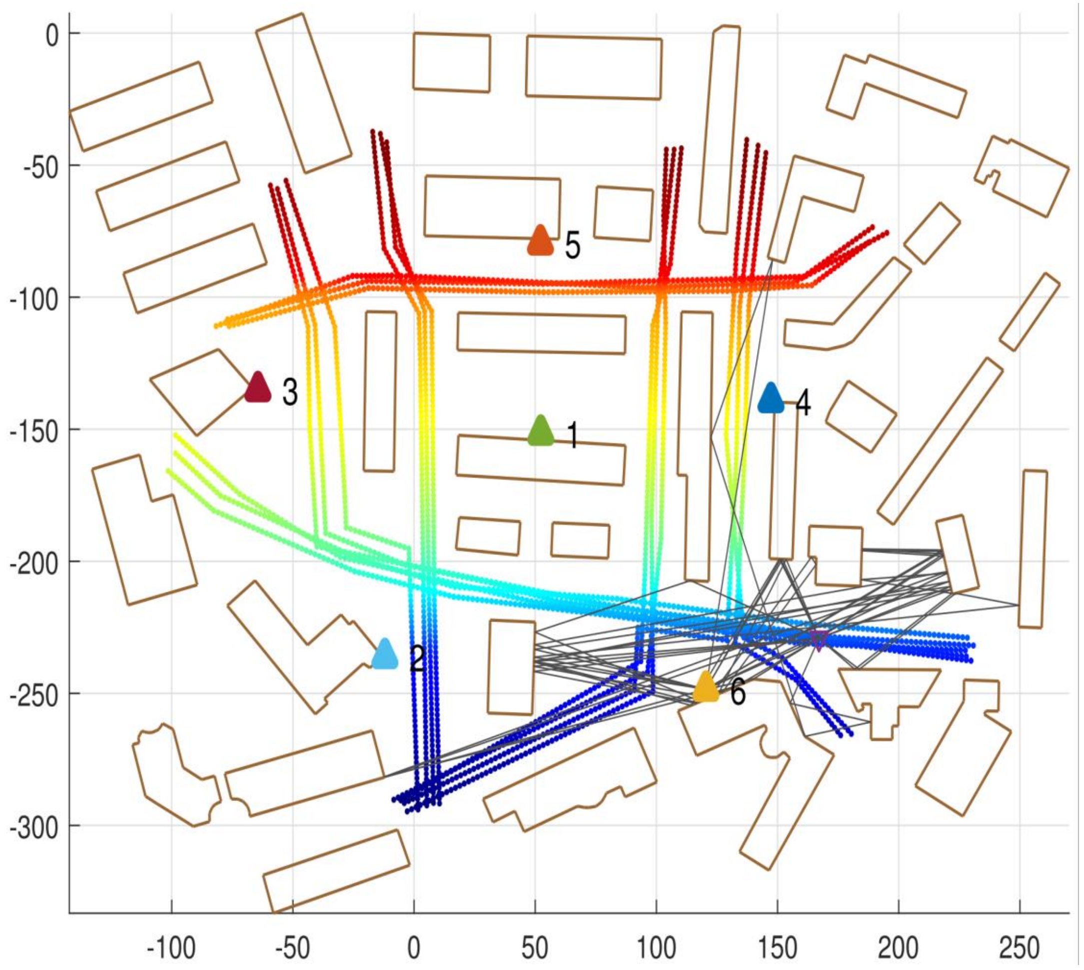
$$\mathcal{U}^{(b)} = \{\mathbf{C}_{L+1}^{(b)}, \ldots, \mathbf{C}_{L+U}^{(b)}\} \text{ with } [t_1, \ldots, t_U] \text{ and } \left\{ \gamma_n^{(b)} \right\}$$

CSI feature extraction

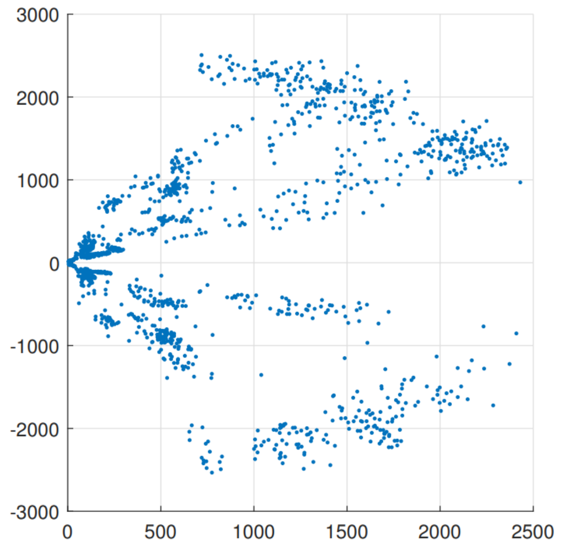
- MUSIC
- Power Angular Profile（PAP）

$$\mathbf{f} = [\lambda_1, \ldots, \lambda_{\hat{P}}, \phi_1, \ldots, \phi_{\hat{P}}]$$

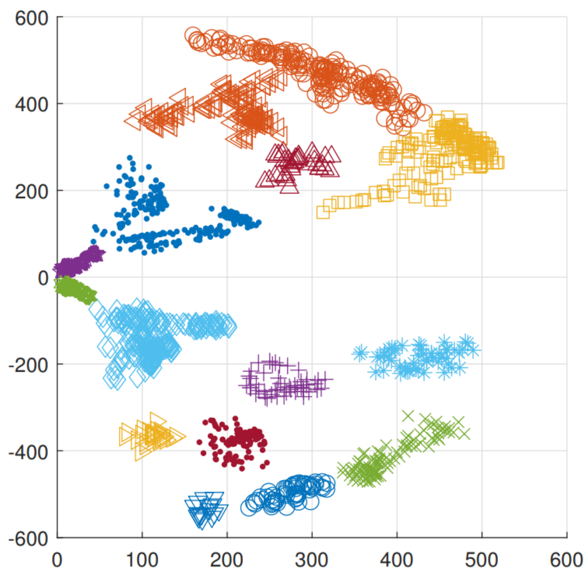




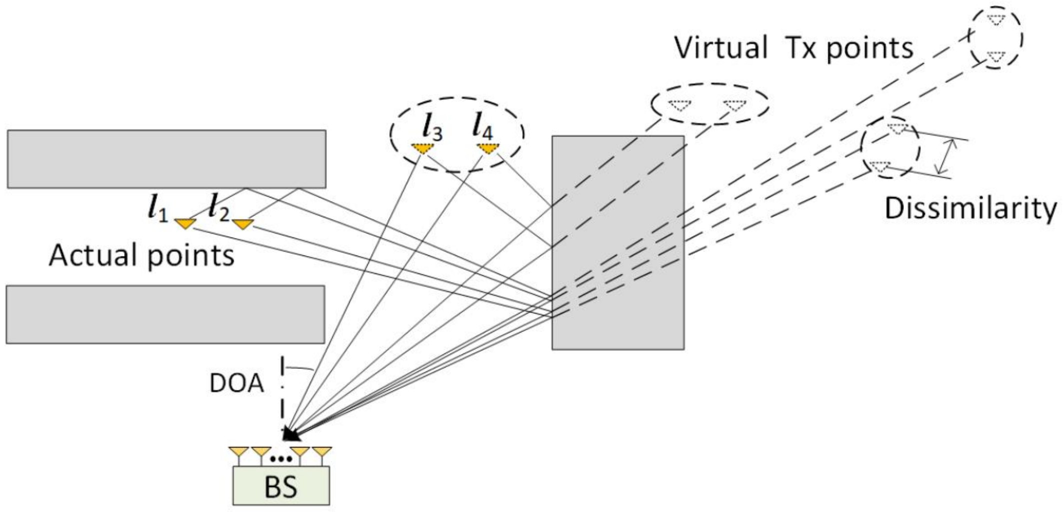
Local CSI dissimilarity learning



(a)



(b)



Point clouds of virtual Tx points：

a) without scattering loss compensation;
b) with scattering loss compensation and DBSCAN clustering.

Dissimilarity metric deduced from a virtual Tx point cloud

Global graph construction

- For each BS b, we have a local CSI dissimilarity matrix

$$\mathbf{D}^{(b)} \in \mathbb{R}^{(L+U)\times(L+U)}$$

- Construct a global dissimilarity matrix

$$D_{m,n} = \left(\sum_{b=1}^{B} v_b\right)^{-1} \sum_{b=1}^{B} v_b D^{b}_{m,m}$$

where v_b is a reliability weight

Global graph construction

- If node n is in the set of k_e nearest neighbors of node m, nodes m and n are connected in the graph
- If the timestamps t_m, t_n of two nodes m, n satisfy $|t_m - t_n| < T_{th}$, connect nodes m and n in the graph.
- Denote $\mathcal{A} = \{1, \ldots, L\}$ and $\mathcal{B} = \{L+1, \ldots, L+U\}$, if the nodes m and n are connected, then the weight $w_{m,n}$ is given by

$$w_{m,n} = \begin{cases} \alpha e^{\frac{-D_{m,n}}{\theta_s^2}} + (1-\alpha) e^{\frac{-\|\mathbf{p}_m - \mathbf{p}_n\|_2}{\theta_d^2}}, & \text{if } n, m \in \mathcal{A}, \\ \alpha e^{\frac{-D_{m,n}}{\theta_s^2}} + (1-\alpha) e^{\frac{-|t_m - t_n|}{\theta_t^2}}, & \text{if } n, m \in \mathcal{B}, \\ e^{\frac{-D_{m,n}}{\theta_s^2}}, & \text{otherwise.} \end{cases}$$

Constrained manifold learning

Objective function:

$$\boxed{f(\mathbf{Z}) = \sum_{n=1}^{L} \|\mathbf{z}_n - \mathbf{p}_n\|_2^2} + \gamma \boxed{\sum_{m=1,n=1}^{L+U} w_{m,n} \|\mathbf{z}_m - \mathbf{z}_n\|_2^2.}$$

Alignment cost

Manifold Smoothness

Tradeoff coefficient

Constrained manifold learning

$$f(\mathbf{Z}) = \sum_{n=1}^{L} \|\mathbf{z}_n - \mathbf{p}_n\|_2^2 + \gamma \mathrm{Tr}\left(\mathbf{Z}^{\mathrm{T}}\boldsymbol{\Lambda}\mathbf{Z} - \mathbf{Z}^{\mathrm{T}}\mathbf{W}\mathbf{Z}\right)$$
$$= \mathrm{Tr}\left[(\mathbf{Z} - \mathbf{Q})^{\mathrm{T}}\mathbf{J}(\mathbf{Z} - \mathbf{Q}) + \gamma\mathbf{Z}^{\mathrm{T}}\mathbf{L}\mathbf{Z}\right],$$

$$\mathbf{J} = \mathrm{diag}\left\{\underbrace{1, \ldots, 1}_{L}, \underbrace{0, , \ldots, 0}_{U}\right\}$$

$\mathbf{L} = \boldsymbol{\Lambda} - \mathbf{W}$ is the graph Laplacian

$\mathbf{Q} = [\mathbf{P}, \hat{\mathbf{P}}] \in \mathbb{R}^{(L+U)\times 2}$

Channel Chart

$$\boxed{\mathbf{Z} = (\gamma\mathbf{L} + \mathbf{J})^{-1}\mathbf{J}\ \mathbf{Q}}$$

Performance Evaluation

- Mean localization error(MLE)

$$MLE = \frac{1}{U}\sum_{n=1}^{U} \|\mathbf{z}_{L+n} - \mathbf{p}_{L+n}\|_2$$

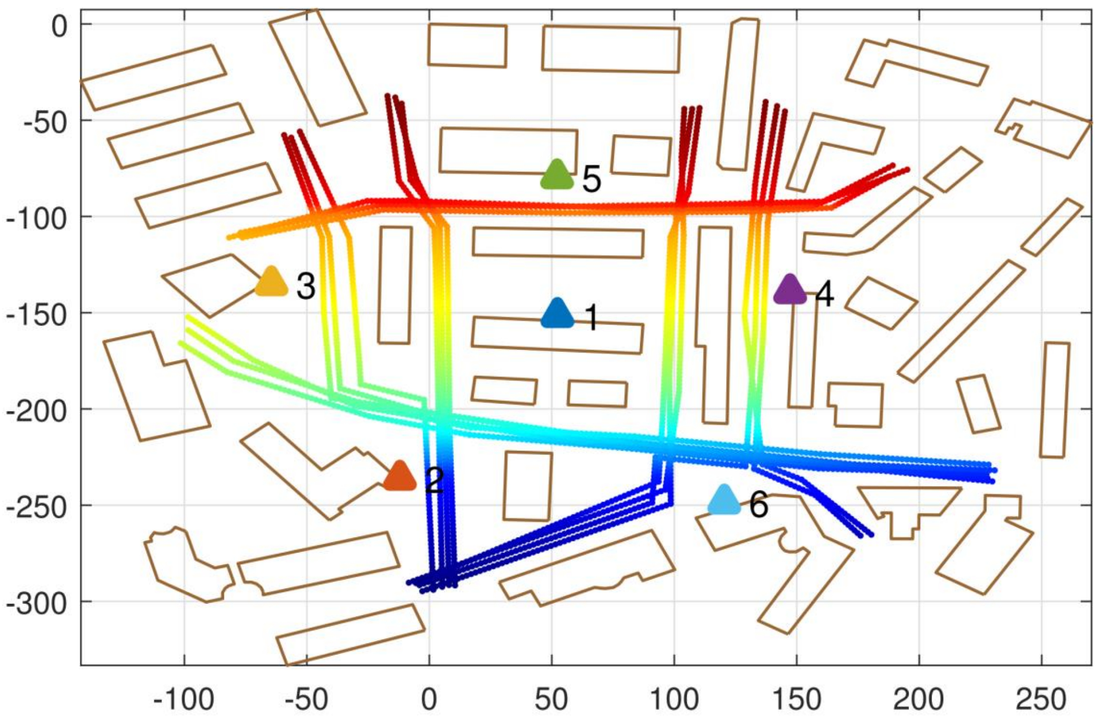
- *Kruskal's stress* (KS)

$$KS = \sqrt{\frac{\sum_{n,m}(\delta_{n,m} - \beta d_{n,m})^2}{\sum_{n,m}\delta_{n,m}^2}}$$

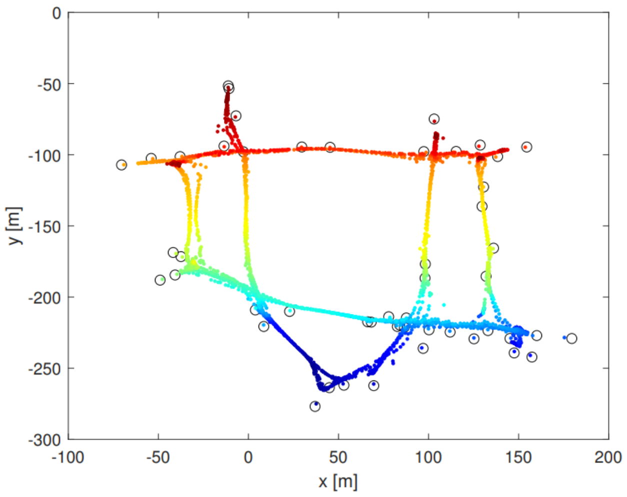
- Trustworthiness(TW) and continuity (CT)
  - TW and CT have values in [0 1] and larger values imply better preservation of neighborhood relationship

Simulated Urban mmWave Cellular Network

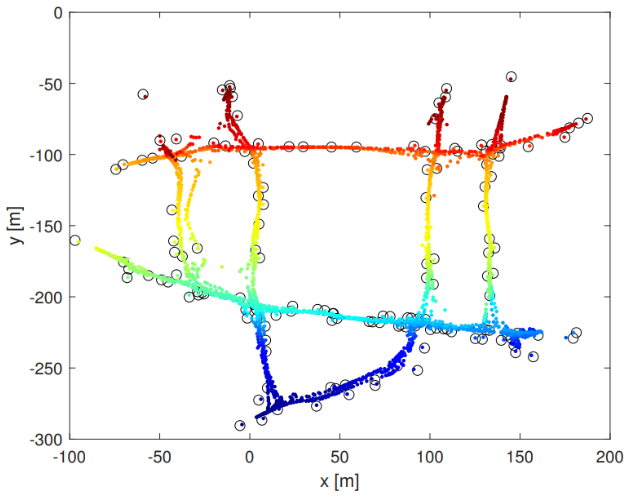
- GIS map data from OpenStreetMap (OSM)
- 6 BSs with ULAs, each has M = 16 elements
- A ray-tracing channel model is used to generate the multi-path channels
- The carrier frequency is 28 GHz, system bandwidth is 256 MHz with 128 OFDM subcarriers
- UEs transmit reference signals with a fixed power of 23 dBm
- UEs move along the roads with a average speed of 5 meters per second
- We collect 3000 CSI samples from UE traces



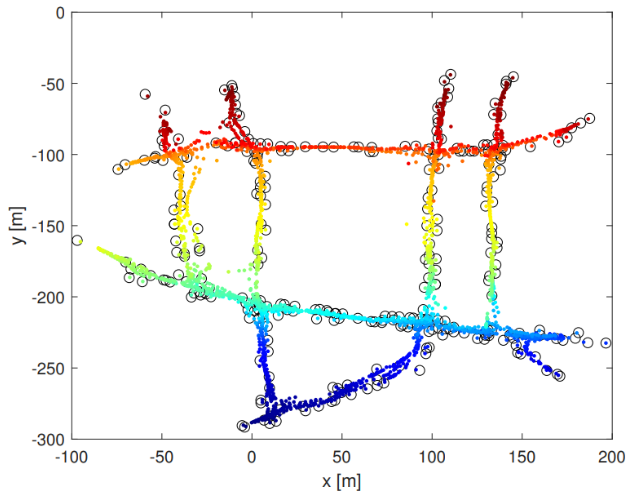
SS-MPCC Performance



(a) $L = 50.$



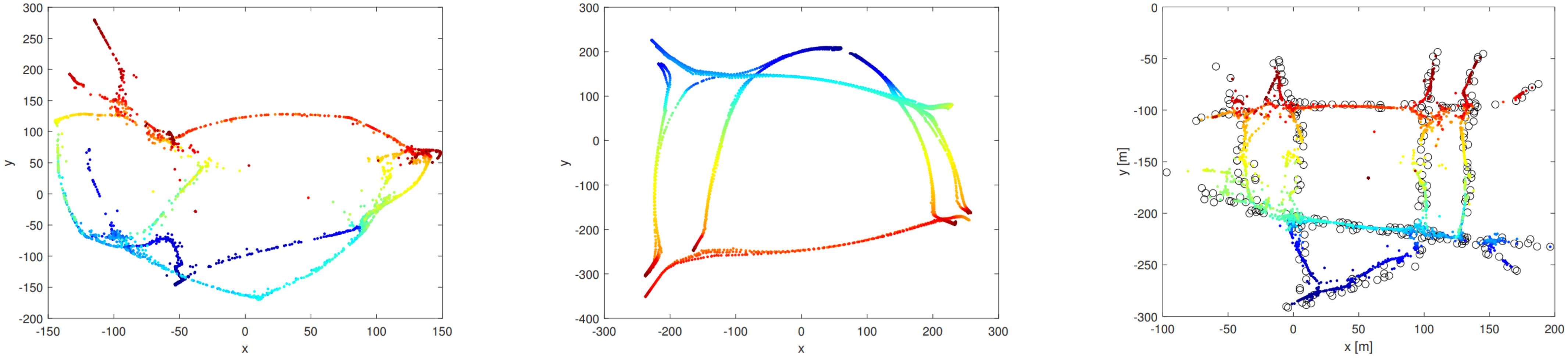
(b) $L = 150.$



(c) $L = 300.$

Visualization of the localization performance with different numbers of labeled CSI samples, number of unlabeled samples is U = 3000. The MLEs are 12.6, 6.8 and 5.6 m for L =50, 150 and 300 labeled samples. The positions for labeled samples are marked by circles.

Performance Comparison



(a) unsupervised LE.

(b) LE with timestamps.

(c) LE with 300 labeled samples and no timestamp.

Visualization of the channel charts learned by

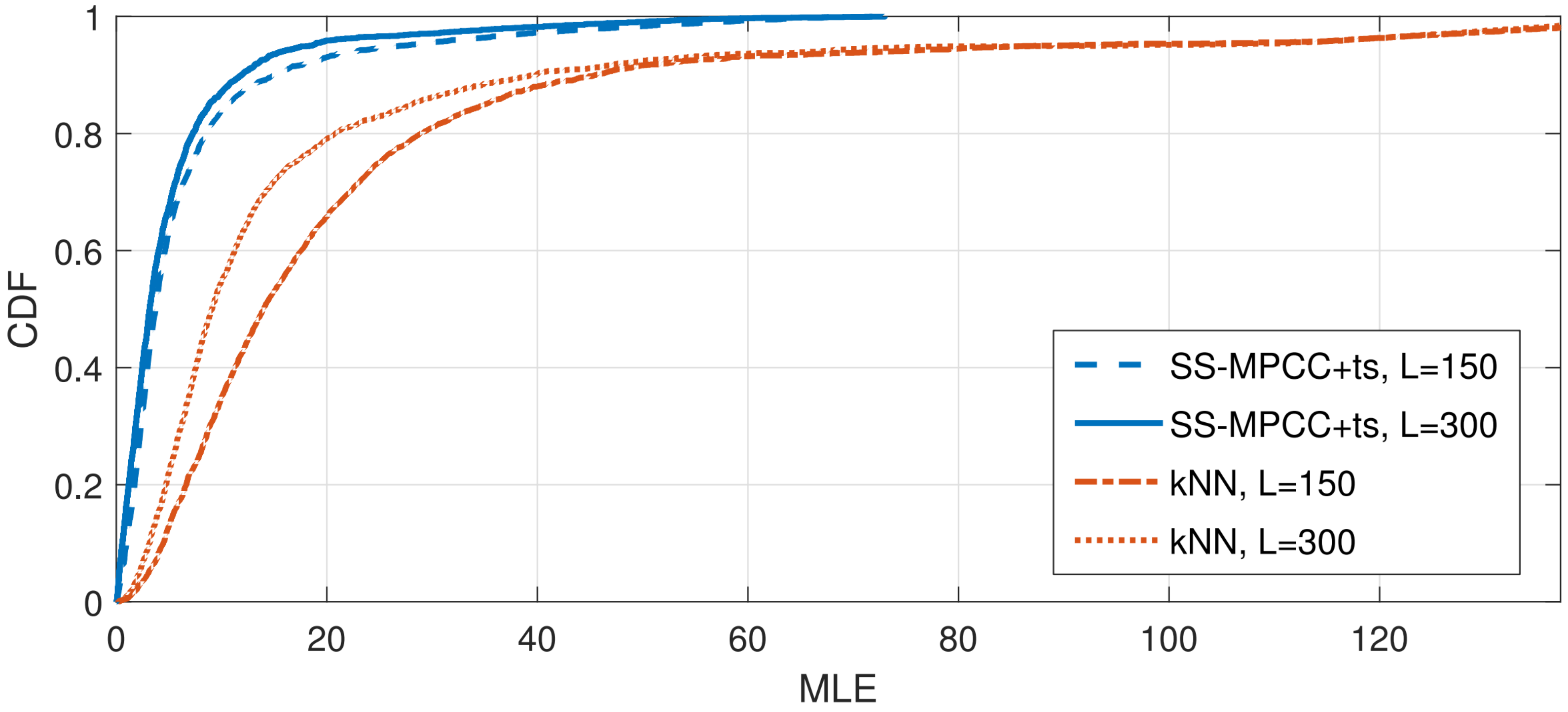
(a) unsupervised LE
(b) LE with timestamps
(c) LE with L=300 labeled samples and no timestamp.

Performance Comparison

TABLE I
PERFORMANCE COMPARISON

		kNN	MPCC	SS-MPCC		
Timestamps		$\times$	$\times$	✓	$\times$	✓
L		300	$\times$	$\times$	300	300
MLE [m]		18.8	N/A	N/A	16.7	**5.6**
KS		.2547	.3593	.1938	.2540	**.0768**
TW	$K = 50$	.9699	.9629	**.9951**	.9819	.9950
	$K = 100$	.9689	.9529	.9898	.9814	**.9956**
CT	$K = 50$	.9641	.9711	.9943	.9735	**.9968**
	$K = 100$	.9591	.9645	.9912	.9719	**.9973**

Performance Comparison



Conclusion

- Side-information can be incorporated in SS-MPCC to support large-scale network-side localization and tracking in a distributed manner.
- Multi-BS CSI feature fusion and incorporation of timestamps to increase manifold smoothness can be implemented in global graph construction based on graph Laplacian.
- SS-MPCC is able to perform large-scale network-side positioning for scenarios with realistic UE motion, even with a very small portion of labeled data.
- SS_MPCC could be implemented for varying number of BSs, with spatially sparse labeled samples, and does not require accurate network synchronization.
- Future research directions include out-of-sample mapping to locate new samples on the channel chart for real-time positioning applications, and filtering algorithms for multi-target tracking