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:

\[ h_{t,f} = \sum_{l=1}^{P} \alpha_{t,f}^{(l)} s(\phi_{t}^{(l)}) + n \]

\[ C = \mathbb{E}_f \left[ h_{t,f} h_{t,f}^{H} \right] \]

Labeled CSI date set:

\[ \mathcal{L}^{(b)} = \{ C_1^{(b)}, \ldots, C_L^{(b)} \} \quad \text{with} \quad P = [p_1, \ldots, p_L] \]

Unlabeled CSI date set:

\[ \mathcal{U}^{(b)} = \{ C_{L+1}^{(b)}, \ldots, C_{L+U}^{(b)} \} \quad \text{with} \quad [t_1, \ldots, t_U] \quad \text{and} \quad \{ \gamma_{n}^{(b)} \} \]
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

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

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

• Construct a global dissimilarity matrix

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

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

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

Objective function:

\[
f(Z) = \sum_{n=1}^{L} \|z_n - p_n\|^2_2 + \gamma \sum_{m=1, n=1}^{L+U} w_{m,n} \|z_m - z_n\|^2_2.
\]
Constrained manifold learning

\[ f(Z) = \sum_{n=1}^{L} \|z_n - p_n\|^2_2 + \gamma \text{Tr} \left( Z^T \Lambda Z - Z^T W Z \right) \]

\[ = \text{Tr} \left[ (Z - Q)^T J (Z - Q) + \gamma Z^T L Z \right], \]

\[ J = \text{diag} \left\{ \underbrace{1, \ldots, 1}_L, \underbrace{0, \ldots, 0}_U \right\} \]

\[ L = \Lambda - W \text{ is the graph Laplacian} \]

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

Channel Chart

\[ Z = (\gamma L + J)^{-1} J Q \]
Performance Evaluation

• Mean localization error (MLE)

\[ MLE = \frac{1}{U} \sum_{n=1}^{U} \| z_{L+n} - p_{L+n} \|_2 \]

• 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 an average speed of 5 meters per second
- We collect 3000 CSI samples from UE traces
SS-MPCC Performance

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

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

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Performance Comparison

Graph showing Cumulative Distribution Function (CDF) of MLE for different algorithms and parameter settings.
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.