Leveraging triplet loss and nonlinear dimensionality reduction for on-the-fly channel charting

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Context

- Channel charting (CC) aims at mapping wireless channels to a so-called chart.
- Unlike user localization, CC is an unsupervised task.
- Deep learning-based CC models are generally computationally expensive.
- Building on earlier work, we present a hybrid approach to CC:
  - Structure of a model-based neural network with few parameters.
  - Smart initialization based on an adapted channel distance measure and a manifold learning algorithm (Isomap).
  - Training using a triplet loss exploiting temporal information obtained from the channel collection process.

Problem formulation

Given a set $\{\mathbf{h}_i\}_{i=1}^{N}$ of N channel vectors, learn a function $\mathcal{F}$ that takes as input the channel vectors $\mathbf{h} \in \mathbb{C}^M$ and produces low-dimensional representations $\mathbf{z} \in \mathbb{R}^D$

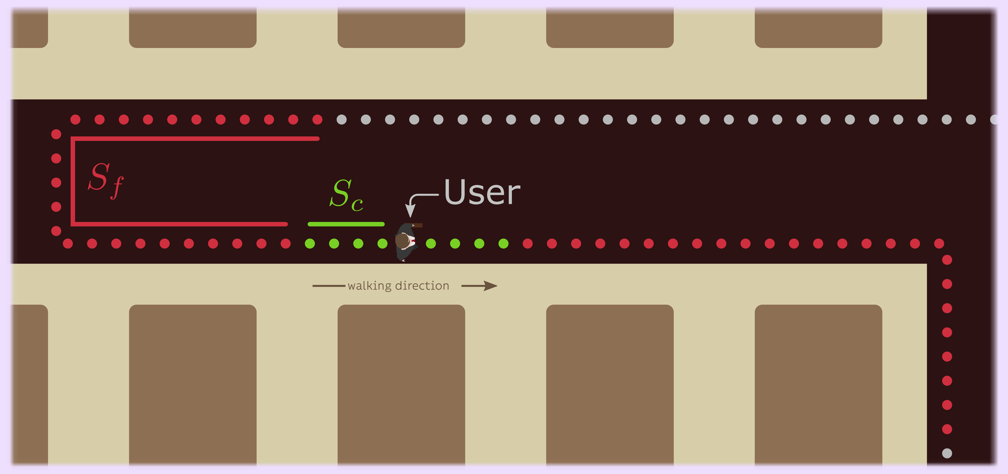
$$\mathcal{F} \colon \mathbb{C}^M \to \mathbb{R}^D$$
$$\mathbf{h}_i \mapsto \mathcal{F}(\mathbf{h}_i) = \mathbf{z}_i.$$

A successfully learned chart is a map that preserves the local geometry of the original transmit locations.

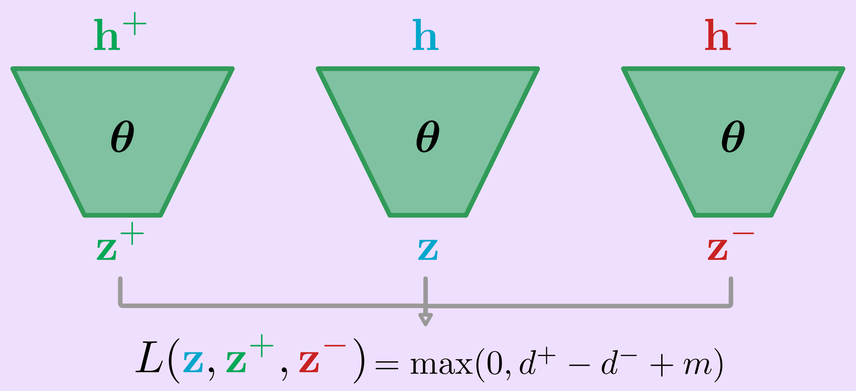
Training

Triplet construction

A user is walking along a path and their channel vectors are collected periodically at a constant rate. The time-correlated nature of channels is exploited to construct triplets of anchor, close and far examples for each channel subsequently used to train the neural network.



Triplet loss



For each triplet, we compute the projection using the hybrid encoder. A triplet loss [3] quantifies the error of the model by comparing the distance of the anchor to the close example, d^+, and its distance to the far example, d^-.

Initialization

Manifold learning

The initialization step of the hybrid encoder relies on a manifold learning algorithm, namely Isomap [1]. Supplied with a distance matrix of the channels, the algorithm computes their projections on the low-dimensional space. Accordingly, a good distance measure is key to learning a chart with adequate properties.

Distance measure

The traditional Euclidean distance is unsuitable when it comes to channel vectors. We rely on a more adequate distance that removes the sensitivity of channel vectors to the fast variations of the global phase [2]. It is defined as

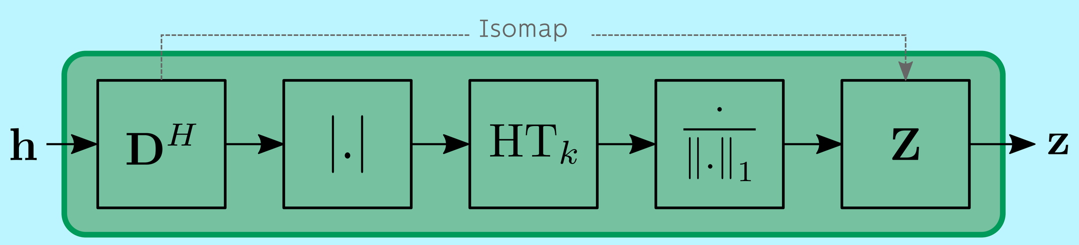
$$d^\star(\mathbf{h}_i, \mathbf{h}_j)^2 = 2 - 2\frac{|\mathbf{h}_i^H \mathbf{h}_j|}{\|\mathbf{h}_i\|_2 \|\mathbf{h}_j\|_2}.$$

Structure

Hybrid encoder

- Initialization: Select a small subset of channels $\mathbf{D}$, compute their projections using Isomap and the distance measure $\mathbf{Z}$.
- Convex combination of the projections of the k channels most correlated with the input weighted by their correlations.

This algorithm is implemented in the form of a neural network where the leanable weights are matrices $\mathbf{D}$ and $\mathbf{Z}$.

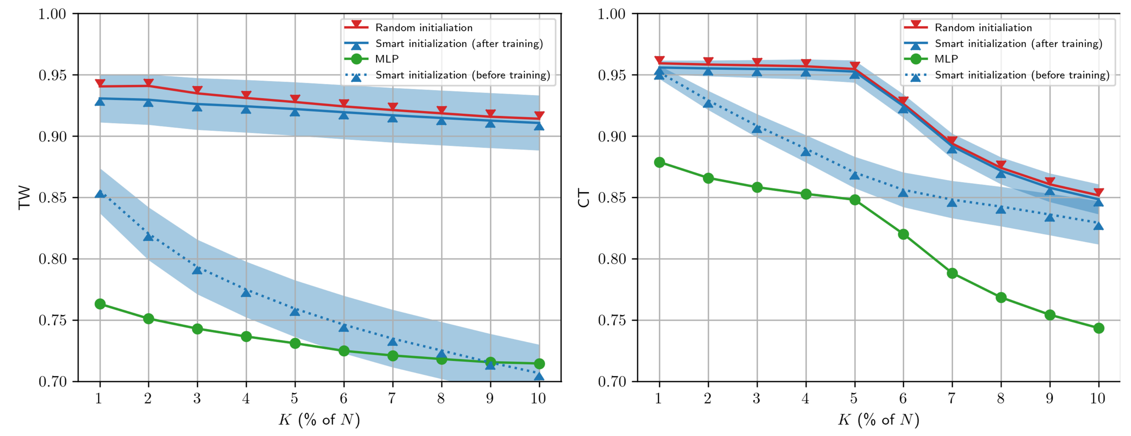


Experiments

We compare 4 versions of the proposed model:
- A generic MLP.
- The hybrid encoder where $\mathbf{D}$ (and subsequently $\mathbf{Z}$) are generated randomly.
- The hybrid encoder before training.
- The hybrid encoder after training.

Models are compared in terms of trustworthiness (TW) and continuity (CT).
Evaluation is performed on the DeepMIMO dataset ('O1' scenario) [4]. 5910 MIMO channels (UPA 8x8, 3.5GHz, 16 subcarriers, 20MHz BW) are generated, 100 of which are used to populate matrix $\mathbf{D}$.

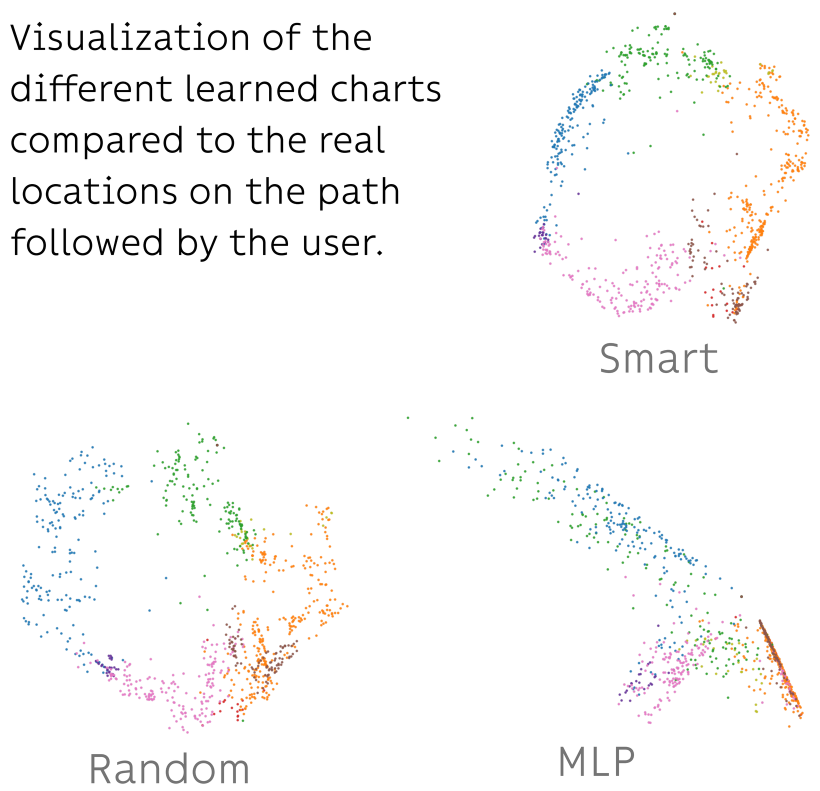
Results



We evaluate multiple instances of the smartly initialized and trained model where a different subset of channels is selected each time to construct $\mathbf{D}$. The blue area shows the variance across the evaluations.

Results show that the hybrid model smartly initialized and trained perfoms better than both the MLP and the untrained version. It also perfoms better than the randomly initialized version for some configurations of matrix $\mathbf{D}$.

Visualization of the different learned charts compared to the real locations on the path followed by the user.



Perspectives

- In-depth analysis of CC when applied to less complex scenarios (e.g. LoS, single path, etc.).s
- Improve the initialization procedure of $\mathbf{D}$ by developping an algorithm that picks the optimal subset of channel vectors.
- Improve triplet construction by keeping the more meaningful triplets with regard to model training.
- Investigate the impact of each hyperparameter.
- Explore CC applications: precoding, user localization, resource allocation, etc.

References

[1] J. B. Tenenbaum, V. de Silva, and J. C. Langford, “A Global Geometric Framework for Nonlinear Dimensionality Reduction,” Science, vol. 290, Art. no. 5500, Dec. 2000.
[2] L. Le Magoarou, “Efficient Channel Charting via Phase-Insensitive Distance Computation,” IEEE Wireless Commun. Lett., vol. 10, no. 12, pp. 2634–2638, Dec. 2021.
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[4] A. Alkhateeb, “DeepMIMO: A Generic Deep Learning Dataset for Millimeter Wave and Massive MIMO Applications,” in Proc. of Information Theory and Applications Workshop (ITA), San Diego, CA, Feb. 2019, pp. 1–8.