Mobility-Induced Graph Neural Network for Radio-Based Indoor Positioning

Kyuwon Han, Seung Min Yu, Seong-Lyun Kim, and Seung-Woo Ko

***Abstract*—In this paper, we propose an algorithm called *Graph CDA*, which combines GNN and Combinatorial Data Augmentation (CDA) method. The main idea behind our proposed algorithm is utilization of a user's mobility-induced graph and self-supervised learning techniques. As a result, the proposed algorithm has reduced the average RMSE 48.9 percent in the simulation compared to CDA method.**

***Index Terms*—Indoor positioning, Graph neural network, Data augmentation, Self-supervised learning**

I. Proposed method: Graph CDA

Consider a scenario in which a user is moving through a specific space over time. In this space, the user measures ranging distances from N points to M access points (APs) while moving. These N points are defined as nodes, and their corresponding node features are denoted as F, obtained from the preliminary estimated locations (PELs) provided by CDA. This graph structure can be represented by an ordered pair $G = (V, E)$ with node feature F, where V is a set of nodes, and E is the representation of edges linked with pairs of nodes. We put the graph G into a a Graph Convolution Network (GCN). The k-th layer's vector of the GCN is

$$\mathbf{h}_k = \mathrm{ReLU}(\hat{\mathbf{A}} \cdot \mathbf{h}_{k-1} \cdot \mathbf{W}_{k-1}), \tag{1}$$

where $\mathbf{h}_1 = F$, $\hat{\mathbf{A}} = \mathbf{D}^{-\frac{1}{2}}\mathbf{A}\mathbf{D}^{-\frac{1}{2}}$, and $\mathbf{D}$ is a degree matrix $\mathbf{D} = \mathrm{diag}\{d_1, d_2, ..., d_N\}$ with $d_i = \sum_{j=1}^{N} a_{ij}$. The adjacency matrix $\mathbf{A}$'s components, denoted as a_{ij}, are defined as:

$$a_{ij} = \begin{cases} 1 & \text{if } |\tau_i - \tau_j| \leq \Delta, \\ 0 & \text{otherwise,} \end{cases} \tag{2}$$

where τ_n is a instant when the node n requests the ranging. The loss function f to optimize the GCN is

$$f = \arg\min_{\mathbf{W}} \sum_{n \in \mathcal{S}} \|y_n - x_n\|^2, \tag{3}$$

where y_n is a output of network and x_n is a corresponding ground-truth position. $\mathbf{W}$ is a set of weights consists of f and $\mathcal{S}$ is a set of known ground-truth position's index. We expand (3) by utilizing the self-supervised learning loss as below:

$$f = \arg\min_{\mathbf{W}} \sum_{n \in \mathcal{S}} \|y_n - x_n\|^2 + \sum_{n \in \mathcal{S}^c} \|y_n - \hat{x}_n\|^2, \tag{4}$$

where $\hat{x}_n$ is a estimated user position by the CDA method. If the $|\mathcal{S}|$ goes 0, (3) becomes fully self-supervised learning.

II. Performance verification

We conducted a performance comparison among three algorithms: the proposed method, the CDA method outlined in [1], and the GCN-based algorithm described in [2], using a simulation. For both the Graph CDA and GCN algorithms, results vary depending on the initial starting point. Therefore, after 100 iterations, the average of the Root Mean Square Error (RMSE) was computed for the results. In our simulation, we positioned 20 APs randomly within a $30\text{m} \times 30\text{m}$ area and installed a $6\text{m} \times 6\text{m}$ square obstacle at the center. The user traversed a total distance of 150 meters with the 1m/s and took a ranging measurement from all APs every 1 second. We modeled the ranging error as a Gaussian distribution $N(0, 0.5)$ when there were no obstacles between the user and an AP. In other cases, the error was modeled as the summation of a Rayleigh-distributed with $\sigma = 3$ and a Gaussian distribution with $N(1, 0.5)$. We set $\Delta = 2$ seconds for the adjacency matrix.

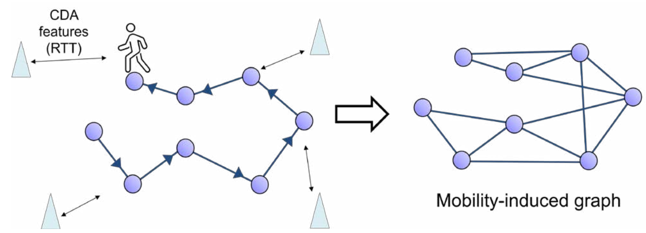

Fig. 1. We represent the user's location as a node and generate the user's mobility as an adjacency matrix and convert the ranging measurements into node features through the CDA method.

TABLE I
The RMSE of each method

Method	CDA	GCN	Graph CDA	Graph CDA w/ SS
RMSE (m)	1.0784	0.8703	0.6689	0.5507

We stacked two layers of the GCN and evaluated the proposed Graph CDA and the comparison groups in an environment where $|S| = 50$. The results are presented in Table I. The average RMSE of the proposed Graph CDA with self-supervised learning (SS) was 0.5507 [m], a reduction of 48.9 percent compared to CDA and 36.7 percent compared to GCN. Introducing self-supervised learning caused a slight improvement in performance for the proposed Graph CDA, decreasing by 17.6 percent from 0.6689 to 0.5507, which are using the loss function (3) and (4), respectively.

III. Concluding remarks

In this paper, we introduce a GNN-based learning approach that utilizes a user's mobility-induced graph for ranging-based positioning. We expand our algorithm by utilizing the semantic knowledge of mobility in a fully self-supervised manner and are currently verifying it through real-world datasets. Our algorithm has the potential for further performance enhancement by integrating other sensor fusion techniques.

References

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K. Han and S.-L Kim are with Yonsei University, Seoul, Korea. S. M. Yu is with the Korea Railroad Research Institute, Uiwang, Korea. S.-W. Ko is with Inha University, Incheon, Korea (email: swko@inha.ac.kr).