

RSSI とクラウドセンシングに基づく屋内測位のためのドメイン適応グラフ畳み込みネットワーク

Domain Adversarial Graph Convolutional Network Based on RSSI and Crowdsensing for Indoor Localization

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Abstract

In recent years, due to the wider WiFi coverage and the popularization of mobile communication devices, the technology of indoor positioning using WiFi fingerprints has been rapidly developed. Currently, most supervised methods need to collect a large amount of data to construct fingerprint datasets, which is labor-intensive and time-consuming. To solve the problem, we proposed a novel WiDAGCN model that can be trained with a few labeled site survey data and unlabeled crowdsensing WiFi fingerprints. To comprehensively represent the topology structure of the data, we constructed heterogeneous graphs according to the received signal strength indicators (RSSIs) between the waypoints and WiFi access points (APs). We focus on the graph convolutional network (GCN) method and the representation of graph-level features, which were rarely involved in previous WiFi indoor localization studies. Then, we try to minimize the difference between the source and target domains and make full use of the unlabeled data in the target domain using the domain adversarial training scheme. A public indoor localization dataset containing different buildings was used to evaluate the performance of the model. The experimental results show that our system can achieve a competitive localization accuracy in large buildings such as shopping malls.

1 Introduction

Accurate indoor localization technology can support many smart applications sensing the environment and give users better experiences. Using existing WiFi infrastructure to build a localization system has become an attractive, cheap and convenient solution due to the ubiquitousness of indoor WiFi signals. Received Signal Strength Indication (RSSI) fingerprint are often used as inputs of the localization model. To ob-

tain a reliable dataset, it is labor-intensive and time-consuming to conduct a site survey to collect WiFi signals. Collecting data from users is a practical way to lighten the burden of the site survey. But the RSSIs can also be affected by reflection and diffraction constantly happen in indoor environment. What is more, in a multi-level building, signals from an access point (AP) can be received by devices on multiple floors, resulting in different RSSI values from the same AP. That may cause a single 2D coordinate label corresponding to multiple different features. Therefore, aligning the distribution of data from different sites or floors is necessary to get more accurate results. The other thing that may get overlooked is, for a single waypoint, the order of the RSSI should not affect the feature and result. But common methods of previous studies are designed for fixed dimensional data instances, and the neglect of the permutation invariance is not trivial. Although not on the problem of indoor localization, there have been some studies focusing on the permutation invariance of the GCN model. And with the help of graph convolutional networks (GCN), the information hidden in the topology connections between APs and way-

points can be extracted. In this research, we propose a semi-supervised WiFi Domain Adversarial Graph Convolutional Network (WiDAGCN) model and a supervised WiFi Attention Graph Convolutional Network (WiAGCN) model. Our model can be trained by a few labeled data and unlabeled crowdsensing data. In this way, we can lighten the burden of data collection and enhance the robustness of the model.

2 Methodology

2.1 Graph Construction

In this research, we use the encoded bssids as the feature of AP nodes, and the 2D coordinates as the feature of waypoint nodes. For the edges of the graph, they represent the relationship between APs and waypoints, so we can set the edge feature as the RSSI value between the starting point and the end point of the edge.

First, consider the situation of the known environment. The waypoint to predict (yellow node in Fig. 1) does not have coordinate features so we make the node a new node type. All the neighbors of the waypoint to predict are selected and added into the graph. Third, the 2nd-order neighbors are randomly selected to reduce the complexity of the graph. The situation in the unknown new environment is similar to that in the source domain, except that most of the waypoints in the target domain only have known fingerprint features and no labels. For this reason, waypoints with unknown labels are marked in the same way as waypoints to predict in the source domain. We propose a WiAGCN model and a WiDAGCN model. While GCN can express the

deep graph feature, it also guarantees the permutation invariant of the model. The structure of WiAGCN is shown in Fig. 2.

Three different level features are concatenated to obtain the final regression result. However, it is difficult for this WiAGCN model to use few labeled data to train a robust model. Therefore, we propose the WiDAGCN model, which can be trained by the semi-supervised method, making full use of unlabeled data. The structure of the WiDAGCN model is shown in Fig. 2. The shallow layers of WiDAGCN is same as the WiAGCN model, so that we can use the pretrained model as a reliable initial condition. The difference is that the adversarial method is used to minimize the difference between the source and target domains. We expect that the model can extract some cross-domain features, make the regressor can give accurate positioning results while the domain discriminator can not identify the domains from which data come from.

3 Results

Traditional algorithms without neural networks, KNN and decision tree are implemented to compare the accuracy. We also implement models of previous indoor localization systems, fully-connected network with shortcut connections (FCSC) and DCNN in our environment. When use 40% labeled data (220~702 pieces of data) to train the model, the FCSC can achieve an accuracy of 8.88 meters and DCNN can achieve an accuracy of 25.72 meters. The results show that it is difficult to train a reliable

large-scale deep neural network in the case of sparse data. It is worth mentioning that graph-based methods achieve the best results, and our WiAGCN/WiDAGCN outperforms general GCNs. On the whole, the positioning accuracy is basically improved after the adversarial component is added. Our WiAGCN can achieve an accuracy of 5.32 meters while WiDAGCN can achieve 4.84 meters.

Table 1: Impact of labeled training set size on average errors (unit: m)

Model	Size of Labeled Training Dataset					
	1%	5%	10%	20%	30%	40%
KNN	25.46	22.87	22.49	22.17	21.91	21.45
Decision Tree	24.84	16.41	14.63	12.51	11.42	11.06
FCSC	20.17	20.13	18.84	10.06	9.41	8.88
DCNN	29.63	28.95	28.29	26.94	26.21	25.72
Deep Sets	13.45	9.39	8.22	6.03	5.61	5.62
GCN	10.05	7.80	6.95	6.22	5.83	5.56
WiAGCN (Proposed)	9.67	7.35	6.58	5.97	5.58	5.32
WiDAGCN (Proposed)	9.09	7.59	6.04	5.67	5.20	4.84

4 Conclusion

We provide a new indoor localization system based on semi-supervised graph convolutional network. Our WiDAGCN model can employ both labeled and unlabeled data, which allows us to make full use of WiFi signal records collected from user’s devices without the need to give the ground truth labels. In addition, our supervised WiAGCN also performs well while the labeled data are insufficient.

We test the performance of models with permutation invariance, and the result shows that permutation invariant features can indeed improve the accuracy of the indoor localization problem. What is more, we aggregate the whole subgraph features to get graph-level permutation invariant representations.

Few studies have focused on graph-based indoor localization in large practical application scenarios. We train and test our model on a large-scale indoor location public dataset and achieve remarkable performance. With a few or dozens of labeled data, room-level positioning accuracy can be achieved in a large-scale building.

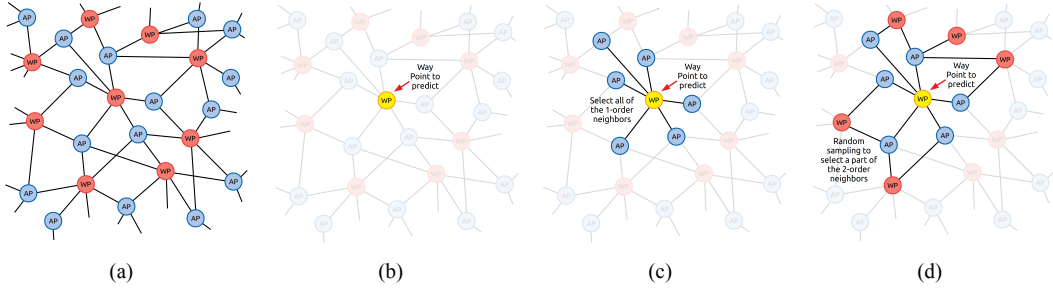


Figure 1: The steps of subgraph construction. (a) Construct the large graph. (b) Select the waypoint node to predict and mask the feature of this node. (c) Select the 1st-order neighbors of the waypoint to predict. (d) Select the 2nd-order neighbors of the waypoint to predict.

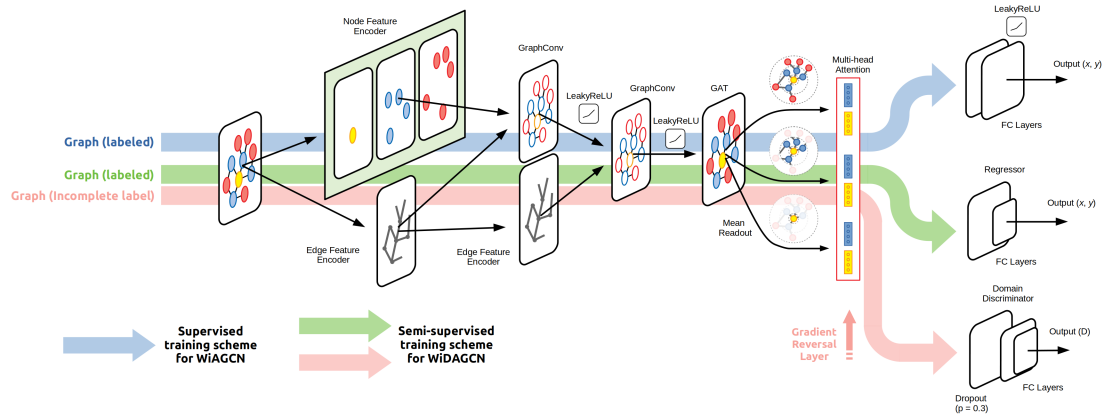


Figure 2: The structure of WiAGCN/WiDAGCN model. The part where the blue line passes through represents the structure of WiAGCN, and the part where the green line and pink line pass through represents the structure of WiDAGCN.