Demo: WiMU: Real-time Indoor Localization via Wi-Fi/IMU Fusion with Minimal Site Survey

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Abstract

Due to the ubiquitous deployment of WiFi infrastructure, numerous studies have employed WiFi RSSI fingerprinting for indoor localization. However, fingerprinting methods necessitate labour-intensive site surveys for fingerprint collection and location annotation. To address these limitations, we propose WiMU, a real-time indoor localization system that integrates WiFi and inertial measurement unit (IMU) data to enhance the real-time performance and accuracy of localization. WiMU operates on commodity WiFi infrastructure without the need for additional hardware, leveraging crowd-sourced user trajectories to learn spatial representations of access points (APs). These representations can be fine-tuned with minimal labeled data to support effective localization. Extensive evaluations demonstrate that WiMU reduces the cost of building an indoor localization system while ensuring high positioning accuracy, paving the way for the large-scale deployment of real-time indoor localization systems.

Keywords

Indoor Localization, Real-time Localization, WiFi RSSI Fingerprinting, Sensor Fusion, Graph Neural Network

1 Introduction

Indoor localization has gained significant attention in recent years. With the wide deployment of WiFi technology, many works leverage existing WiFi infrastructure for indoor localization. Among existing approaches, WiFi Received Signal Strength Indicator (RSSI) fingerprinting stands out as the only method that relies on no additional infrastructure. However, conventional fingerprinting requires extensive site surveys to gather labeled fingerprints.

Unlike prior studies, we introduce WiMU, a real-time localization system that fuses WiFi and IMU data with a more practical site survey setting. We assume that large amounts of unlabeled trajectories are easily accessible when users move freely through the buildings. Each trajectory contains several waypoints with WiFi RSSI readings, noted as reference points (RP). Though the waypoints' locations are unknown, the IMU data from the mobile devices can provide rich proximity information. Crucially, distances between RPs and access points (APs) can be derived from RSSI measurements, whereas inter-RP distances can be estimated via inertial sensor data. WiMU utilizes such relative location information to build an AP proximity graph and trains a graph neural network (GNN) to generate latent representations for each AP. These AP representations are then aggregated based on RSSI weighting to synthesize RP representations. Finally, a lightweight regression model is trained to map the RP representations to physical coordinates only using a small set of labeled RPs. However, the commodity mobile phones limit the sampling frequencies of WiFi. Thus, a Pedestrian Dead Reckoning (PDR) algorithm is applied to compensate for the intermediate location predictions. Lastly, the results from the WiFi module and the PDR algorithm are fused together by a particle filter for more accurate location estimation.

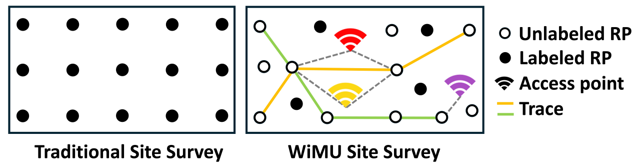

Figure 1: Comparison between traditional and WiMU site survey settings

We implement WiMU and evaluate it on a large-scale Microsoft indoor location and navigation dataset [1]. Extensive experiments show that WiMU achieves the lowest localization errors in large commercial buildings compared with SOTA baselines.

2 System Design

Figure 2 illustrates WiMU. It begins by constructing an AP-RP graph from trajectory data, then refining the graph into an AP proximity graph. Using a GNN model, AP representations are derived and aggregated to form RP representations. These labeled RPs and their locations train a regression model. These models remain frozen for online inference. Besides, the PDR algorithm leverages IMU data to predict the location from the previous location. Lastly, two predictions are fused to obtain a more accurate estimation.

Graph Intialization. The AP-RP graph is constructed from trajectory data, where nodes represent APs and RPs, and edges denote the distance between them. For AP-RP edges, distances are estimated using Wi-Fi RSSI via the Log-distance Path Loss (LDPL) model. RP-RP distances are estimated using IMU data with the PDR algorithm.

Graph Refinement. Subsequently, we utilize the AP-RP graph to obtain distances between APs and refine it to an AP graph, where each node refers to an AP and each edge represents the

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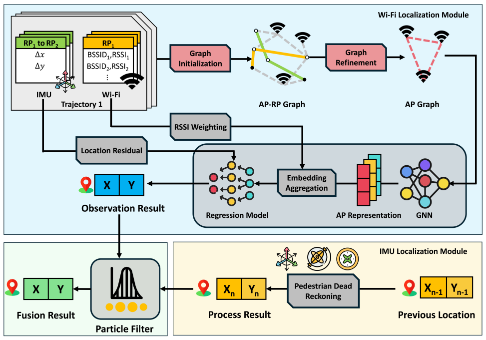


Figure 2: WiMU overview.

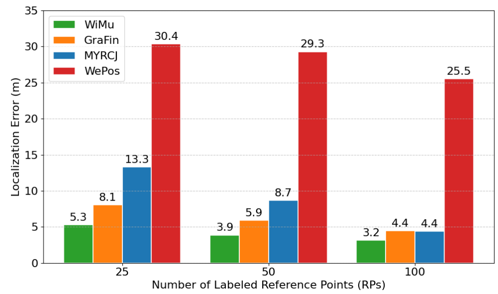


Figure 3: Localization error with different amount of labeled RPs.

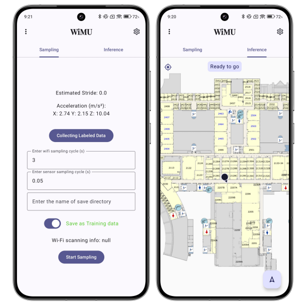


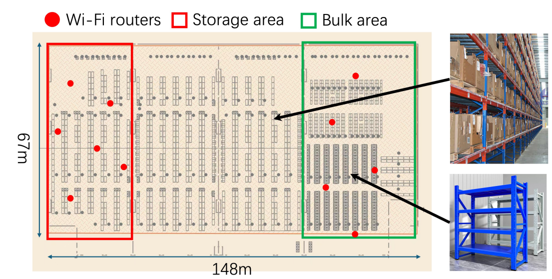
Figure 4: User interface of WiMU App.

distance between two APs. The distance between APs is computed by averaging the path lengths of all possible paths between them in the AP-RP graph.

Model training. With the refined AP graph, a variational graph auto-encoder (VGAE) and a multi-layer perceptron (MLP) work together to learn AP representations and predict locations. The VGAE creates node representations and reconstructs the graph through self-supervised training. Subsequently, these representations average to generate the RPs' representation. These representations, along with location labels, are used to train an MLP. During the pre-training stage, the models are trained using unlabeled data and the AP graph, with the objectives of reconstructing the AP graph and predicting the displacements of unlabeled RPs. Subsequently, in the fine-tuning stage, the models are adjusted to predict locations using labeled RPs.

Particle filter. In addition to WiFi prediction, the PDR algorithm uses previous location data and IMU readings to estimate locations. These results are then combined with WiFi predictions using a particle filter to enhance accuracy. In addition, magnetic field strengths, mobile phone postures, and AP RSSI are measured to adjust the parameters of the filter dynamically.

(a) Test area on a university campus.



(b) Test area in a logistic warehouse.

Figure 5: Two real-world deployment scenarios.

3 Evaluation and Demonstration

We implement WiMU and conduct extensive experiments on 30 buildings (each >10,000 m^2) selected from the Microsoft Indoor Navigation dataset [1], comparing it with three baselines [2–4]. Figure 3 shows that WiMU improves by at least 29% compared to GraFin, another GNN-based localization system. It also significantly outperforms MYRCJ, the best RSSI fingerprinting-based method in the competition. Additionally, WiMU demonstrates robustness against a reduction in the number of RPs, with its localization error increasing by only 2.1 m, surpassing the performance of other baselines.

For demonstration, we implement an Android app for data sampling and online inference, with the user interface shown in Figure 4. The app and records WiFi RSSI and IMU readings as users move indoors. It also enables the data collector to label RPs by pinpointing their locations on the map. After data collection, the data is sent to a GPU server for model training. During online inference, the app transmits real-time WiFi RSSI data to the server for location prediction. As illustrated in Figure 5, WiMU was evaluated in both a university campus and a warehouse setting. In the shaded region of Figure 5a, we gathered 15 unlabeled trajectories and 35 labeled RPs within a 2-hour period, achieving an average localization error of 4.6 m. In the warehouse, we collected 29 trajectories and 45 labeled RPs in the storage area, and 62 trajectories with 60 labeled RPs in the bulk area, resulting in average localization errors of 4.61 m and 5.22 m respectively.

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