

Graph-Based Floor Separation Using Node Embeddings and Clustering of Wi-Fi Trajectories

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ABSTRACT Vertical localization, particularly floor separation, remains a major challenge in indoor positioning systems operating in GPS-denied multistory environments. This paper proposes a fully data-driven, graph-based framework for blind floor separation using only Wi-Fi fingerprint trajectories, without requiring prior building information or knowledge of the number of floors.

In the proposed method, Wi-Fi fingerprints are represented as nodes in a trajectory graph, where edges capture both signal similarity and sequential movement context. Structural node embeddings are learned via Node2Vec, and floor-level partitions are obtained using K-Means clustering with automatic cluster number estimation.

The framework is evaluated on multiple publicly available datasets, including a newly released Huawei University Challenge 2021 dataset and a restructured version of the UJIIndoorLoc benchmark. Experimental results demonstrate that the proposed approach effectively captures the intrinsic vertical structure of multistory buildings using only received signal strength data.

By eliminating dependence on building-specific metadata, the proposed method provides a scalable and practical solution for vertical localization in indoor environments.

INDEX TERMS community detection, floor detection, graph-based clustering, indoor positioning, machine learning, node2vec, RSSI, vertical localization, Wi-Fi fingerprinting.

I. INTRODUCTION

INDOOR positioning has garnered significant attention in recent years, driven by rapid technological advances and the growing reliance on indoor location-based services. As urbanization accelerates, a substantial portion of human activity now occurs within indoor environments such as shopping malls, airports, offices, and hospitals [1]. This trend has led to an increased demand for reliable and accurate indoor positioning systems (IPSs), which are essential for applications including indoor navigation, security management, asset tracking, and personalized customer services. Unlike outdoor systems that rely on Global Positioning System (GPS) signals, IPSs face unique challenges due to signal obstructions caused by walls, furniture, and complex architectural layouts [2].

A particularly complex issue in indoor positioning is vertical localization—determining a user's floor level in multistory buildings. Signal leakage between floors, especially with Wi-Fi and other radio signals, can lead to overlapping

signal patterns, making it difficult to accurately identify the correct floor. This issue is further compounded in open architectural spaces such as atriums and balconies, where signals reflect and propagate across multiple levels [3]. Environmental dynamics, user movement, and interference from nearby devices introduce additional variability, further complicating vertical positioning [4].

Among various IPS technologies, Wi-Fi fingerprinting has emerged as a prominent solution due to its low deployment cost and ability to utilize existing wireless infrastructure. This technique typically involves two phases: an offline phase, where signal strength measurements from access points are collected to build a fingerprint database, and an online phase, where real-time signals are matched against this database to estimate the user's location [5]. Despite its advantages, Wi-Fi fingerprinting is susceptible to signal fluctuation and multipath interference, which can reduce localization accuracy. To address these limitations, recent studies have incorporated

machine learning models that improve robustness to signal noise and variability [6], [7].

In parallel, graph-based approaches are gaining traction in indoor localization due to their ability to model complex spatial and signal relationships. In these methods, Wi-Fi fingerprints are represented as nodes in a graph, while the relationships—based on signal similarity or contextual transitions like stairways and elevators—are captured by weighted edges [8]. This graph structure allows for a more nuanced representation of the indoor environment compared to traditional techniques.

In this study, we introduce a novel graph-based approach for clustering building floors using Wi-Fi fingerprint similarity. We construct a graph where each node corresponds to a Wi-Fi fingerprint, and edges are weighted based on signal distance metrics and contextual information. To extract meaningful representations from this graph, we apply Node2Vec [9], a graph embedding technique that learns low-dimensional vector embeddings of nodes. These embeddings are then clustered to distinguish between different floor levels. Our method is evaluated using multiple publicly available datasets to demonstrate robustness and generalizability across different indoor environments. In addition to the Huawei University Challenge 2021 dataset—introduced and publicly released as part of this work—we further adapt the widely used UJIIndoorLoc [10] benchmark to the floor separation problem, enabling comprehensive cross-dataset evaluation. This multi-dataset experimental design ensures that the proposed framework is not tailored to a single environment or data collection campaign, but instead captures generalizable structural properties of multistory indoor spaces. As part of this work, we preprocess and publicly release the dataset, along with our implementation code, to support further research in the community¹.

The remainder of the paper is organized as follows: Section II reviews related work; Section III presents the methodology; Section IV describes the experiments; Section V provides results and analysis; Section VI addresses the discussion; and Section VII concludes with a discussion and future directions.

II. RELATED WORK

Floor detection in multistory environments remains a pivotal challenge in indoor localization, particularly where vertical positioning accuracy is critical. A recent comprehensive survey by Mostafa et al. [11] categorizes the primary obstacles in this domain into input-level challenges, such as sensor noise and signal ambiguity, and system-level challenges, including calibration overhead and portability. While the literature presents a diverse array of sensor-based and data-driven approaches—ranging from barometric pressure sensing and Inertial Measurement Units (IMUs) to Wi-Fi RSSI analysis—robustness against environmental variability remains an open problem. This section critically reviews prominent

methodologies and delineates the specific advantages of Wi-Fi RSSI-based clustering, which constitutes the backbone of our proposed framework.

A. BAROMETRIC PRESSURE, IMU, AND MULTIMODAL APPROACHES

Barometric pressure sensors are frequently employed for vertical localization due to the inverse correlation between atmospheric pressure and altitude. Huang et al. [12] demonstrated that fusing barometric data with Wi-Fi and accelerometer signals can achieve high accuracy. Similarly, the “pressure-pair” method proposed by Yi et al. [13] leverages pressure variations alongside smartphone sensors to refine altitude estimation. However, as noted in recent reviews [11], these systems inherently suffer from pressure drift caused by environmental fluctuations, often necessitating fixed reference sensors which limit scalability [14].

Complementing pressure sensors, Inertial Measurement Units (IMUs) facilitate vertical tracking by capturing kinematic patterns. To overcome the limitations of individual sensors, recent studies have shifted towards multimodal fusion. Zhou et al. [15] proposed a robust localization framework integrating Wi-Fi fingerprints, magnetic field data, and visual features. Their approach utilizes a fusion mechanism to compensate for the instability of single-source signals, such as magnetic interference or visual occlusion [15]. Despite these improvements, IMU-based and multimodal fusion methods often require complex calibration and high computational resources on mobile devices, limiting their generalization in diverse scenarios [11], [14].

B. WI-FI RSSI-BASED FLOOR DETECTION

In contrast to hardware-dependent sensor methods, Wi-Fi RSSI-based approaches exploit the ubiquity of existing wireless infrastructure. However, these methods face what Mostafa et al. describe as “Signal Space Ambiguity,” where complex structures like atriums cause signals to propagate freely between floors [11].

Fingerprinting techniques are widely adopted but face scalability and stability issues. To address scalability, Kim et al. [16] proposed a hierarchical deep neural network utilizing Stacked Autoencoders (SAE) to extract latent features. Recognizing the sequential nature of user movement, Elesawi and Kim [17] advanced this hierarchical approach by integrating Recurrent Neural Networks (RNNs), which capture temporal dependencies in RSSI data. Building on these concepts, Li et al. [18] introduced “Linked Deep Neural Networks” (LDNN) with stagewise training, explicitly linking building and floor modules for large-scale deployments. More recently, addressing temporal instability, Lin et al. [19] proposed a Seq2Seq-based floor detection scheme that models RSSI fluctuations as time-series sequences, effectively mitigating the “ping-pong” effect at floor boundaries.

While these deep learning methods enhance robustness [20], they inherently rely on extensive labeled training data, complex training pipelines, or sequential data availabil-

¹Source code and dataset available at: github.com/kahramankostas/DetectFloor

ity. Alternatively, distance estimation and clustering offer a more hardware-independent and data-efficient solution. By deriving range estimates from signal features [21], clustering algorithms can group spatially coherent points, mitigating ambiguity through structural analysis rather than absolute signal matching.

C. GRAPH-BASED SPATIAL MODELING AND CLUSTERING

Machine learning classifiers have shown promise in handling multimodal data for floor detection [22], [23]. However, graph-based methods provide a more structural approach to modeling spatial relationships. By representing signal proximity—such as RSSI-derived distances—as weighted graphs, space can be partitioned efficiently using community detection algorithms.

Methods such as Louvain, Infomap, and Leiden are pivotal in this domain. While Louvain is noted for its computational efficiency [24], the Leiden algorithm has recently emerged as a superior alternative, offering better scalability and guaranteeing well-connected communities [25], [26]. In GPS-denied settings, these clustering techniques enable the identification of physical partitions, such as floors, solely from signal topology [27].

D. GRAPH EMBEDDINGS FOR WI-FI-BASED FLOOR ESTIMATION

Complementing clustering, graph embedding techniques such as Node2Vec, DeepWalk, and LINE capture latent topological features by projecting nodes into low-dimensional vector spaces. While clustering-based methods focus on partitioning the graph directly, embedding-based approaches first transform the graph into a latent vector space, enabling more flexible downstream analysis. Among these methods, Node2Vec balances local and global structural information through biased random walks and has proven effective across various domains [28].

Unlike neural feature extractors that operate directly on RSSI vectors, graph embeddings exploit relational structure induced by user trajectories and signal similarity, without requiring explicit labels or temporal alignment. Despite their potential, the application of graph embeddings to Wi-Fi-based floor estimation remains limited. While feature mapping via autoencoders [16], RNN-based architectures [17], and linked deep neural networks [18] has been explored, the specific synergy between RSSI-derived graph structures and embedding-based clustering remains underexplored.

Mostafa et al. [11] emphasize the need for floor detection methods that reduce calibration overhead while maintaining robustness across diverse environments. Addressing this gap, our proposed approach integrates distance-based graph construction with advanced community detection. By leveraging recent insights into signed graph embeddings and non-linear error modeling [29], [30], we aim to provide a scalable and hardware-independent solution that exploits structural consistency across floors without requiring labeled data or prior building information.

III. METHODOLOGY

In this section, we present the formal problem definition, describe the datasets used for evaluation, and detail the proposed graph-based clustering framework. The overall experimental workflow, encompassing graph construction, baseline comparisons, and the proposed Node2Vec-based embedding pipeline, is illustrated in Fig. 1.

A. PROBLEM FORMULATION

The fundamental objective of this study is to perform *blind floor separation* in multistory indoor environments. Unlike supervised localization tasks that require labeled training data for every floor, we formulate this as an unsupervised graph clustering problem. Although clustering is performed at the fingerprint level, all evaluations are conducted in a trajectory-consistent manner, ensuring that performance metrics reflect coherent user movement patterns rather than isolated signal observations.

Formally, let $\mathcal{T} = \{T_1, T_2, \dots, T_n\}$ be a set of user trajectories collected within a building of unknown height. Each trajectory T_i consists of a sequence of time-stamped Wi-Fi fingerprints $f_j = (RSSI, t)$. The problem involves partitioning \mathcal{T} into k disjoint clusters $\{C_1, C_2, \dots, C_k\}$, such that:

- 1) All trajectories within a cluster C_m belong to the same physical floor.
- 2) The number of floors k is not known *a priori* and must be estimated from the data.
- 3) The partition minimizes signal variance within clusters while maximizing the separation between clusters.

The inputs for this problem are generic to most fingerprinting scenarios: (1) Received Signal Strength Indicator (RSSI) values from visible Access Points (APs), (2) Sequential continuity information (i.e., which fingerprints belong to the same walking path), and (3) Sparse elevation hints (e.g., detection of elevator or stairs usage) if available. The core challenge lies in the unsupervised nature of the task, compounded by signal fluctuations and architectural similarities (e.g., atriums) that cause significant RSSI overlap between different floors.

B. DATASETS

To validate the robustness and generalizability of our framework, we employ two distinct datasets representing different architectural scales and collection methodologies.

1) Huawei University Challenge 2021

The primary experiments are conducted using the dataset from the Huawei University Challenge 2021. Designed for large-scale floor prediction, this dataset provides a comprehensive underexplored benchmark. Our unsupervised method processes all available trajectories as a single corpus, utilizing the provided ground-truth labels exclusively for final accuracy evaluation, not for training. The dataset includes:

- `fingerprints.json`: Individual Wi-Fi fingerprints with AP signal strengths.
- `steps.csv`: Sequential connections between fingerprints in a trajectory.

- `elevations.csv`: Pairs of fingerprints indicating vertical transitions.
- `estimated_wifi_distances.csv`: Noisy pairwise distance estimations.
- `GT.json`: Ground-truth labels for validation.

2) Validation on UJIIndoorLoc Dataset

To evaluate the framework beyond the Huawei environment, we incorporated the UJIIndoorLoc dataset, a widely used benchmark covering three buildings with up to five floors. The dataset provides two predefined subsets, commonly referred to as Training (T) and Validation (V), which we treat as two independent datasets in our experiments. Since our approach is unsupervised, we do not follow the traditional supervised paradigm of training on one subset and testing on another. Instead, the proposed pipeline is applied separately to each subset to assess consistency and reproducibility across different data distributions originating from the same environment.

Trajectory Generation and Graph Construction: Since UJIIndoorLoc consists of discrete Wi-Fi fingerprints, we apply a preprocessing pipeline to structure the data into a graph representation compatible with our methodology:

- 1) **Trajectory Generation:** Raw fingerprints are grouped into trajectories based on User and Phone identifiers. A temporal threshold of $\Delta t = 600s$ is used to segment distinct walking sessions. Trajectories are further split whenever a change in building or floor attributes is detected, ensuring floor-level semantic integrity.
- 2) **Graph Construction:**

- **Nodes:** Each valid Wi-Fi fingerprint (after filtering weak signals with $RSSI \neq 100$) is represented as a node.
- **Horizontal Edges:** Sequential fingerprints within the same trajectory are connected via step edges to preserve temporal continuity.
- **Synthetic Vertical Edges:** Unlike the Huawei dataset, UJIIndoorLoc does not provide explicit labels for vertical transitions. To maintain graph connectivity for the GNN and Node2Vec embedding processes, synthetic inter-trajectory edges are introduced solely to ensure global graph connectivity in datasets lacking explicit trajectory continuity. These edges do not encode any floor identity, ordering, or vertical supervision, and are used only as a structural mechanism to prevent graph fragmentation. This design ensures the resulting graph remains a single connected component while preserving semantic distinctions across floors.

This transformation results in graph structures comprising 13 distinct classes, corresponding to building–floor combinations, for both independent subsets. Although UJIIndoorLoc contains three separate buildings with 4, 4, and 5 floors respectively, we model the environment as a single abstract structure with 13 floor levels. This abstraction aligns with

the objective of floor separation and allows the dataset to be treated as a single structured environment within the proposed framework.

C. EDGE WEIGHTING AND SCENARIO DESIGN

The topology of the constructed graph is governed by the accuracy of the edge weights, which represent the proximity between fingerprints. To systematically analyze how the quality of the input distances affects clustering performance, we investigate three distinct distance estimation strategies across our datasets, yielding the six experimental scenarios summarized in Table 1.

TABLE 1. Summary of Experimental Scenarios for Edge Weighting Strategies

	Scenario ID	Distance Source	Description
Huawei	HW-Def	Default Estimates	Original competition distances containing significant noise (Baseline).
	HW-WBDE	WBDE	Distances re-calculated using the proposed supervised ML model on raw RSSI.
UJIIndoorLoc	UJI-Geo-T	Physical Euclidean.	Gold standard graph derived from ground truth coordinates.
	UJI-Geo-V		
	UJI-WBDE-T UJI-WBDE-V	WBDE	Distances recalculated using the proposed supervised ML model on raw RSSI.

- **Default Estimates (Baseline):** This setting utilizes the original, noisy distance values provided in the competition dataset (Scenario: *HW-Def*).
- **WBDE-Based Estimates (Proposed):** In this configuration, distances are recalculated using the proposed supervised Wi-Fi-Based Distance Estimation (WBDE) model, which infers proximity solely from raw RSSI measurements (Scenarios: *HW-WBDE* and *UJI-WBDE*). *WBDE* is a distance estimation framework originally developed in our earlier work [21] to infer physical proximity directly from raw RSSI measurements. In this study, the framework is retrained using a reduced set of datasets, while the core modeling approach remains consistent with the original formulation. The resulting model serves strictly as an external module to compute inter-fingerprint distances within the proposed floor separation pipeline. Compared to the original formulation, the WBDE model employed in this study represents a simplified variant. While the original framework was trained using 11 heterogeneous datasets spanning diverse environments, the version adopted here is retrained on a reduced subset of five publicly available datasets [31]–[35]. This design choice reflects a deliberate trade-off between model complexity and practical applicability, while maintaining sufficient generalization capability for distance estimation. Crucially, the training of WBDE is entirely decoupled from the floor separation task, ensuring that no data from the floor classification datasets (Huawei Challenge 2021 or UJIIndoorLoc) is used for model optimization. The five datasets used for WBDE training [31]–[35] contain

only horizontal positioning data without floor labels, thus preventing any form of information leakage into the unsupervised clustering pipeline. The WBDE model serves strictly as an external distance estimation module, analogous to using a pre-trained ranging sensor.

- **Geometric “Gold Standard”:** For the UJIIndoorLoc dataset, a reference graph is constructed using exact Euclidean distances derived from the ground-truth coordinates (Scenario: *UJI-Geo*). This scenario represents a theoretical upper bound, enabling us to assess whether signal-based distance learning can recover the underlying physical geometry.

D. MOTIVATION: ROLE OF DISTANCE ESTIMATION IN GRAPH CONSTRUCTION

Edge weights constitute the primary mechanism through which spatial relationships are encoded in the trajectory graph. Since the proposed framework relies exclusively on graph topology to infer floor-level communities, inaccuracies in distance estimation can directly distort neighborhood structures and degrade clustering performance.

Indoor Wi-Fi signals are inherently noisy due to multipath propagation and inter-floor leakage, which may introduce spurious connections between fingerprints belonging to different floors. To assess the sensitivity of the proposed framework to such distortions, this study systematically investigates multiple distance estimation strategies, ranging from noisy baseline estimates to distances inferred via a supervised Wi-Fi-Based Distance Estimation (WBDE) model, as well as an idealized geometric reference where available. The quantitative effects of these strategies on clustering performance are analyzed in the Results section.

E. CLUSTERING AND COMMUNITY DETECTION METHODS

We employ a diverse set of algorithms to identify floor-level communities within the constructed graphs.

1) Baseline Community Detection Algorithms

We compare our proposed method against established modularity and flow-based algorithms:

- **Louvain & Leiden:** Modularity optimization methods, with Leiden offering improved connectivity guarantees [24], [36].
- **Label Propagation (LPA):** An efficient, parameter-free algorithm where nodes adopt the majority label of neighbors [37].
- **Infomap:** Uses information theory (random walks) to detect hierarchical structures [38].
- **Fast Greedy:** A heuristic modularity-based approach [28].

2) Graph Representation Learning Models

Unlike the baselines that operate directly on the graph topology, we employ representation learning to embed nodes into a latent vector space ($d = 32$) before clustering.

1) Node2Vec: Generates embeddings by simulating biased random walks, balancing Depth-First (DFS) and Breadth-First (BFS) search strategies to capture both homophily and structural equivalence [39].

2) Graph Neural Networks (GNNs): We extend the framework by incorporating Graph Convolutional Networks (GCN) and Graph Attention Networks (GAT). Unlike shallow embeddings (Node2Vec), GNNs explicitly leverage the adjacency matrix during the forward pass to aggregate neighborhood information.

- **GCN:** Applies a spectral convolution operation, aggregating features from immediate neighbors with equal importance.
- **GAT:** Introduces an attention mechanism to assign learnable weights to different neighbors, allowing the model to focus on the most relevant connections for floor separation.

All generated embeddings (Node2Vec, GCN, GAT) are subsequently clustered using the K-Means algorithm.

3) Automated Cluster Estimation

A critical limitation in unsupervised localization is determining the optimal number of floors (k). To eliminate manual selection, we employ the **Calinski-Harabasz (CH) Index** [40]. The system iteratively evaluates $k \in [3, 20]$ and automatically selects the k that maximizes the ratio of inter-cluster dispersion to intra-cluster dispersion, ensuring an adaptive solution for any building. The selected range $k \in [3, 20]$ follows the official constraints provided in the Huawei University Challenge 2021, where buildings were specified to contain at least three and at most twenty floors. This range reflects a typical and widely observed characteristic of campus-scale and commercial multistory buildings. To preserve methodological consistency and code standardization, the same interval is retained without modification when evaluating the UJIIndoorLoc dataset, despite differences in architectural scale.

F. EVALUATION FRAMEWORK AND METRICS

Since the proposed approach is unsupervised, the output clusters do not inherently possess floor labels (e.g., “Floor 1”). To rigorously evaluate performance against ground truth, we implemented a three-stage evaluation framework comprising label mapping, standard clustering metrics, and statistical validation via bootstrapping. Ground-truth floor labels are used exclusively for post-hoc evaluation and are never accessed during graph construction, embedding generation, or clustering.

1) Cluster-to-Floor Mapping and Classification Metrics

To bridge the gap between unsupervised clustering and physical floor identification, we employed a post-hoc majority voting scheme. This process maps each anonymous cluster C_i to the physical floor label L_j that appears most frequently among the trajectories within that cluster:

$$\text{Label}(C_i) = \arg \max_{L_j} (|C_i \cap L_j|) \quad (1)$$

Once the clusters are mapped to physical floors, the problem can be treated as a multi-class classification task. This allows us to calculate standard classification metrics:

- **Mapped Accuracy:** The ratio of correctly identified fingerprints to the total number of fingerprints after mapping.
- **Mapped F1-Score:** To account for potential class imbalances (variation in the number of fingerprints per floor), we report the weighted F1-Score. This is calculated as the harmonic mean of precision and recall, weighted by the support (the number of true instances for each label).

2) Standard Clustering Metrics

To assess the quality of the partitions independent of the mapping process, we employ three standard structural metrics:

- **Adjusted Rand Index (ARI):** Measures the similarity between the predicted clustering and the ground truth, adjusted for chance. It ranges from -1 to 1 , where 1 indicates perfect agreement.
- **Normalized Mutual Information (NMI):** Quantifies the mutual dependence between the predicted clusters and the true classes, normalized between 0 (no mutual information) and 1 (perfect correlation).
- **Cluster Purity:** Represents the weighted average of the dominant true class proportion within each predicted cluster, assessing the homogeneity of the generated groups.

3) Statistical Validation via Bootstrapping

To ensure the reliability of the reported results and to estimate the variability of the performance metrics, we applied the bootstrap method. For each experimental scenario, we generated 1,000 bootstrap samples by resampling the test data with replacement. We report the mean values for Accuracy and F1-Score, along with their 95% Confidence Intervals (CI). This rigorous statistical approach confirms that the performance improvements observed are robust and not artifacts of specific data splits.

IV. EXPERIMENTS

A. EXPERIMENTAL SCENARIOS AND EDGE WEIGHTING STRATEGIES

To rigorously evaluate the robustness of the proposed framework against signal noise and its dependency on accurate distance estimation, we designed six distinct experimental scenarios summarized in Table 1. These scenarios span two datasets and three distance estimation modalities.

1) Huawei Challenge Scenarios

The Huawei competition dataset was utilized to assess performance in a high-noise environment.

- **HW-Def (Baseline):** Uses the original noisy distance estimates provided in the competition data.
- **HW-WBDE (Proposed):** Replaces the default estimates with distances recalculated using the supervised

WBDE model on raw RSSI values. Importantly, the WBDE model was trained exclusively on external datasets [31]–[35] that contain no floor information, ensuring zero data leakage from the Huawei test set. This comparison isolates the impact of input graph quality on clustering performance.

2) UJIIndoorLoc Scenarios

To validate the generalizability of the approach, experiments were conducted on both the Training (T) and Validation (V) subsets of the UJIIndoorLoc benchmark. The two subsets differ significantly in size, with the Validation set containing approximately 18 times fewer fingerprints than the Training set. To investigate the impact of distance estimation quality on these subsets, we define two distinct experimental scenarios based on the graph construction method:

- **UJI-Geo (Gold Standard):** Graphs were constructed using physical Euclidean distances derived from ground-truth coordinates, representing the theoretical upper bound where accurate geometry is known.
- **UJI-WBDE (Blind Estimation):** Graphs were constructed solely using signal-based distances predicted by the WBDE model without any geometric priors.

V. RESULTS

A. COMPARATIVE ANALYSIS AGAINST BASELINES

The primary evaluation compared the proposed Node2Vec+K-Means pipeline against five traditional community detection algorithms and two GNN-based models across both the Huawei and UJIIndoorLoc datasets. The results are organized across two tables to distinguish between the primary practical application and reference scenarios. Table 2 presents the performance metrics for the proposed framework using signal-based distances (WBDE) across all datasets. Table 3 summarizes the results for the baseline and reference cases, namely the default noisy estimates for Huawei (HW-Def) and the coordinate-based ‘gold standard’ for UJI (UJI-Geo), providing a benchmark for the theoretical upper bound of the system.

1) Performance on Huawei Dataset

As reported in Table 2, the proposed method achieved a mean accuracy of 76.60% (95% CI [0.739, 0.806]) on the challenging Huawei dataset, decisively outperforming the strongest baseline method (GAT with 50.2%), demonstrating a substantial performance margin. This highlights the robustness of the embedding-based approach in high-noise environments where traditional modularity-based algorithms and GNNs struggle to identify global floor structures.

2) Performance on UJIIndoorLoc Dataset

A similar trend was observed in the UJIIndoorLoc benchmark, confirming the method’s generalizability. On the Training subset (UJI-T), the proposed approach achieved a mean accuracy of 66.1% (95% CI [0.542, 0.826]), significantly

TABLE 2. Comprehensive performance comparison HW-WBDE, UJI-WBDE-T, UJI-WBDE-V. Accuracy from 1000 bootstrap iterations with 95% CI.

	Algorithm	ACC	95% CI	F1	ARI	MNI	Purity
HW-WBDE	Fast Greedy	0.330	[0.299, 0.373]	0.206	0.006	0.014	0.942
	GAT	0.502	[0.469, 0.548]	0.444	0.250	0.250	0.529
	GCN	0.399	[0.369, 0.454]	0.296	0.093	0.118	0.465
	Infomap	0.344	[0.315, 0.392]	0.265	0.034	0.045	0.825
	Label Prop.	0.339	[0.309, 0.383]	0.234	0.016	0.033	0.868
	Leiden	0.330	[0.299, 0.380]	0.220	0.014	0.020	0.924
	Louvain	0.329	[0.299, 0.375]	0.221	0.014	0.020	0.924
	Node2Vec	0.766	[0.739, 0.806]	0.753	0.669	0.664	0.757
UJI-WBDE-T	Fast Greedy	0.223	[0.121, 0.379]	0.135	-0.005	0.171	0.250
	GAT	0.355	[0.237, 0.542]	0.325	0.220	0.600	0.785
	GCN	0.253	[0.153, 0.449]	0.216	0.144	0.491	0.796
	Infomap	0.118	[0.052, 0.323]	0.029	0.000	0.000	0.121
	Label Prop.	0.000	[0.000, 0.000]	0.000	0.000	0.000	1.000
	Leiden	0.224	[0.121, 0.409]	0.131	0.003	0.200	0.234
	Louvain	0.175	[0.086, 0.358]	0.087	0.003	0.157	0.174
	Node2Vec	0.661	[0.542, 0.826]	0.686	0.428	0.733	0.899
UJI-WBDE-V	Fast Greedy	0.206	[0.139, 0.320]	0.101	-0.003	0.020	0.205
	GAT	0.513	[0.431, 0.661]	0.478	0.299	0.532	0.544
	GCN	0.474	[0.382, 0.602]	0.425	0.275	0.471	0.546
	Infomap	0.180	[0.115, 0.293]	0.056	0.000	0.000	0.180
	Label Prop.	0.205	[0.139, 0.350]	0.100	0.001	0.035	0.206
	Leiden	0.204	[0.131, 0.303]	0.111	0.003	0.056	0.199
	Louvain	0.203	[0.139, 0.311]	0.113	0.003	0.056	0.199
	Node2Vec	0.594	[0.512, 0.738]	0.572	0.358	0.614	0.757

surpassing the best-performing baseline (GAT at 35.5%). Consistency was maintained on the Validation subset (UJI-V), where our method yielded an accuracy of 59.4%, whereas traditional algorithms like Fast Greedy and Louvain remained below 25%. The slightly lower accuracy on the Validation subset can be attributed to two factors: (1) the substantially smaller dataset size (approximately 18 times fewer fingerprints), which results in a sparser graph structure and wider confidence intervals, and (2) the temporal gap of three months between data collection periods, introducing potential environmental changes. Notably, the performance gap between Node2Vec and baselines remains consistent across both subsets, demonstrating the robustness of the proposed approach to variations in data scale and temporal conditions. These results demonstrate that the proposed graph construction effectively captures floor separation even in buildings with different architectural layouts and AP densities.

3) Statistical Significance and Structural Integrity

Statistical significance was confirmed via McNemar's tests ($p < 0.001$) across all scenarios, allowing us to reject the null hypothesis of equal error rates for all baselines. Furthermore, a structural analysis reveals a critical limitation of traditional methods. Although algorithms such as Fast Greedy and Louvain achieved high Cluster Purity scores ($> 90\%$), their near-zero Adjusted Rand Index (ARI) values indicate severe over-segmentation, producing numerous fragmented small clusters rather than coherent floor-level communities. In contrast, the proposed Node2Vec-based method preserves global structural consistency, achieving substantially higher ARI scores (e.g., 0.669 for Huawei) while maintaining strong cluster purity.

B. IMPACT OF EDGE WEIGHTING STRATEGIES: ANALYSIS OF THE SIX SCENARIOS

A central contribution of this study is the investigation of how distance estimation quality influences clustering performance. The results across the six scenarios (Table 1) yield two key observations.

a: Noise Reduction in Complex Environments (Huawei Scenarios)

Replacing the noisy competition-provided distances (HW-Def) with ML-based WBDE estimates (HW-WBDE) results in a significant accuracy improvement for Node2Vec (from 69.3% to 76.6%). This confirms that the WBDE model effectively suppresses signal fluctuations, yielding a cleaner graph topology in which intra-floor connections dominate over inter-floor leakages.

b: Equivalence to Physical Geometry (UJI Scenarios)

The most striking result is observed in the UJIIndoorLoc dataset. As shown in Fig. 2, the clustering performance achieved using purely signal-derived distances (UJI-WBDE) is statistically indistinguishable from that obtained using ground-truth geometric distances (UJI-Geo). This equivalence holds consistently for both the Training and Validation subsets, demonstrating that the proposed graph construction method preserves the relative neighborhood structure of the physical environment solely from RSSI data, without requiring physical reference points or manual calibration.

C. STRUCTURAL INTEGRITY AND ERROR ANALYSIS

The robustness of the proposed framework is further supported by the confusion matrices presented in Fig. 4. The Node2Vec-based approach exhibits strong diagonal dominance, indicating consistent correct classification across floors. The remaining errors are primarily confined to adjacent floors or sparse transition regions. In contrast, baseline methods display highly dispersed confusion patterns, frequently merging distinct floors or fragmenting a single floor into multiple unrelated communities. This observation confirms that learning latent node embeddings captures the global semantic structure of indoor spaces more effectively than methods relying solely on local modularity optimization.

$$CH(k) = \frac{BGSS/(k-1)}{WGSS/(n-k)}, \quad (2)$$

where $BGSS$ and $WGSS$ denote the between-group and within-group dispersion, respectively, and n is the total number of samples. The optimal number of clusters is then selected as

$$k_{\text{opt}} = \arg \max_k CH(k). \quad (3)$$

VI. DISCUSSION

A. PERFORMANCE ANALYSIS AND COMPARISONS

The proposed Node2Vec-based approach demonstrates decisive superiority over traditional community detection al-

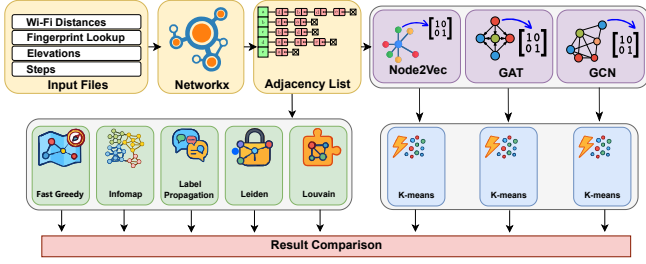


FIGURE 1. Overview of the experimental workflow. The trajectory graph is used as input for both the baseline community detection algorithms (Louvain, Leiden, Infomap, Label Propagation, Fast Greedy) and the proposed Node2Vec+KMeans pipeline. While baseline methods operate directly on the graph structure, the proposed approach first transforms the graph into a 32-dimensional embedding space using Node2Vec, followed by clustering with K-Means.

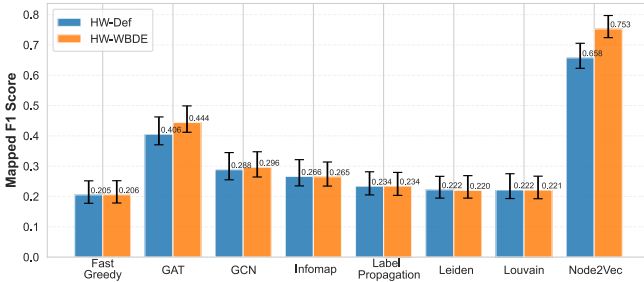


FIGURE 2. Mapped F1 scores of different community detection and representation learning algorithms evaluated on the Huawei dataset. Error bars indicate 95% confidence intervals estimated from 1,000 bootstrap iterations.

gorithms. The WBDE employed in this study serves as a supporting tool to analyze how distance quality affects graph-based floor separation, rather than as a primary contribution. The core contribution lies in demonstrating that, given sufficiently reliable distance estimates, the proposed Node2Vec-based framework can recover floor-level structure in a fully unsupervised manner.

B. THE LIMITATION OF GNNs IN WI-FI ENVIRONMENTS

A critical observation from our experiments is the consistently weaker performance of Graph Neural Network models (GCN and GAT) compared to the Node2Vec-based approach. Although GNNs are theoretically more expressive, their effectiveness relies heavily on informative and stable node features. In the context of Wi-Fi fingerprint graphs, node attributes are inherently high-dimensional, sparse, and prone to signal noise, which severely limits the reliability of neighborhood feature aggregation.

Furthermore, floor separation in multistory environments is predominantly a *topology-driven* problem rather than a *feature-driven* one. Nodes on the same floor may not exhibit strong attribute similarity due to signal fluctuations, yet their relative structural positions within the trajectory graph remain consistent. Under these conditions, the message-passing mechanisms in GNNs tend to cause over-smoothing, blurring inter-floor boundaries and reducing separability. In contrast,

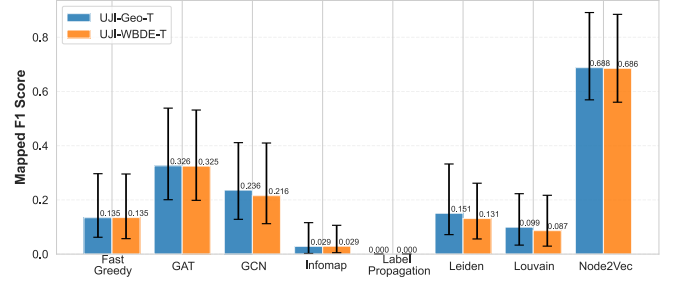


FIGURE 3. Mapped F1 scores of different community detection and representation learning algorithms evaluated on the UJI dataset. Error bars indicate 95% confidence intervals estimated from 1,000 bootstrap iterations.

Node2Vec leverages random-walk-based exploration to capture latent global and mesoscopic connectivity patterns without relying on explicit feature aggregation. This structural sensitivity allows Node2Vec to preserve floor-level cohesion while maintaining vertical separation, explaining its superior stability across all scenarios.

C. STATISTICAL SIGNIFICANCE AND STRUCTURAL INTEGRITY

Beyond standard accuracy, an analysis of clustering-specific metrics reveals a clear trade-off between intra-cluster purity and global structural alignment. While baselines often achieved very high Purity (82–94%), their low Adjusted Rand Index (ARI) and Normalized Mutual Information (NMI) scores point to a critical *completeness problem*. Traditional algorithms excel at creating small, internally pure sub-clusters but fail to reconstruct the complete structure of a single floor. In summary, traditional community detection algorithms fail to model the semantic structure required for this task. By leveraging learned embeddings, our approach successfully balances local cohesion with global separation, demonstrating the significant value of graph representation learning for clustering in complex, noisy indoor environments.

D. SENSITIVITY TO GRAPH TOPOLOGY AND DATASET CHARACTERISTICS

A comparative analysis of the results on Huawei (Fig. 3) and UJIIndoorLoc (Fig. 2) reveals a striking contrast in algorithmic stability. While baseline methods like Infomap and Label Propagation maintain moderate performance on the Huawei dataset, they exhibit near-zero accuracy and high variance on the UJIIndoorLoc dataset. This discrepancy can be attributed to the fundamental differences in data generation and resulting graph topology.

The Huawei dataset consists of continuous, dense walking trajectories, naturally forming well-connected communities that facilitate flow-based clustering algorithms. In contrast, the UJIIndoorLoc dataset was originally comprised of discrete fingerprints. Although we reconstructed trajectories using heuristic constraints, the resulting graph likely possesses a more fragmented or ‘artificial’ topology with sparser connectivity compared to the organic movement traces in Huawei.

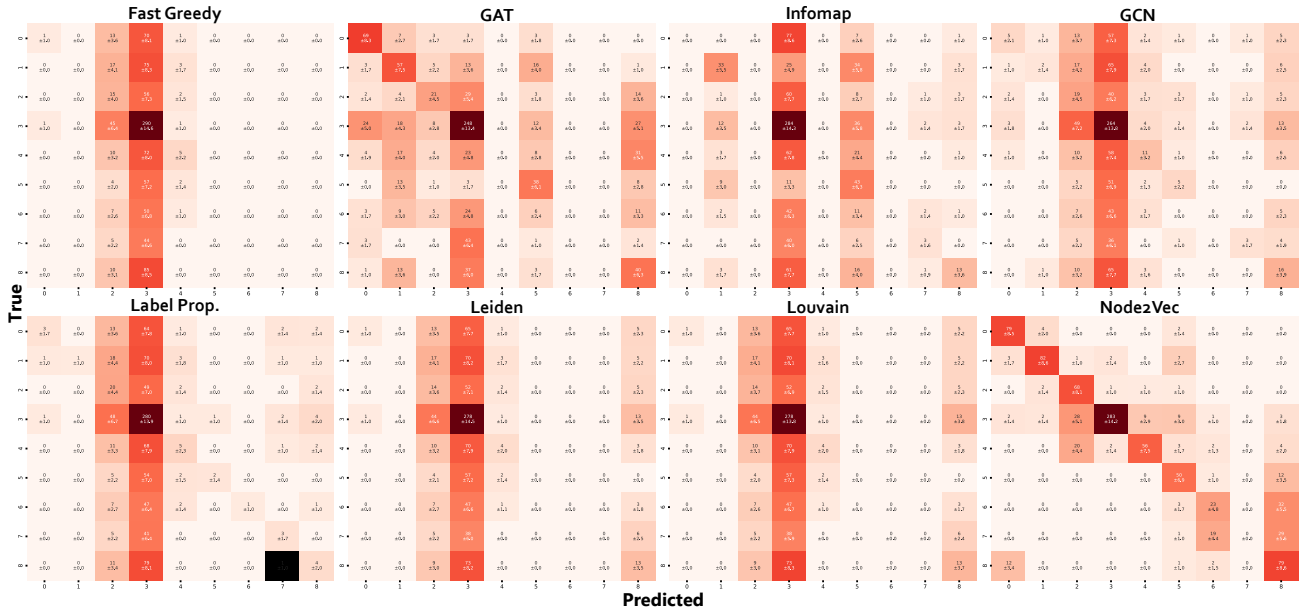


FIGURE 4. Confusion matrices for the six clustering methods. Strong diagonal dominance in the Node2Vec matrix contrasts with the dispersed predictions of the baselines.

Traditional flow-based algorithms (e.g., Infomap) and local propagation methods (e.g., LPA) are highly sensitive to such topological irregularities; they fail to propagate labels across the sparse, synthetic edges of the UIJ graph, leading to the observed collapse in performance. Conversely, the proposed Node2Vec approach demonstrates remarkable robustness. By sampling the graph via biased random walks and learning low-dimensional embeddings, our method successfully bridges these topological gaps. This confirms that embedding-based clustering is not only more accurate but also significantly more resilient to the structural quality of the input graph, making it ideal for scenarios where continuous trajectory data must be reconstructed from discrete samples.

An additional consideration in interpreting the UIJIndoorLoc results is the substantial size disparity between the Training and Validation subsets. The Validation set contains approximately 18 times fewer fingerprints, resulting in a significantly sparser graph with fewer nodes and edges. This reduced data volume directly impacts the statistical reliability of performance estimates, as reflected in the wider confidence intervals observed for UIJ-WBDE-V compared to UIJ-WBDE-T (Table 2).

Despite this challenge, the proposed Node2Vec approach maintains a consistent performance advantage over baselines across both subsets. The margin of superiority remains substantial (approximately $2\times$ better than the best baseline in both cases), indicating that the embedding-based framework is resilient not only to topological irregularities but also to variations in dataset scale.

VII. CONCLUSION

This study presented a robust graph representation learning framework for unsupervised floor separation. By combining

Node2Vec embeddings with adaptive clustering, the proposed method effectively models the latent topology of indoor environments from noisy Wi-Fi trajectories. Our comprehensive evaluation across six experimental scenarios highlighted two major contributions. First, on the Huawei dataset, improving edge weights via our WBDE model significantly boosted accuracy to 76.60%, outperforming traditional community detection algorithms by a large margin. Second, and most notably, experiments on the UIJIndoorLoc benchmark demonstrated that our purely signal-based graph construction yields clustering results statistically equivalent to those obtained from a ground-truth geometric graph. This validates that the proposed framework can autonomously recover the structural layout of a building without requiring physical reference points or floor plans. Future work will focus on validating this approach on heterogeneous devices and integrating real-time online clustering for live navigation applications.

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TABLE 3. Comprehensive performance comparison HW-Def, UIJ-Geo-T, UIJ-Geo-V datasets. Accuracy from 1000 bootstrap iterations with 95% CI.

Data	Algorithm	ACC	%95 CI	F1	ARI	NMI	Purity
HW-Def	Fast Greedy	0.330	[0.301,0.383]	0.205	0.006	0.014	0.942
	GAT	0.494	[0.463,0.560]	0.406	0.153	0.282	0.580
	GCN	0.390	[0.359,0.443]	0.288	0.087	0.103	0.454
	Infomap	0.345	[0.314,0.395]	0.266	0.034	0.045	0.825
	Label Propagation	0.338	[0.309,0.385]	0.234	0.016	0.033	0.868
	Leiden	0.328	[0.296,0.382]	0.222	0.014	0.020	0.924
	Louvain	0.328	[0.298,0.377]	0.222	0.014	0.020	0.924
	Node2Vec	0.693	[0.663,0.734]	0.658	0.581	0.600	0.758
UIJ-Geo-T	Fast Greedy	0.222	[0.121,0.435]	0.135	-0.005	0.171	0.250
	GAT	0.372	[0.254,0.555]	0.326	0.259	0.631	0.775
	GCN	0.286	[0.186,0.466]	0.236	0.157	0.508	0.810
	Infomap	0.122	[0.052,0.259]	0.029	0.000	0.000	1.121
	Label Propagation	0.000	[0.000,0.000]	0.000	0.000	0.000	1.000
	Leiden	0.225	[0.138,0.379]	0.151	0.006	0.261	0.234
	Louvain	0.173	[0.086,0.353]	0.099	-0.004	0.178	0.169
	Node2Vec	0.661	[0.525,0.898]	0.688	0.428	0.733	0.899
UIJ-Geo-V	Fast Greedy	0.206	[0.139,0.336]	0.102	-0.003	0.020	0.205
	GAT	0.333	[0.252,0.455]	0.196	0.199	0.365	0.323
	GCN	0.463	[0.366,0.626]	0.426	0.267	0.483	0.541
	Infomap	0.182	[0.115,0.279]	0.055	0.000	0.000	0.180
	Label Propagation	0.182	[0.115,0.293]	0.057	0.000	0.000	0.180
	Leiden	0.196	[0.131,0.316]	0.098	-0.005	0.043	0.300
	Louvain	0.196	[0.123,0.307]	0.098	-0.003	0.031	0.197
	Node2Vec	0.594	[0.512,0.736]	0.572	0.358	0.614	0.757

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