WiFi-Based Indoor Positioning Methods and Systems (Postprint)

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Abstract

In modern information-centric society, the demand for indoor positioning continues to grow, with increasingly stringent requirements for system positioning accuracy. Applications include navigation within airports and large shopping malls, conference guidance, resource locating, positioning of underground personnel, and monitoring of elderly and children. This paper presents an in-depth investigation into various challenges of indoor positioning in practical applications. The specific contributions encompass: investigations into positioning methodologies based on uncalibrated signal manifold characteristics, studies on device and temporal transferability in positioning, research on seamless handover positioning across large-scale access points (APs), investigations into vertical-space positioning model transfer within the same building, studies on positioning under conditions of AP sparsity and absence, research on single-AP-based room-level positioning, investigations into calibration-free positioning methodologies, and research on WiFi directional feature-based positioning. Experimental results demonstrate that WiFi-based indoor positioning technology is maturing progressively, and its positioning accuracy and system usability are advancing the technology toward the goal of cost-effective practical deployment.

Full Text

Preamble

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Abstract

In modern information-driven life, the demand for indoor positioning is increasing, with ever-higher requirements for system accuracy. Applications include navigation in airports and large shopping malls, conference guides, resource location, tracking of underground workers, and monitoring of elderly and children. This paper conducts in-depth research on various practical challenges in indoor positioning applications, including: positioning methods based on uncalibrated signal manifold features, device and temporal transfer for positioning, seamless handover positioning across large-scale access point (AP) deployments, vertical space positioning model transfer across identical building structures, positioning under AP-sparse and AP-absent conditions, single-AP room-level positioning, calibration-free positioning methods, and positioning based on WiFi directional characteristics. Experiments demonstrate that WiFi-based indoor positioning technology is maturing, with its positioning accuracy and system usability advancing toward the goal of low-cost practical deployment.

Keywords: WiFi, indoor positioning, manifold regularization, transfer learning, large-scale positioning, vertical space positioning, access point absence, single access point positioning, directional access point positioning

1 Introduction

With the rapid development and widespread deployment of wireless communication technologies and infrastructure, positioning technologies and systems have attracted significant attention from both research and industry. Numerous studies and applications have emerged, ranging from GPS-based outdoor positioning to short-range technologies using infrared and ultrasound, and more recently to WiFi signal-based indoor positioning. These technologies each have distinct operating principles and are suited for different scenarios and applications. GPS, based on satellite communication, is currently the most widely used positioning technology, offering stable and reliable performance. However, its limitation lies in requiring line-of-sight visibility to satellites, making it ineffective indoors or within buildings.

Over the past decade, many indoor positioning systems have been proposed, including AGPS, ultrasonic positioning systems, Bluetooth, infrared positioning, and cellular base station positioning. Each of these systems has specific application scopes and limitations. For instance, AGPS and cellular methods require infrastructure modifications at high cost; Bluetooth has limited detection range; and ultrasonic and infrared signals are susceptible to obstruction by media.

In recent years, signal-strength-based positioning using IEEE 802.11b/g wireless local area networks (WLAN) has gained increasing attention. Most mainstream PDAs and laptops now have built-in wireless cards, providing convenient hardware support for this positioning technology. The fundamental principle of signal-strength-based positioning is to estimate the distance between the receiver and signal source based on received signal strength. Compared to time-of-arrival (TOA), time-difference-of-arrival (TDOA), and angle-of-arrival (AOA) techniques, it requires no additional hardware and, more importantly, is less susceptible to interference from obstacles. It does not suffer dramatic accuracy degradation due to complex indoor environments. Current research in this area includes work from Microsoft Research, IBM, Intel, Carnegie Mellon University, University of Pittsburgh, and University of Maryland internationally, and Hong Kong University of Science and Technology, National Chiao Tung University, Institute of Computing Technology of the Chinese Academy of Sciences, and Zhejiang University domestically.

The greatest challenge for indoor positioning technology lies in environmental diversity and dynamics. Differences exist between small and large buildings, single-floor and multi-floor structures, AP distributions across different buildings, signal occlusion by objects, varying temperature and humidity effects on signal attenuation across time periods, and inherent AP signal instability. All these conditions affect positioning performance. This paper addresses these aspects through comprehensive research, achieving notable results.

The remainder of this paper is organized as follows: Section 2 investigates various practical challenges in indoor positioning, presenting corresponding solutions and experimental results; Section 3 introduces typical indoor positioning application scenarios; Section 4 concludes the paper and outlines future work.

2.1.1 Background

Traditional machine learning methods use only labeled data (feature vector/label pairs) for training. However, obtaining labeled data for indoor positioning is generally difficult, time-consuming, and labor-intensive, often requiring professional expertise. In contrast, unlabeled data is relatively easy to acquire. Semi-supervised machine learning algorithms train using large amounts of unlabeled data combined with small amounts of labeled data, reducing workload while achieving better performance. Manifold regularization is such a semi-supervised learning algorithm that effectively combines spectral graph theory, manifold learning, and regularization in reproducing kernel Hilbert spaces (RKHS). Building upon this framework, we proposed an effective semi-supervised algorithm called LapRLS, which achieved second place in the IEEE ICDM 2007 (IEEE International Conference on Data Mining) data mining competition.

2.1.2 Manifold Regularization for Positioning

Similar to other machine learning algorithms applied to positioning, our proposed LapRLS algorithm consists of two phases: offline training and online positioning.

Offline Training Phase: First, training data is prepared, comprising partially labeled signal sequences from user trajectories and discrete signal data. Undetectable signals are filled with the minimum value of -100 dBm. Given the high noise characteristics of signals, we apply Gaussian smoothing to signal sequences based on the assumption that users cannot traverse large distances in short time periods, and signals should decay smoothly rather than jump dramatically. This effectively removes noise and improves positioning accuracy. Next, the graph Laplacian matrix L is computed. When constructing the adjacency matrix W, we consider both signal strength similarity and temporal similarity. For signal strength, each signal vector s S is connected to its k nearest neighbors using Minkowski distance as the similarity function. Temporally, signal vectors s and s are connected if their time interval Δt is below a threshold. This adjacency matrix yields the Laplacian matrix L = D - W, where D is a diagonal matrix whose elements correspond to row sums of W. Finally, the LapRLS algorithm learns the mapping from signal s to location l, treating x and y coordinates separately to obtain optimal coefficients and , yielding regression functions f (s) and f (s).

Online Positioning Phase: Test data consists entirely of unlabeled user trajectory signal sequences, with undetectable signals filled as -100 dBm. The same Gaussian smoothing preprocessing is applied. For each test signal vector ŝ, its position is estimated as (f (ŝ), f (ŝ)) using the regression functions from training.

2.1.3 Experimental Results

These experiments used all test data (2,137 samples). Training samples included 505 labeled data points plus an additional 2,691 unlabeled data points used by our algorithm. [Figure 1: see original paper] shows positioning accuracy across different distance errors for various algorithms. The results demonstrate that using unlabeled data improves positioning accuracy—for instance, accuracy within 1.5m error improves by approximately 10% over K-Nearest Neighbor (KNN) and 25% over regularized least squares (RLS).

2.2.1 Background

Wireless signals are susceptible to environmental changes, causing existing positioning models to degrade sharply when signal distributions shift. A key challenge is maintaining high accuracy while updating models with minimal labeled data. In our work, we proposed LuMA, a manifold alignment-based dimensionality reduction method that constructs aligned manifolds in low-dimensional space for two datasets with different distributions, enabling knowledge transfer across domains.

2.2.2 Manifold Construction and Alignment

Manifold Construction: The dataset is treated as graph vertices to construct a weighted graph describing local adjacency relationships. The weight matrix W is computed with non-zero weights for neighboring points. The graph Laplacian is constructed as L = D - W. A real-valued mapping function f: V → is defined on graph vertices. The optimal manifold embedding f* solves the optimization problem arg min_f f Lf, whose solution consists of eigenvectors corresponding to the smallest l_d non-zero eigenvalues of L, forming a low-dimensional embedding preserving original data structure.

Manifold Alignment: Separate mapping functions f: X → and g: Y → are defined for datasets X and Y, with known correspondences y_i x_i C. Aligned manifold optimization solves: min_{f,g} Σ||f(x_i) - g(y_i)||² + f L_Xf + g L_Yg. The first term measures differences at corresponding points, while the latter two ensure smoothness in low-dimensional space. As → ∞, this enforces hard constraints f(x_i) = g(y_i). Solving the Rayleigh quotient yields a joint Laplacian matrix from L_X and L_Y, whose eigenvectors provide the optimal solution and establish point correspondences between datasets.

2.2.3 Experimental Results

We deployed a WLAN environment in an indoor floor, collecting data on a 1m×1m grid at different times (morning, afternoon) and with different devices (laptop, mobile phone). Three experiments were conducted: temporal transfer, device transfer, and combined temporal-device transfer. Comparison models included: Source Domain Model (SDM) showing degradation of old models; Target Domain Model (TDM) representing best possible accuracy; and Linear Shift Model (LSM) as a common transfer approach. [Figure 2: see original paper], [Figure 3: see original paper], and [Figure 4: see original paper] show performance comparisons under different conditions. Overall, transfer learning significantly improves accuracy over SDM and effectively leverages source domain knowledge with limited target domain data, outperforming simple linear transfer methods in stability.

2.3.1 Background

Signal attenuation limits AP coverage, creating complex AP detection patterns across large indoor areas. When dividing large regions into sub-areas, different AP sets are typically detected in each. Consequently, many APs remain undetectable across numerous sub-areas during large-scale indoor positioning. Our measurements in the ICT-CAS hall revealed that the same AP exhibits varying signal strengths at different locations—strong in some areas, weak or undetectable in others. Traditional methods designed for fixed regions with consistent AP sets handle rare missing APs by assigning minimum values (-100 dBm). However, in large areas where such absence is frequent, this approach introduces significant errors. We proposed LAM (Large-scale Area Manage) to maximize useful signals while eliminating those causing fluctuations or negative effects. Different positioning models are trained for each wireless coverage area, which can independently select optimal AP combinations without constraints, requiring only initial sub-area determination rather than finding APs detectable throughout the entire region.

2.3.2 LAM Algorithm Flow

The LAM algorithm comprises several steps: (1) For each point P__j, initialize G__AP__j using the InfoGain algorithm; (2) Divide the region into N sub-areas; (3) Compute AP selection for each sub-area; (4) Update selected APs when changes occur; (5) Iterate until convergence. Here, G__AP__j represents the available positioning signal set for each calibration point P__j.

2.3.3 Experimental Results

Experiments demonstrate that LAM substantially improves large-scale positioning accuracy. compares accuracy metrics: the first row shows accuracy using a unified model across the entire region, while subsequent rows show per-sub-area accuracy after region division. The final row indicates the average accuracy across all sub-areas using LAM, confirming its effectiveness.

2.4.1 Background

Beyond planar large-area positioning, vertical space positioning is needed to determine floor and location within buildings. However, training positioning models for each floor requires extensive data collection and manual labeling, demanding substantial resources. Sharing training data across floors with similar physical structures offers significant practical value. We investigated this in our work, proposing TRM (Transfer Regression Model) for 3D positioning with promising results.

2.4.2 TRM-Based 3D Indoor Positioning

We address a regression problem across three datasets: variables X and Y have functional relationship Y = f(X), representing two training datasets that may have different sizes without one-to-one correspondence. An intermediate variable Z exists, with relationships Z = g(X) and Y = h(Z). The regression model f must: (1) utilize abundant unlabeled samples, and (2) effectively leverage Z' s information during X-Y training. TRM introduces dataset Z and decomposition functions into the manifold regularization framework, constraining solutions by aligning h and f outputs.

The optimization objective is: (f, *g*, h*) = arg min J(f, g, h). The general regression function form is:* *f*(x) = Σ _i K(x, x_i). The solution shows both unlabeled data and dataset Z participate in determining the regression function. We conducted 3D positioning experiments using TRM: extensive data was collected and labeled on the fourth floor, while only sparse labeled points (dots) were needed on the third floor to estimate unknown locations (crosses).

2.4.3 Experimental Results

Two experiments were designed: (1) without TRM, using only limited labeled data from the third floor; (2) with TRM, incorporating fourth-floor training data. shows results for error thresholds (ED) where predictions exceeding ED are considered errors. TRM significantly improves accuracy—at ED =1m, accuracy increases from 51.5% to 65.2% (26.6% improvement); at ED =2m, from 66.7% to 78.3% (17.4% improvement); at ED =3m, from 85.3% to 89.6% improvement. Comparisons with SVM and BP regression show TRM achieves better accuracy and stability as the number of participating APs increases.

2.5.1 Background

Indoor positioning is challenging because environmental changes affect accuracy. Most existing algorithms focus on weather and user equipment while assuming stable signal sources—a premise often violated in practice. This section addresses dynamic source problems where APs fail due to damage or power loss, causing information loss or sparse distribution that degrades positioning accuracy. This issue is frequently ignored or addressed by filling missing signals with fixed values (e.g., -100 dBm), which creates distribution mismatch between test and training data, severely reducing accuracy. Our work investigates robust system enhancement through effective dynamic source recovery.

2.5.2 FixMR and FixMRT Methods

We developed FixMR based on manifold regularization to address dynamic source problems. FixMR comprises three components: loss function, complexity regularization term, and smoothness regularization term. It exploits the shared local linear structure between two-phase data to construct regression functions between sources, enabling accurate missing signal estimation. [Figure 8: see original paper] illustrates the FixMR algorithm flow.

Building on FixMR, we proposed FixMRT with adaptive neighborhood selection. This approach adaptively selects neighboring points based on manifold curvature changes to more accurately describe curve structure and estimate signal values. [Figure 9: see original paper] shows the adaptive neighborhood selection flow.

2.5.3 Experimental Results

[Figure 10: see original paper] compares FixMR with k-nearest neighbor, SVR, and RLS, showing FixMR achieves higher accuracy by leveraging low-dimensional manifold consistency, reaching 85% signal recovery accuracy within 10 dBm error. [Figure 11: see original paper] examines the ratio of unlabeled to labeled data impact on estimation error. [Figure 12: see original paper] compares FixMRT with other methods, showing FixMRT achieves 90% accuracy within 10 dBm, surpassing FixMR (85%), k-NN (70%), SVR (55%), and RLS (48%). [Figure 13: see original paper] and present positioning accuracy comparisons, demonstrating FixMRT approaches the accuracy of fault-free scenarios (Prime curve), achieving 88% within 3m, as it improves both signal estimation and positioning through adaptive neighborhood selection.

2.6.1 Background

Traditional machine learning-based indoor positioning uses multiple simultaneously received AP signals. However, some scenarios only receive stable signals from a single source, such as museum visitors or supermarket shoppers where few wireless sources are consistently available. Single-AP positioning with reasonable accuracy is therefore practically significant. We proposed a WLAN-based indoor positioning technology combining electromagnetic attenuation models with machine learning, resulting in the MulMR algorithm that integrates statistical and rule-based approaches.

2.6.2 MulMR Algorithm

The algorithm simultaneously uses attenuation models and machine learning to obtain distance and angle information from single-source signals. During offline training, mobile terminals collect data across the coverage area. For signal strength-distance samples, multivariate linear regression estimates the attenuation function d = P(s) based on propagation rules. For signal strength-angle samples, manifold regularization learns the mapping = Q(s). Here, s is signal strength, d is distance, and is angle.

During online positioning, received signal strength inputs to both functions to compute distance d and angle . Given the AP' s fixed position (x , y), the mobile terminal' s location (x, y) is calculated using: x = x + d · cos( ), y = y + d · sin( ).

2.6.3 Experimental Results

We evaluated three regression methods: simple linear, compensated linear, and multivariate linear regression. shows multivariate linear regression provides the best function approximation and fit quality, accurately describing the log-distance path loss model relationship between signal strength and distance. For angle prediction, manifold regularization outperformed SVR and BP neural network in both accuracy and curve approximation. Field validation confirms the method achieves room-level accuracy, meeting practical requirements.

2.7.1 Background

Traditional machine learning-based positioning involves offline training to build radio maps from extensive labeled samples, followed by online matching. The major obstacle to practical deployment is the labor-intensive calibration process. Avoiding offline data labeling has become a research focus.

2.7.2 Calibration-Free Adaptive Positioning Technology

We proposed a calibration-free adaptive technique using pre-deployed reference points with known positions to provide dynamic spatiotemporal benchmarks. Differential features extracted from signal strength differences between any two APs serve as input for regularized least squares regression to model the relationship between physical position and signal differences. During offline training, differential features are extracted from received signal strength (RSS) to build the mapping; during online positioning, test device RSS is processed similarly for matching. We validated this with both decision-based (Nearest Neighbor, NN) and probabilistic (Bayesian Inference, BI) approaches, denoted DIFF-NN and DIFF-BI.

The experimental environment covered 27m×17m divided into 161 grid points. DataSet1 contained 161×200 samples collected at 5Hz using an IBM R60 laptop; DataSet2 contained 161×10 samples at 0.5Hz using a Dopod O2 phone. Using DataSet1 for training and DataSet2 for testing, [Figure 16: see original paper] and [Figure 17: see original paper] show cumulative probability distributions. Direct RSS-based positioning achieves only 20% (NN) and 12% (BI) accuracy within 3m, highlighting the need to handle inter-device signal variations. DIFF-NN and DIFF-BI achieve 62% and 58% accuracy respectively within 3m, outperforming ratio-based features (42% NN, 49% BI) and matching linear mapping methods (61% NN, 52% BI) without requiring extra calibration data.

Combining this with reference point models further enhances calibration-free adaptability. Two reference point distributions were tested: uniform placement at room centers (Distribution 1) and uniform placement at room corners (Distribution 2). Five algorithms were evaluated: propagation model (PM), calibration-free feature extraction (CALIBREE), NN-DIFF, RLS-DIFF, and SVR-DIFF. [Figure 18: see original paper] and [Figure 19: see original paper] show the algorithm maintains good accuracy and robustness to reference point distribution changes without requiring additional calibration.

2.8.1 Background

In signal-strength-based positioning, APs emit signals in concentric circles, making signal strength similar at equal distances. Multiple APs are typically needed to reduce error, which complicates emergency instant positioning scenarios.

2.8.2 Directional Antenna Positioning Technology

We propose combining signal strength methods with directional characteristics. Directional antennas transmit and receive electromagnetic waves strongly in specific directions while having minimal gain elsewhere. Using directional APs reduces the emission region from a circle to a sector, improving precision. [Figure 20: see original paper] illustrates a directional antenna. [Figure 21: see original paper] compares scenarios: (A) one omnidirectional AP yields circular estimation region R; (B) one directional AP yields sector region R' constrained by beam angle; (C) two omnidirectional APs reduce the region through intersection; (D) two directional APs further reduce it through sector intersection. Our implementation uses two directional APs, combining directional advantages with sensor-free signal strength methods to provide a cost-effective, deployable, high-accuracy solution for large indoor areas.

2.8.3 Experimental Results

The experimental environment covered approximately 15m×24m divided into 75 grids. Two directional APs were placed at midpoints of east and north boundaries. A Moto A3100 phone collected 75×100 samples. [Figure 22: see original paper] shows signal strength distribution—strong within radiation angles, weak or absent outside. Overlapping two such distributions partitions the area into small zones ([Figure 23: see original paper]), enabling k-NN classification for position estimation. shows positioning accuracy with training sets of 5, 9, 13, and 21 random points, demonstrating satisfactory performance even with only 2 APs.

3.1 Indoor Positioning Application Systems

WiFi positioning has matured in research while rapidly developing commercially. WiFi-based RTLS solutions leverage existing infrastructure without additional hardware, enabling rapid deployment and significantly reducing initial and support costs. In the US and Europe, WiFi RTLS has become mainstream for hospital asset, equipment, and patient tracking, helping healthcare institutions reduce costs, improve workflows, and enhance care quality. Retail applications provide consumers with location-aware devices to track shopping patterns and interests. WiFi positioning also integrates with search engines for location queries and supports child monitoring in shopping environments.

3.2 Location-Based Multimedia Service System LMSS

Building on our positioning research, we developed the LMSS prototype system deployed at ICT-CAS, providing customized video based on user location. LMSS comprises positioning and video service components. When mobile users enter rooms, LMSS intelligently delivers different video services based on location. We tested this on both laptops and smartphones, with client screenshots shown in [Figure 25: see original paper] and [Figure 26: see original paper].

4 Conclusion and Next Steps

WiFi-based indoor positioning technology and systems have gained widespread attention and application, greatly simplifying information access. As new technologies emerge, positioning accuracy will improve and applications will expand. Current WiFi positioning primarily uses machine learning requiring extensive labeled training data, which is labor-intensive and hinders practical adoption. Overcoming this requires rapid model establishment techniques.

Our future work focuses on: (1) advancing calibration-free technology to drastically reduce labeling effort; (2) investigating relationships between AP quantity/distribution and model accuracy to minimize required APs; (3) studying WiFi attenuation models, identifying empirical parameters affecting accuracy, and exploring adaptive algorithms for universal or training-free models; (4) researching directional antenna characteristics to leverage direction information for improved accuracy; (5) monitoring sensor development and investigating multi-sensor fusion algorithms.

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Note: Figure translations are in progress. See original paper for figures.