

Enhancing Wi-Fi RSSI-Based Indoor Positioning with a Covariance-Weighted Distance Metric

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Abstract— This study proposes a distance metric for Wi-Fi RSSI-based indoor positioning systems to improve data collection efficiency. In traditional fingerprinting-based localization, the instability of RSSI signals necessitates repeated measurements at each reference point to ensure accurate localization. To address this limitation, we introduce a covariance-weighted distance metric that incorporates the spatial variability of RSSI signals through a covariance matrix. Experimental results demonstrate that the proposed metric achieves comparable or higher localization accuracy with fewer repeated measurements, particularly in open environments, thereby reducing deployment time and cost. In closed environments, the metric provides slight improvements over conventional Euclidean and cosine distances. This work highlights the potential of leveraging spatial RSSI variability to enhance the efficiency of indoor positioning systems.

Keywords— *Wi-Fi, Indoor Positioning, Fingerprinting, Distance Metric, RSSI*

I. INTRODUCTION

Wi-Fi-based indoor positioning is critical in environments where GPS signals are weak. Among existing techniques, fingerprinting is widely adopted due to its simplicity and general applicability. In fingerprinting, received signal strength indicator (RSSI) data are collected at multiple reference points during the offline phase to construct a fingerprint database. In the online phase, a user's location is estimated by comparing real-time RSSI vectors with the database [1] [2] [3] [4] [5][6].

RSSI signals are unstable due to multipath propagation, reflections, and interference. Consequently, repeated measurements at each reference point are typically required to achieve consistent accuracy, significantly increasing data collection effort, deployment time, and cost [1][5][6].

Existing distance metrics such as Euclidean, cosine, and Mahalanobis distances have limitations in exploiting the spatial variability of RSSI signals. Euclidean and cosine distances ignore correlations among signal dimensions, while Mahalanobis distance, using the inverse covariance matrix, tends to compress directions of high variance, potentially diminishing meaningful spatial variations [2][5].

To address these limitations, we propose a covariance-weighted distance metric that directly incorporates the covariance matrix of RSSI signals across multiple reference points, emphasizing how signals co-vary spatially. This metric allows the extraction of discriminative features with fewer measurements, improving fingerprinting efficiency. We evaluate the metric's performance under both open and closed spatial structures and compare it to conventional distance metrics in terms of localization accuracy and measurement efficiency.

II. RELATED WORK

A. RSSI-Based Indoor Localization

Fingerprinting is a prevalent RSSI-based localization technique. Its primary advantage lies in utilizing existing Wi-Fi infrastructure without modification. Despite its simplicity, RSSI variability due to environmental effects often limits localization accuracy and consistency [1][5][6].

B. Distance Metrics and Measurement Efficiency

Distance metrics determine the similarity between fingerprint databases and real-time RSSI measurements. Euclidean and cosine distances are common but fail to capture correlations and spatial variations. Mahalanobis distance accounts for variable correlations but may compress high-variance directions. Recent studies [3][4][5][6] have proposed methods to leverage RSSI variability, reduce repeated measurements, and enhance localization efficiency. Our proposed metric directly leverages covariance to emphasize spatial signal variations, allowing fewer repeated measurements to achieve reliable localization.

III. DATASET AND METHODOLOGY

A. Dataset

Data were collected in an indoor building environment at 60 reference points. At each point, 20 RSSI measurements were taken with at least six-minute intervals, resulting in 1,200 measurements. Reference points were categorized into open (21 points) and closed (21 points) environments, while 18 points were excluded from analysis. Data were structured as vectors per location and measurement repetition and preprocessed for classification.

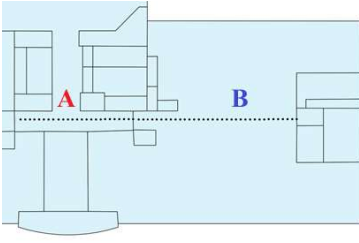


Fig. 1. Indoor Layout and Measurement Paths.

The measurement points were categorized according to spatial characteristics: closed environments (e.g., narrow corridors, partitioned rooms), consisting of 21 reference points (Fig. 1, Group A), and open environments (e.g., wide corridors, open spaces), consisting of another 21 reference points (Fig. 1, Group B). The remaining 18 points were excluded from the analysis.

The collected RSSI data were represented as vectors based on both location and measurement repetition. These vectors were further transformed into a structured format using a pivot table, followed by preprocessing to refine the dataset for classification experiments. This procedure ensured the construction of consistent input vectors that reflect both spatial characteristics and signal quality of the measurement environment.

B. Methodology

- **Distance Metrics:** Three distance-based algorithms were compared: Euclidean, cosine, and the proposed covariance-weighted distance.
- **Covariance-Weighted Distance:** Unlike Mahalanobis distance, the covariance matrix itself (not its inverse) is used to compute distance, capturing co-variations of RSSI signals across all reference points.
- **Classification Procedure:** To evaluate location classification performance, pairs of measurement points were constructed. For each class (reference point), an average RSSI vector was computed from the training data. Test samples were then compared with these class-average vectors, and the closest match determined the predicted location. This process is visually illustrated in Fig. 2.
- **Evaluation:** Accuracy was measured against the number of repeated measurements, and performance differences were analyzed between open and closed environments. Results were visualized to show convergence trends with increasing measurements.

IV. RESULTS

A. Open Environment

In open environments, the proposed covariance-weighted distance achieved the best performance. It reached the accuracy level of conventional Euclidean and cosine distances with significantly fewer repeated measurements, indicating effective capture of subtle spatial variations in AP signals (Fig. 3–5).

B. Closed Environment

In closed environments, the performance difference was minimal. The complex spatial structure, such as walls and

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for each pair of points (A, B) in all_point_pairs:
    # Step 1: Compute average RSSI vectors ( $\mu_A$ ,  $\mu_B$ )
    mu_A = average of training samples at point A
    mu_B = average of training samples at point B

    correct = 0
    total = 0

    # Step 2: Classify each test sample from point A or B
    for each x_test in test samples from A or B:
        sim_A = distance_function(x_test, mu_A)
        sim_B = distance_function(x_test, mu_B)

        # Step 3: Predict the point with higher similarity
        predicted = A if sim_A > sim_B else B

        # Step 4: Evaluate prediction
        if predicted == true_label of x_test:
            correct += 1
            total += 1

    # Step 5: Compute classification accuracy
    accuracy = correct / total

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Fig. 2. Pseudocode for Point-Pair Classification Based on RSSI Profiles

obstacles, produces distinct RSSI patterns. Traditional metrics, therefore, remain effective, and the proposed method provided only marginal improvement (Fig. 6–8).

V. DISCUSSION

This study proposed an approach to improve data collection efficiency in Wi-Fi RSSI-based indoor localization systems by employing a covariance-weighted distance metric. Experimental results demonstrate that the proposed method achieves higher accuracy with fewer repeated measurements in open environments. This can be attributed to the inherent spatial variability of RSSI signals, which reflects the unique propagation characteristics of each location. Unlike traditional Euclidean distance, which ignores such variability, or Mahalanobis distance, which compresses it through normalization, the covariance-weighted distance emphasizes how RSSI values co-vary across multiple reference points. This effect is analogous to principal component analysis, effectively expanding distances along directions with greater variance and enhancing discrimination between locations.

The point-pair classification approach further illustrates the effectiveness of this method. By constructing average RSSI vectors for each reference point from training data and comparing them with test samples, the method classifies the most similar location, providing a structured way to evaluate classification performance (Fig. 2). Results indicate that, in open environments with relatively uniform signal distributions, subtle spatial variations are captured efficiently, reducing the need for extensive repeated measurements. In contrast, closed environments with walls and obstacles inherently produce pronounced RSSI pattern differences, allowing traditional Euclidean and cosine metrics to remain effective. Consequently, only marginal improvements were observed in such environments.

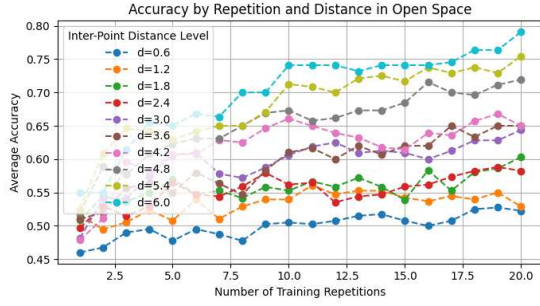


Fig.3. Localization Accuracy by Repetition and Distance in an Open Space (Cosine).

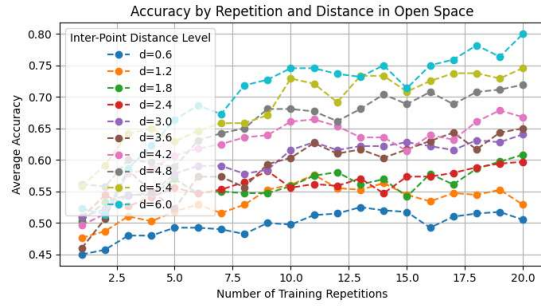


Fig.4. Localization Accuracy by Repetition and Distance in an Open Space (Euclidean).

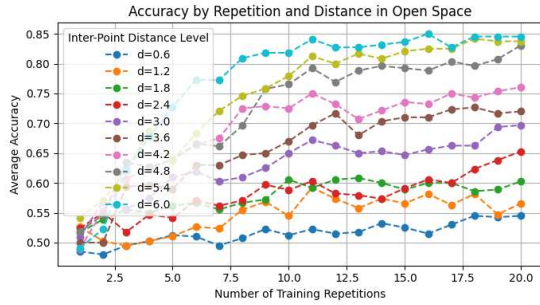


Fig.5. Localization Accuracy by Repetition and Distance in an Open Space (Weighted).

VI. CONCLUSION

The proposed covariance-weighted distance method highlights the potential of leveraging the spatial variability of RSSI signals to improve localization efficiency. It offers a practical means to reduce both the time and cost associated with fingerprinting-based system deployment, particularly in open indoor spaces.

Limitations of this study include the relatively small number of reference points (21 per environment type) and the focus on a single building structure, which may affect generalizability. Future work will extend this approach by incorporating dynamic environmental variations, validating the method across diverse architectural structures, and

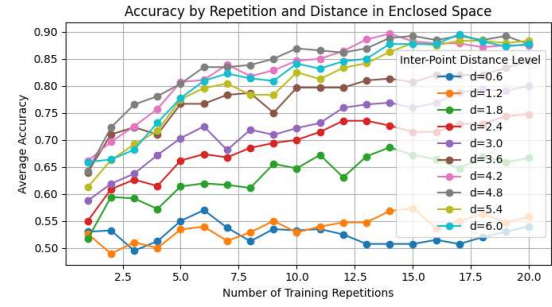


Fig.6. Localization Accuracy by Repetition and Distance in an Enclosed Space (Cosine).

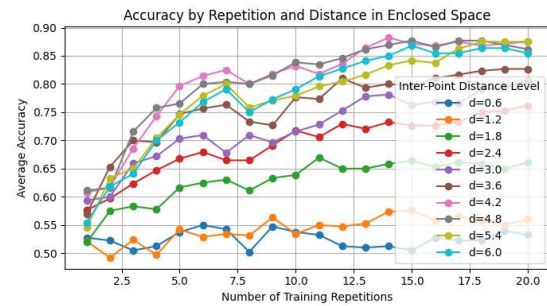


Fig.7. Localization Accuracy by Repetition and Distance in an Enclosed Space (Euclidean).

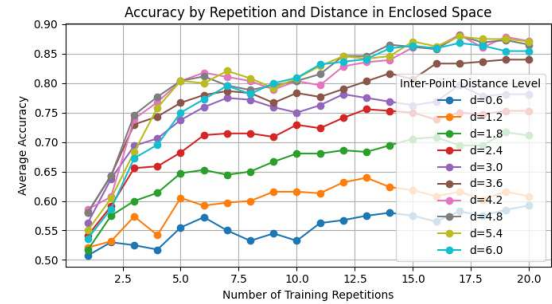


Fig.8. Localization Accuracy by Repetition and Distance in an Enclosed Space (Weighted).

exploring integration with machine learning models to further enhance robustness and scalability.

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