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Performance Evaluation of Radio Fingerprinting Localization

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Abstract: This paper introduces a radio fingerprinting localization method for positioning unknown radio transmitters (URTs) based on received signal strength difference (RSSD). The method incorporates Kalman filter (KF) preprocessing, principal component analysis (PCA), similarity measures, and weighted k-nearest neighbors (WKNN). First, the Kalman filter is applied to the received signal strength (RSS) measurements to reduce noise. Next, PCA is used for dimensionality reduction and decorrelation by extracting the principal components from the RSSD data. In the final stage, the similarity between offline and online principal component databases is measured using various metrics, while WKNN estimates the transmitter's position by assigning weights to nearby reference points (RPs). Simulations are conducted to evaluate the impact of preprocessing, the number of PCA components, and the choice of similarity measures on localization performance. The results provide a comprehensive analysis of the trade-offs between these techniques, highlighting their effectiveness in different environments and conditions for fingerprinting-based WLAN localization.

Keywords: Fingerprinting, Localization, RSSD, PCA, WKNN

Introduction

Recent technological advancements in mobile networks, coupled with the increasing demand for security, have led to the diversification of techniques for locating wireless device users. Radio signals, which are integral to daily life, play a crucial role in communication systems, facilitating applications such as mobile searches, emergency communications, and public safety (Zhang et al., 2019). However, these systems remain susceptible to interference from unauthorized or illegal transmissions. Unlicensed radios and intentional jammers, collectively known as Unauthorized Radio Transmitters (URTs), pose significant threats by illegally occupying wireless communication channels. As a result, the accurate detection of URTs has become a prominent area of research, drawing considerable attention in recent years.

In this context, radio fingerprinting technology has gained widespread adoption, particularly for indoor localization. This technique involves creating a database of radio fingerprints unique to a specific environment. Most previous research on radio fingerprinting localization techniques uses RSS due to its availability in various environments and the fact that it does not require additional hardware. RSS measurements are collected during

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the offline phase, and once the system is deployed, real-time measurements from the online phase are compared to the offline data to determine the location of URT (Zafari et al., 2019).

The accuracy of fingerprint-based localization depends not only on the precision of RSS measurements but also on the effectiveness of the algorithm used to match real-time measurements with the offline RSS fingerprint database during the testing phase (Polak et al., 2021). However, even at the same location and within the same time interval, RSS values varied due to differences in the power output and antenna gain of the radio transmitters. RSSD-based fingerprint positioning techniques, which operate by calculating the difference in RSS among access points (APs), effectively eliminate the influence of radio emitter power and antenna gain (Zhang et al., 2023). Compared to traditional RSS methods, RSSD-based approaches offer greater stability in heterogeneous environments and enhance the ability to locate URTs.

In Guenther & Julian)2016), a study on Wi-Fi location fingerprinting in indoor environments explores the use of Wi-Fi signal strength for positioning. The study evaluates nine distance metrics—including Manhattan, Euclidean, Chebyshev, and Cosine distances—to determine the most effective metric for accurate positioning. In (Zhang et al., 2019). A new KNN-based geo-location method utilizing RSSD and virtual reference points is proposed to improve URT localization. (Le et al., 2021) . Present an indoor positioning method that enhances accuracy and reduces power consumption by utilizing RSS fingerprints. This approach involves selecting fixed APs in the offline phase, applying PCA, and employing kernel-based ridge regression. (Zhou et al., 2021). Propose a robust fingerprint localization method using an adaptive KNN approach that dynamically selects the optimal number of neighbors. Additionally, (Zhang et al., 2023). İnvestigate a method based on RSSD, PCA, and the Pearson correlation coefficient to enhance feature extraction and reduce redundancy and cross-correlation in fingerprint data.

In this paper, we evaluate URT localization performance in WLAN networks by analyzing both accuracy and computational complexity (running time) based on various simulation parameters. These include the application of the Kalman filter, the number of PCA components used for dimensionality reduction, the choice of K in the WKNN algorithm, and different similarity test metrics. Specifically, the RSS measurements are preprocessed using a Kalman filter to reduce noise. Subsequently, the RSSD is calculated, and PCA is employed for dimensionality reduction in the offline phase. In the online phase, we apply the Kalman filter again on the RSS of URT, calculate the RSSD, and project the online RSSD onto the PCA coefficients derived from the offline phase. Various similarity tests are utilized to evaluate the similarity between the reduced datasets. Based on the results of these similarity tests, RPs are selected, and the WKNN algorithm is applied to accurately estimate the position of the URT. The remainder of this paper is organized as follows: Section 2 provides an overview of radio fingerprinting localization. Section 3 describes the system model used in the study. Section 4 presents the results and discussion. Finally, Section 5 concludes the paper, summarizing key findings and potential directions for future work.

Fingerprint Localization

Radio fingerprinting localization is a widely adopted technique for indoor positioning due to its high accuracy and ability to manage the complexities of indoor signal propagation. Unlike other methods, it does not require line-of-sight measurements of APs, has low complexity, and is well-suited for complex environments (Subedi & Pyun, 2017). This makes it widely applicable for accurate indoor localization, even in environments with challenging signal conditions. fingerprinting localization, typically require an environmental survey to collect fingerprints or features of the environment, which enhances the system's positioning accuracy. In this work, RSSD of different APs, which are deployed for network services, is used as feature location. The method consists of two main phases as shown in Figure 1, the offline phase and the online phase (Abed & Abdel-Qader, 2019).

In the offline phase, the area of interest is divided into grid points, referred to as RPs, each identified by Cartesian coordinates (x_i, y_i). At each RP, RSSD measurements between pairs of APs are collected along with the (x_i, y_i)coordinates of each RP to build a comprehensive fingerprinting database. These fingerprinting represent the unique signal characteristics of the environment and are stored for future comparison in the localization process. During the online phase, real-time RSS values received from the URT are converted into RSSD measurements by various APs within the area of interest. These RSSD measurements are then compared to entries in the fingerprinting database to estimate the URT's location using a pattern matching algorithm. The localization process determines the closest match between the real-time RSSD values and the stored fingerprints to accurately estimate the URT's position. To further enhance accuracy, multiple similarity metrics can be applied to determine the optimal match, with the final location estimated through an average or weighted calculation of the closest reference points.

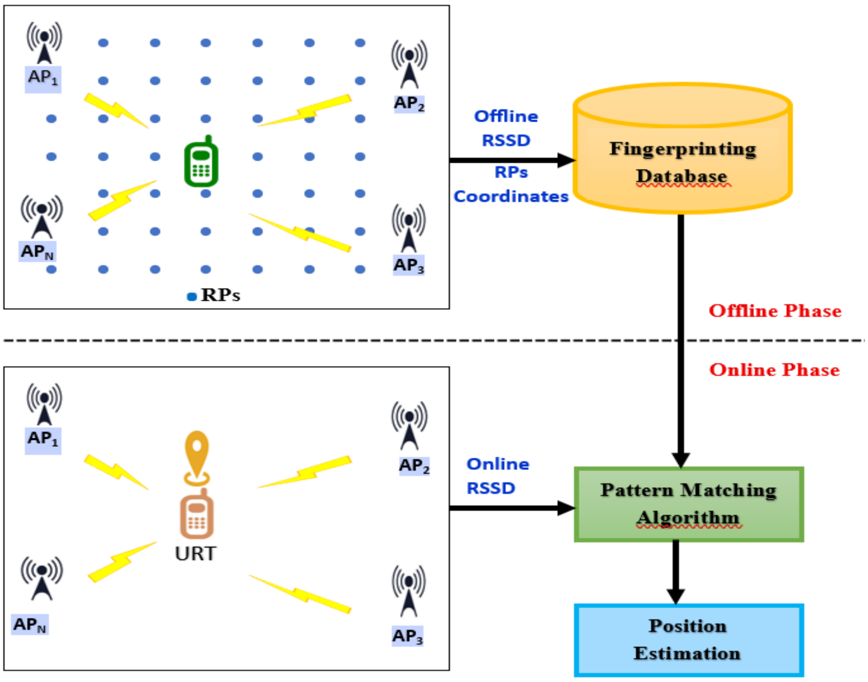

Figure 1. Radio fingerprinting localization method

System Model

In this section, we present the methodology employed by the proposed positioning system for estimating the location of a URT. The operational process of the RSSD-based PCA-WKNN fingerprinting positioning system consists of two primary phases: the offline database creation phase and the online positioning phase, as illustrated in Fig. 2.

During the offline phase, an appropriate grid distance is selected to partition the area into sub-positioning zones, with each vertex representing a RP. In our system, twelve APs are uniformly deployed. A known radio emitter is sequentially positioned at each RP, allowing for the collection of RSS measurements at each AP. Each RP corresponds to a unique set of location fingerprint vectors, capturing specific scene characteristics. Additionally, a Kalman filtering preprocessing step is employed to reduce noise in the RSS measurements, further improving the accuracy of the positioning system. The RP coordinates, along with the differences in observations from the APs, constitute the offline RSSD database. Notably, the RSSD values of adjacent calculations exhibit significant spatial and temporal correlation. To enhance computational efficiency in the online phase, we apply PCA on the offline database to extract the PCA coefficients, which are subsequently used to reduce dimensionality for both the offline and online databases.

In the online phase, real-time RSS from the URT is received by the APs. The same Kalman filtering preprocessing applied in the offline phase is utilized during this phase. Subsequently, the URT RSSD database is constructed through difference operations. Dimensionality reduction and decorrelation processing of the RSSD are performed using the previously computed PCA coefficients. The primary objective of the online positioning phase is to identify the most closely related reference point (RP) combinations. Similarity is evaluated by calculating various similarity metrics. The results are based on the WKNN algorithm, ultimately facilitating the selection of RP coordinates to estimate the URT's position.

RSSD Database Generation

In a positioning area with *K* RPs and *N* APs, the offline RSS fingerprint database, initially records RSS measurements from various APs, resulting in multidimensional features that characterize each RP. After applying Kalman filtering, the RSSD values are calculated, transforming the data into an RSSD fingerprint database, as depicted in Table 1 (Zhang et al., 2023).

Table 1. The offline RSSD fingerprint database.

Coordinates	RSSD sample			
(x_1, y_1)	$RSSD_{1,1-2}$	$RSSD_{1,2-3}$	...	$RSSD_{1,N-1}$
(x_2, y_2)	$RSSD_{2,1-2}$	$RSSD_{2,2-3}$	...	$RSSD_{2,N-1}$
(x_3, y_3)	$RSSD_{3,1-2}$	$RSSD_{3,2-3}$	...	$RSSD_{3,N-1}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
(x_K, y_K)	$RSSD_{K,1-2}$	$RSSD_{K,2-3}$	...	$RSSD_{K,N-1}$

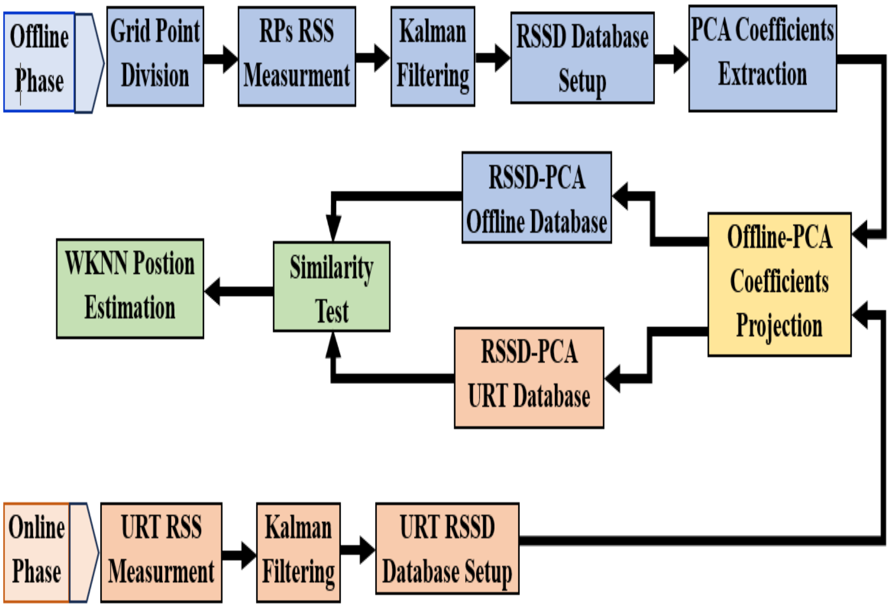

Figure 2. Flowchart of the studied scheme

PCA is used to reduce the feature space dimensions and eliminate correlation among original features without losing critical information. The offline RSSD sample matrix, denoted as $RSSD_{off}$ is structured as follow:

$$RSSD_{off} = \begin{pmatrix} RSSD_{1,1-2} & RSSD_{1,2-3} & \dots & RSSD_{1,N-1} \\ RSSD_{2,1-2} & RSSD_{2,2-3} & \dots & RSSD_{2,N-1} \\ \vdots & \vdots & \vdots & \vdots \\ RSSD_{K,1-2} & RSSD_{K,2-3} & \dots & RSSD_{K,N-1} \end{pmatrix} \tag{1}$$

Where $RSSD_{i,j}$ represents the RSSD value for the *i-th* RP and *j-th* AP. PCA coefficients (principal components) are extracted from $RSSD_{off}$. This process involves calculating the covariance matrix *C* of $RSSD_{off}$. Eigenvalue decomposition is then performed on *C*, yielding the matrix of eigenvectors, *P*. The eigenvectors are sorted in descending order according to their corresponding eigenvalues, with the top c eigenvectors selected as the c principal components. These selected eigenvectors are then combined to construct the projection matrix W (Jiang et al., 2021). Both the offline and online RSSD databases are then reduced by projecting onto the matrix W. The dimension reduction and RSSD decorrelation processing can be expressed as follows:

$$PRSSD_{off} = RSSD_{off}.W \tag{2}$$

Where $PRSSD_{off}$ is the reduced representation of the offline database. Similarly, during the online phase, the same matrix W is used to project the online RSSD data:

$$PRSSD_{on} = RSSD_{on}.W \tag{3}$$

Where $PRSSD_{on}$ is the reduced representation of the online database.

Similarity Testing

After dimensionality reduction, similarity between the reduced offline and online RSSD databases is evaluated using various similarity metrics. These metrics quantify the closeness of the reduced feature vectors to estimate the position accurately. Specifically, Euclidean distance, Manhattan distance, Chebychev distance, Cosine similarty and correlation are applied as similarity measures to compare the reduced representations. The description of each similarity test, as outlined in (Moghtadaiee & Dempster, 2015;Guenther & Julian, 2016). İs discussed in the following subsection.

Euclidean Distance

Euclidean distance quantifies the shortest distance between two points in a Cartesian coordinate system, effectively measuring the straight-line distance between two vectors.

$$d_e = \sqrt{\sum_{j=1}^{c}\left(PRSSD_{off,j} - PRSSD_{on,j}\right)^2} \tag{4}$$

where *c* is the number of principal components selected during PCA dimonsionality reuction.

Manhattan Distance

Manhattan distance, also known as city block distance, boxcar distance, or absolute value distance, is a commonly used metric for measuring similarity. This distance metric represents the distance between points on a grid-based.

$$d_m = \sum_{j=1}^{c}\left(PRSSD_{off,j} - PRSSD_{on,j}\right)^2 \tag{5}$$

Chebychev Distance

Chebychev distance, also known as the minimax metric or infinity norm. This distance calculation determines the maximum absolute difference between the corresponding elements of two vectors. It represents the greatest magnitude along any dimension of the vector space and is particularly useful in systems where calculation time is critical, as it can serve as an efficient alternative to other distance metrics. The Chebyshev distance is given by:

$$L_\infty = \max_c\left|PRSSD_{off,c} - PRSSD_{on,c}\right| \tag{6}$$

Cosine Distance

Cosine distance, d_{cos}, is a measure of similarity between two vectors rather than a traditional distance or dissimilarity metric. It calculates the angular separation between vectors, with values ranging from -1 to 1, where higher values indicate greater similarity between the vectors. By subtracting this similarity term from 1, the result can be interpreted as a vector distance. A higher cosine similarity value signifies a smaller angular separation, indicating that the two objects are more alike.

$$d_{cos} = 1 - \frac{\sum_{j=1}^{c} PRSSD_{off,j} \cdot PRSSD_{on,j}}{\left(\sum_{j=1}^{c} PRSSD_{off,j}{}^2 \cdot \sum_{j=1}^{c} PRSSD_{on,j}{}^2\right)^{1/2}} \tag{7}$$

Correlation Distance

Correlation distance measures the similarity between two vectors based on the linear relationship of their values. Unlike other distance metrics, correlation distance quantifies the degree to which one vector varies in relation to the other, with values ranging between -1 and 1. A value close to 1 indicates strong positive correlation (similar direction), 0 indicates no correlation, and -1 indicates strong negative correlation (opposite direction).

$$d_{cor} = \frac{\sum_{j=1}^{c}(PRSSD_{off,j} - \overline{PRSSD_{off}}).(PRSSD_{on,j} - \overline{PRSSD_{on}})}{\left(\sum_{j=1}^{c}(PRSSD_{off,j} - \overline{PRSSD_{off}})^2 . \sum_{j=1}^{c}(PRSSD_{on,j} - \overline{PRSSD_{on}})^2\right)^{1/2}} \tag{8}$$

Where $\overline{PRSSD_{off}}$ and $\overline{PRSSD_{on}}$ are the mean values of $PRSSD_{off}$ and $PRSSD_{on,}$, respectively.

For position estimation, the RP coordinates with the highest coefficients are selected. We use WKNN algorithm to obtain the estimated coordinate(x_{URT}, y_{URT}) of the URT, which is expressed by:

$$\begin{cases} x_{URT} = \frac{1}{K}\sum_{i=1}^{K} x_i \\ y_{URT} = \frac{1}{K}\sum_{i=1}^{K} y_i \end{cases}) \tag{9}$$

where (x_i, y_i) represents the coordinate of the *i-th* RP and *K* is the number of selected RPs

Results and Discussion

In this section, we present simulations that were conducted to assess the performance of a wireless localization system based on radio fingerprinting for URT positionning. The goal of these simulations is to evaluate the impact of different parameters and preprocessing techniques on localization accuracy and computational efficiency. The performance was analyzed under varying conditions, including the application of Kalman filter preprocessing, PCA components, similarity tests, and influnce of varying WKNN values. The simulation takes place in a 2D area of 100×100 meters. The environment consists of 12 fixed APs positioned throughout the area, which provide RSS measurements.The performance criteria used in these simulations include Localization error, defined as the distance between the estimated position of the URT and its true position. This error measures the system's accuracy. Running time which reflects the computational efficiency of the system under different configurations,

APs Distribution and URT Trajectory

The simulation area is divided into a grid of RPs spaced 0.5 meters apart. 12 fixed APs are positioned throughout the area, to ensure sufficient coverage, as shown in Figure 3. To simulate the movement of the URT, a series of key reference points was selected to form a path covering a significant part of the environment, dipected in Figure Y. The step size between trajectory points is set to 0.5 meters, allowing for detailed and precise simulation of the URT's motion

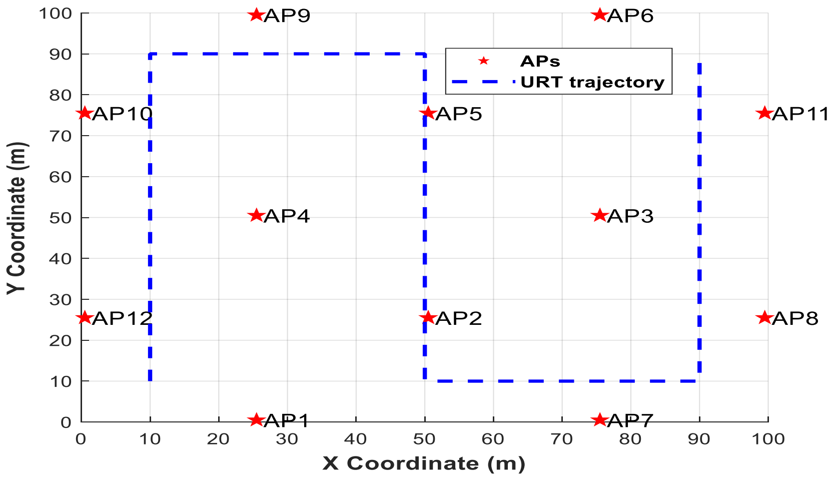

Figure 3. APs distribution and URT trajectory with 0.5m steps

RSS Modeling

To generate the RSS values in an indoor environment, a log-distance path loss model is used in (Zhang et al., 2019). This model is defined by the following equation:

$$P(d_{p,q}) = P(d_0) - 10.\alpha.log\frac{d_{p,q}}{d_0} + x_q$$

where:

- $P(d_{p,q})$ is the RSS at the q-th RP located at a distance $d_{p,q}$ p-th AP,
- $P(d_0)$ is the RSS at the reference distance d_0,
- d_0 is the reference distance,
- α is the path loss exponent,
- $d_{p,q}$ represents the distance between the p-th AP and the q-th RP,
- x_q is a Gaussian random noise following the distribution $N(0,\sigma^2)$,
- σ^2 represents the variance of the RSS measurement.

For our simulation, the following values for the model constants were used: $P(d_0)=10$ dB, $d_0=1$meter, $\alpha=1.8$ and $\sigma^2=5.2$ dB

Simulation Setup and Results

In the following subsections, we present the detailed results of various simulations. The process begins with the application of Kalman filter preprocessing on the RSS measurements. After preprocessing, we compute the RSSD by calculating the difference between the RSS values of different APs at the same RP. Next, we analyze the impact of PCA and various similarity tests on localization accuracy and computational complexity. Finally, the influence of different WKNN values on the performance of the radio fingerprinting localization system is evaluated, with a focus on both accuracy and efficiency.

Impact of Kalman Filter

In this simulation, we employ the Euclidean distance metric with 80 WKNN to estimate the position of URT. The objective is to compare the localization error under two scenarios: one without preprocessing and another where a Kalman filter is applied to RSS measurements during both the offline and online phases. The Kalman filter is utilized to reduce noise in the RSS data, aiming to enhance the localization accuracy.

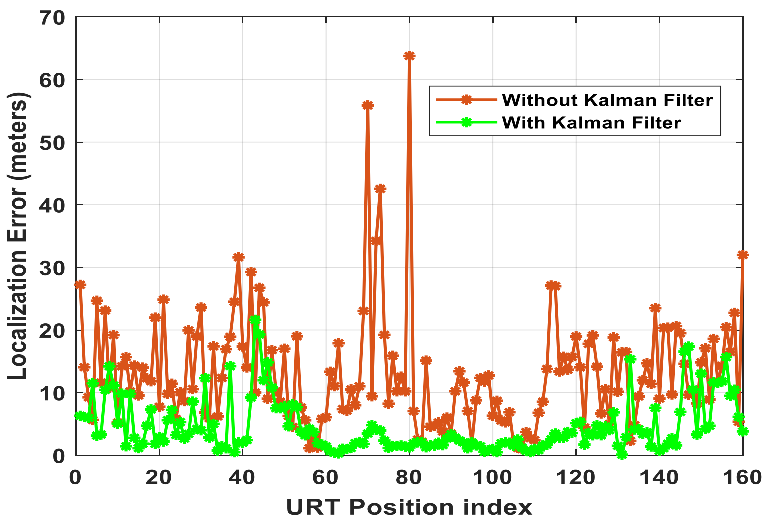

Figure 4. Localization error of URT.

The simulation results demonstrate that incorporating the Kalman filter leads to a significant reduction in localization error. The Kalman filter effectively smooths the RSS measurements, minimizing the impact of noise and fluctuations. Consequently, this improves the accuracy of matching real-time RSS data with the precomputed fingerprint database, yielding more precise location estimates. These findings underscore the importance of filtering techniques, such as the Kalman filter, in enhancing the reliability of indoor localization systems.

Impact of PCA Components

This simulation evaluates the effect of PCA on the accuracy and computational efficiency of fingerprinting-based localization. PCA is applied with varying numbers of components, ranging from 3 to 9, to assess its impact on localization error. PCA components 1 and 2 are excluded from the analysis due to their insignificant results, while components beyond 9 (i.e., 10 and 11) yield similar outcomes to those with 9 components, offering no further improvement.

The similarity between the online and offline RSSD databases is determined using correlation, while location estimation of the URT is achieved using 80 WKNN. A Kalman filter is also implemented in both the offline and online phases to reduce noise in the RSS measurements. Additionally, we compare these results with a scenario in which PCA is not applied, aiming to find an optimal balance between dimensionality reduction for improved computational speed and accurate localization performance.

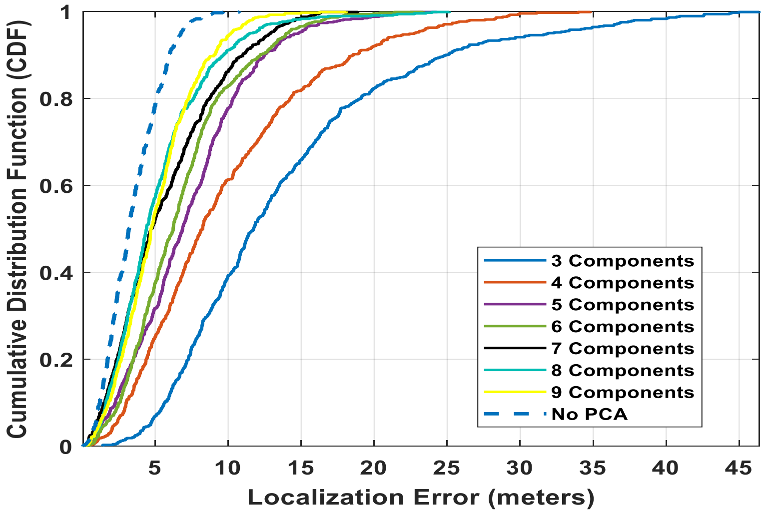

Figure 5. CDF of localization error for PCA components

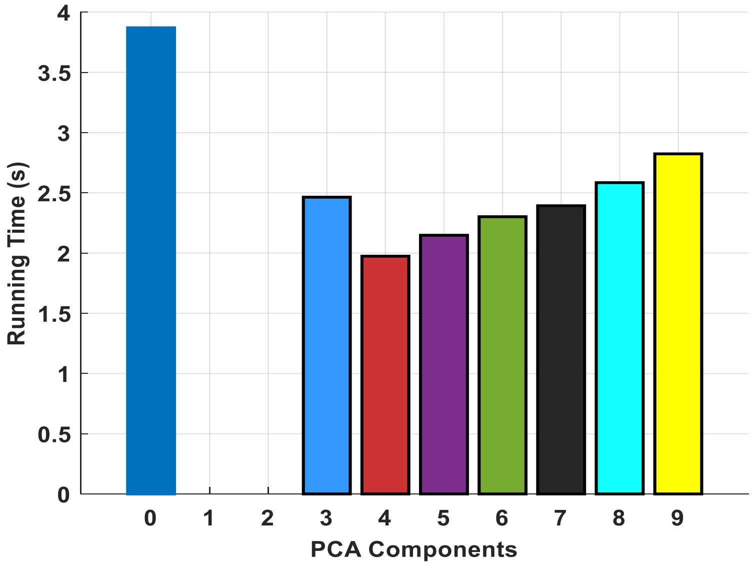

Figure 6. Runing time vs. PCA components (Including no PCA)

The simulation results, as illustrated in figures 5 and figure 6, reveal several important insights regarding the impact of PCA components on both localization accuracy and computational efficiency. Firstly, as the number of PCA components increases, the localization error decreases. This improvement occurs because higher numbers of PCA components retain more significant features from the original RSSD data, enhancing the system’s ability to distinguish between different locations. However, beyond eight components, the localization accuracy shows minimal improvement, indicating that the additional components contribute marginally to error reduction. Secondly, the running time exhibits a positive correlation with the number of PCA components, reflecting the increased computational complexity required for higher-dimensional data. Notably, an anomaly is observed when using three PCA components, where the running time is unexpectedly higher. This irregularity could be attributed to inefficiencies in processing lower-dimensional data within the PCA framework. Lastly, performing localization without PCA yields a marginally lower localization error since no information is lost during dimensionality reduction. However, this comes at the cost of significantly longer running times, highlighting the computational inefficiency associated with handling high-dimensional data directly.

These findings underscore the trade-off between localization accuracy and computational cost. While using up to eight PCA components strikes a balance between minimizing error and maintaining efficient processing times, further increases in components offer diminishing returns in accuracy while imposing a heavier computational complexity.

Impact of Similarity Tests

In this simulation, we investigate the effectiveness of various similarity tests. Utilizing 8 PCA components, we apply an 80 WKNN algorithm alongside a Kalman filter for noise reduction in both the offline and online RSS databases. The aim is to compare the performance of different similarity metrics, including Euclidean, Manhattan, Chebyshev, Cosine, and Correlation, to determine their impact on localization accuracy and computational efficiency.

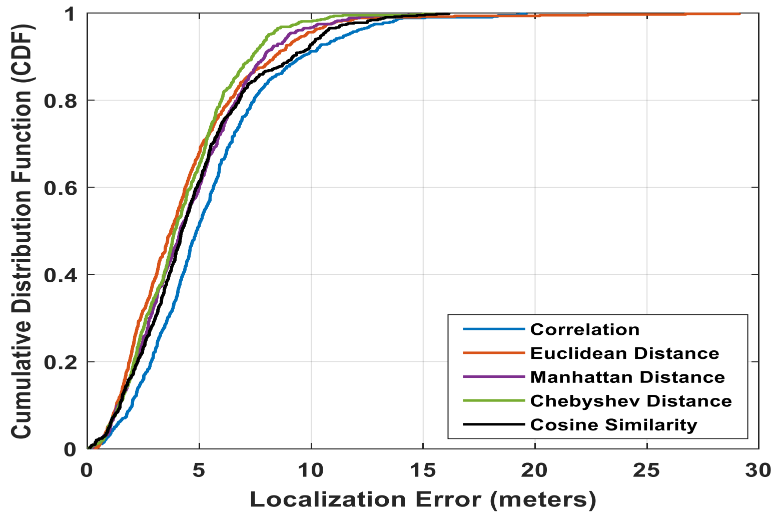

Figure 7. CDF of localization error for ifferent similarity measures

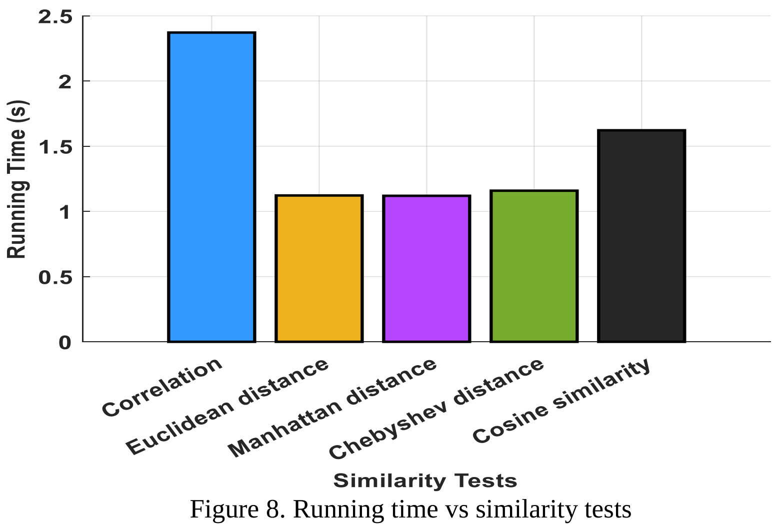

Figure 8. Running time vs similarity tests

The comparison between the different similarity measures—Euclidean, Manhattan, Chebyshev, Cosine, and Correlation—reveals several important findings related to both localization accuracy and computational efficiency. From the perspective of accuracy, the Euclidean and Chebyshev distance metrics provide the best performance, yielding the lowest localization error. Manhattan distance and Cosine similarity perform slightly worse but are still close in terms of accuracy to the best-performing metrics. The correlation-based similarity measure, however, exhibits the poorest accuracy, resulting in higher localization errors compared to the other methods. In terms of computational efficiency, Euclidean, Manhattan, and Chebyshev distances demonstrate the best performance with comparable running times, making them the most computationally efficient in this comparison. Cosine similarity incurs a higher computational cost, resulting in a longer running time. Correlation, while being the least accurate, also presents the highest running time, performing worse than Cosine in terms of speed.These results suggest that Euclidean and Chebyshev distances provide the best trade-off between accuracy and computational efficiency, making them ideal choices for practical fingerprinting localization applications. In contrast, correlation should be avoided due to both its lower accuracy and higher computational burden.

Impact of WKNN Values

In this simulation, the impact of varying WKNN values on localization error was evaluated using Euclidean distance as the similarity measure and applying a Kalman filter to RSS measurements during both the offline and online phases. By testing WKNN values ranging from 10 to 150, the goal was to determine the optimal number of neighbors that minimize localization error.

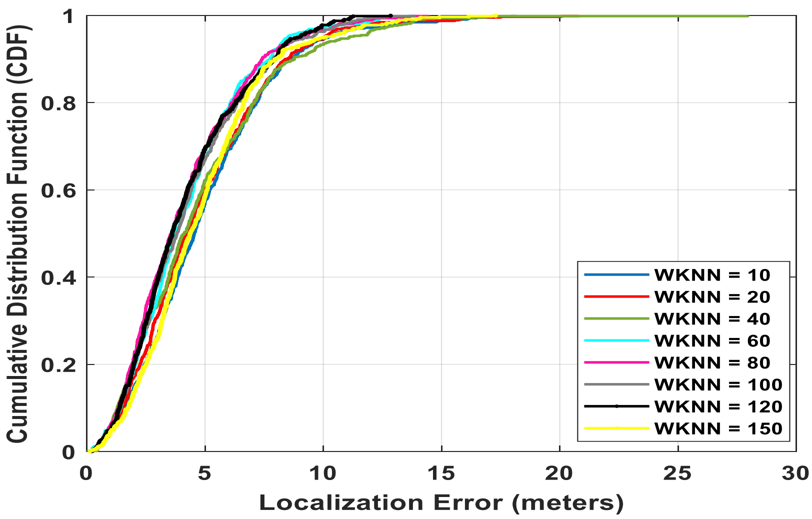

Figure 9. CDF of localization error for different WKNN values

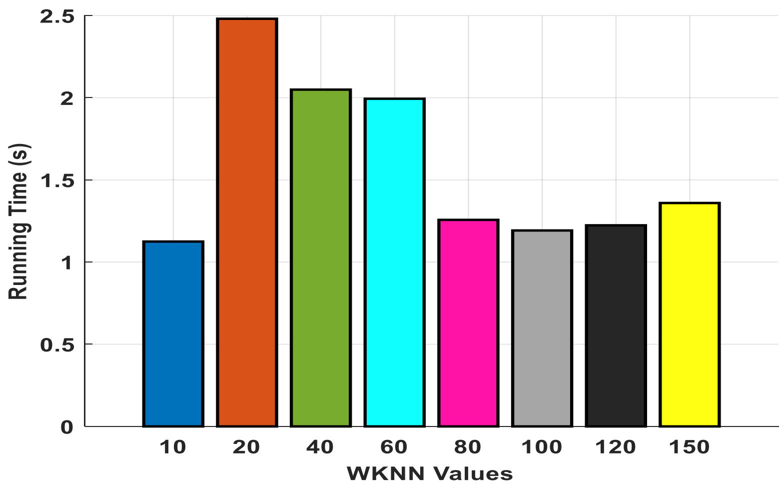

Figure 10. Running time vs. WKNN values

The results of the localization error analysis reveal an optimal range for WKNN values between 60 and 120, where localization accuracy is consistently high. Specifically, WKNN values of 60, 80, 100, and 120 show the best performance in terms of accuracy. In contrast, lower WKNN values (10, 20, 40) and the higher value of 150 exhibit slightly decreased accuracy, suggesting that an excessively small or large number of neighbors may negatively affect localization precision.

Regarding running time, there is a noticeable variation across different WKNN values. For WKNN = 10, the running time is 1.1248 seconds, which increases as WKNN grows, peaking at WKNN = 20 with 2.4803 seconds. Interestingly, after WKNN = 40 (2.0492 sec), the running time starts decreasing and stabilizes, with the best results found for WKNN = 80 (1.2566 sec) and WKNN = 100 (1.1921 sec). As WKNN increases further, there is a slight increase in running time, reaching 1.3593 seconds for WKNN = 150. The running time results suggest that a WKNN value between 60 and 120 strikes the best balance between high localization accuracy and computational efficiency. Values higher than 120 result in diminishing returns in terms of both accuracy and speed. These findings highlight the importance of selecting an appropriate WKNN value to ensure optimal localization performance in practical systems.

Conclusion

This study evaluates the performance of a radio fingerprinting localization system for localizing URTs in WLAN environments, employing a radio fingerprinting technique based on RSSD. It highlights the crucial role of Kalman filter preprocessing in reducing noise and enhancing localization accuracy. The analysis reveals that using up to eight PCA components achieves an optimal balance between accuracy and computational efficiency, while additional components offer diminishing returns. Among various similarity measures, Euclidean and Chebyshev distances demonstrated superior effectiveness in both accuracy and efficiency, whereas correlation performed poorly. Furthermore, an optimal WKNN range of 60 to 120 was identified, providing a balance between high localization accuracy and computational efficiency. These findings emphasize the importance of judiciously selecting preprocessing techniques, dimensionality reduction methods, similarity measures, and WKNN values to optimize localization performance in practical applications.

Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM Journal belongs to the authors.

Acknowledgements or Notes

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