AN EFFICIENT METHOD FOR BLE INDOOR LOCALIZATION USING SIGNAL FINGERPRINT

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***Abstract*:** The emergence of Bluetooth Low Energy (BLE) technology has created many opportunities for indoor localization. However, extracting fingerprint features from the Received Signal Strength Indicator (RSSI) values of Bluetooth signals often yielded results with significant errors and instability. This study utilizes a Kalman filter to stabilize received RSSI values. It employs Autoencoder and Convolutional Autoencoder models to extract distinctive features and compares random test points with reference points in a database using normalized cross-correlation.

Keywords: Indoor Localization, Fingerprint, Bluetooth Low Energy, Autoencoder.

I. INTRODUCTION

Indoor localization has long been a crucial issue in various large-scale applications today, such as inventory management, equipment tracking, and product monitoring. Currently, there are numerous technologies for indoor positioning, including Wi-Fi, Ultra-Wideband, Bluetooth, optical technology, and infrared. However, these technologies have inherent limitations, such as high production costs, energy consumption, or significant inaccuracies. Bluetooth Low Energy (BLE) technology has been researched and developed to address these challenges. Its advantages include low production cost energy efficiency, and easy deployment.

Nonetheless, it does not match the precision of Ultra-Wideband (UWB) and lacks the coverage of Wi-Fi. Several BLE-based positioning methods have been proposed, among which BLE fingerprinting stands out for its relatively good accuracy. Hence, this research focuses on developing an indoor positioning method based on BLE fingerprinting.

This approach places some Bluetooth beacons (BC) at Predetermined locations. After a predefined period of time, these BCs transmit data packets containing IDs and additional information. The device to be located will continuously collect information and transmit it to the server for processing. The device's location will be estimated based on BLE fingerprint characteristics. This method is divided into two main phases: offline and online. The offline phase collects Received Signal Strength Indicator (RSSI) values from BCs at each reference point (RP). These values are processed to cextract features and stored in a fingerprint map database. The online phase consists of collecting RSSI values from BC signal packets. These values are also used to extract fingerprint features, which are then compared with reference points. The reference points with the most similar fingerprint features are selected to calculate the coordinates of the target location.

Several BLE fingerprinting methods have been proposed. Zou and colleagues [1] applied graph optimization to achieve a best-case accuracy of 1.27 meters. Martin and colleagues [2] employed Gaussian kernel-based fingerprinting with an accuracy below 1.5 meters in 90% of cases. Subedi and colleagues [3] utilized a two-step fingerprint-based approach with an accuracy of 1.05 meters. Li and colleagues [4] utilized an eight neighborhoods template matching mechanism with a 1-meter accuracy.

This paper proposes an indoor localization method based on BLE fingerprinting, specifically fingerprint feature extraction. It involves deploying six BCs around a room, with the RSSI values of each reference point stored in the fingerprint database. RSSI measurements are susceptible to noise, so the Kalman filter and deep learning models like Autoencoders and Convolutional Autoencoders are employed to reduce noise and data dimensionality. The Minkowski distance is calculated between the measured fingerprint and reference fingerprint to identify the k nearest reference points with the measured fingerprint. This information is used to calculate coordinates and assess accuracy.

This paper is organized as follow: Section 2 provides an overview of the dataset construction and the algorithms used. Experimental results are presented and compared with previous research findings in Section 3. Conclusions and future directions are discussed in Section 4.

II. METHOD

The critical steps of indoor positioning using fingerprint features are illustrated in Figure 1. Each step in our proposed method is presented in detail below.

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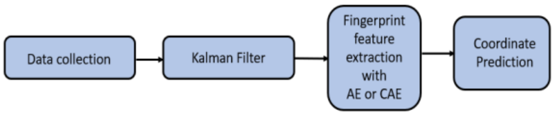

Figure 1. The main steps in the proposed method.

A. Data collection

Let's assume that there are N reference points within the coverage area. At each reference point, RSSI values are measured over a period and organized into the following matrix:

$$R = \begin{bmatrix} r_1(1) & r_1(2) & \cdots & r_1(B) \\ r_2(1) & r_2(2) & \cdots & r_1(B) \\ \vdots & \vdots & \ddots & \vdots \\ r_N(1) & r_N(2) & \dots & r_N(B) \end{bmatrix} \quad (1)$$

In matrix (1), $r_n(b)$ represents the RSSI value at reference point n obtained from beacon b. Here, $n = 1, 2, 3, \dots N$, representing the sequential number of reference points, and
$b = 1, 2, 3, \dots B$, the number of beacons used within a defined range.

B. Kalman Filter

The Kalman filter, introduced by Rudolf E. Kalman and published in 1960 [7] is a widely used tool in control systems. It is employed to estimate the state of a process in the presence of noise in measurements. This method works by determining the estimated state of the process based on actual measurements and the ideal state, to minimize the mean square error between them. The Kalman filter consists of two primary steps: *Prediction* and *Measurement Update* [8], [9]. The visualization of the Kalman filter process is depicted in Figure 2.

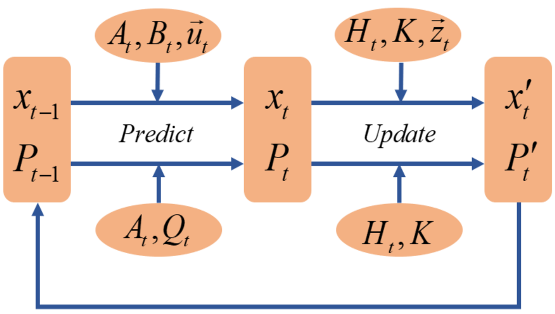

Figure 2. Implementation of the Kalman filter.

Prediction

The current state x_t and error covariance matrix P_t of the process are estimated in a general form as:

$$x_t = A_t x_{t-1} + B_t u_t \quad (2)$$
$$P_t = A_t P_{t-1} A_t^T + Q \quad (3)$$

Where:

- A_t: State transition model matrix
- B_t: Control input model matrix
- u_t: Control vector
- Q_t: Process noise covariance matrix

Measurement Update

The initial task in the update process is to compute the Kalman Gain, as shown in Eq.4:

$$K = P_t H_t^T (H_t P_t H_t^T + R_t)^{-1} \quad (4)$$

Next, the expected state and covariance matrix are updated as per Eq.5 and Eq.6:

$$x'_t = x_t + K(z_t - H_t x_t) \quad (5)$$
$$P'_t = (1 - K_t H_t) P_t \quad (6)$$

where, H is the matrix relating to state x_t through the measurement $z_t = H_t x_t + R_t$, where R_t is a random variable representing the measurement noise covariance. The Kalman filter operates recursively: the *Prediction* process estimates the current provisional state based on the previous state, and then the *Measurement Update* process adjusts the estimate with an actual measurement. These steps are repeated with previous posterior estimates used to predict new prior estimates [9].

With our collected RSSI data, each vector $r_n(b) = \{rssi_1, rssi_2, \dots, rssi_R\}$ is passed through the Kalman filter, with the first value as the average of R samples in each vector:

$$rssi_0 = \frac{1}{R}\sum_{i=1}^{R} rssi_i \quad (7)$$

The Kalman filter enhances the stability of our dataset, thereby improving the fingerprint features for each reference point and enhancing training performance.

C. Fingerprint Features Extraction

1. Autoencoder

Autoencoder (AE) is a neural network model in machine learning and computer vision designed for unsupervised data encoding. It aims to learn a lower-dimensional representation (encoding) for higher-dimensional data, reducing complexity and saving computational resources. AE is often used for dimensionality reduction and feature extraction tasks. Figure 3 provides a visual representation of AE architecture, consisting of *Encoder*, *Code*, and *Decoder*:
Encoder: Receives input data and transforms it into a lower dimensional compressed form. The encoder typically consists of a sequence of neuron layers, learning to extract essential information from the data and represent it as a compressed vector. The neuron layers in the encoder often employ activation functions like ReLU, sigmoid, or hyperbolic tangent.
Code: Contains the compressed data, also known as the output of the encoder. It is a crucial part of the network because it holds the features of the input data.
Decoder: Receives the compressed data from the encoder and attempts to reconstruct the original data. The decoder also consists of a sequence of neuron layers, transforming the compressed data into the original data while minimizing the reconstruction error.

The training process of an Autoencoder aims to minimize the error between the original data and the reconstructed data by adjusting the encoder and decoder weights and parameters. Loss functions commonly include Mean Squared Error (MSE) and Binary Cross-Entropy (BCE).

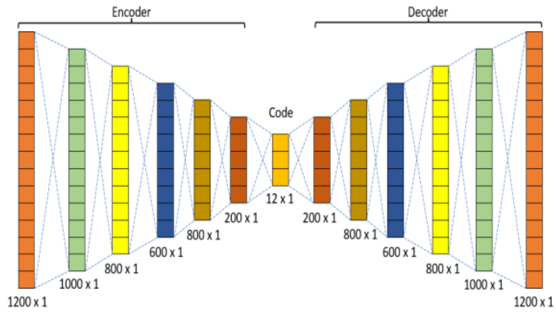

Figure 3. Proposed Autoencoder model structure.

Each reference point in our database has data vectors of size 200×6, which are flattened into 1200×1 vectors to match the input size of the AE model. After passing through the encoder, the data is compressed into a 12×1 code, which is then decoded to produce an output of 1200×1. In this study, the Autoencoder model uses the hyperbolic tangent (tanh) activation function, employs the Adam optimization algorithm, and uses Mean Squared Error (MSE) as the loss function.

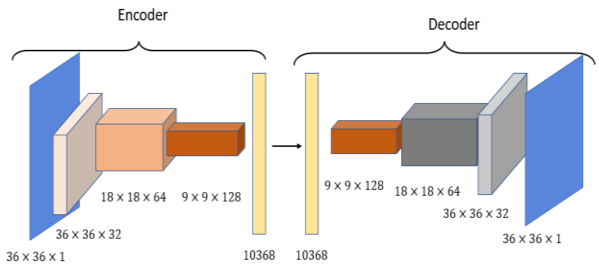

Figure 4. Proposed Convolutional Autoencoder model structure.

Because the input of the CAE model is a matrix, each 1200×1 data vector is transformed into a 36×36 matrix with 96 zero-padding elements.

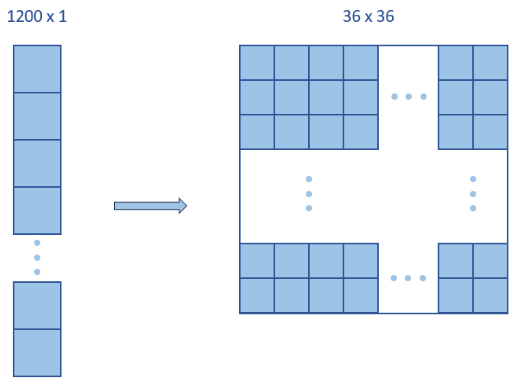

Figure 5. The data vector is converted to matrix form for input to the Convolutional Autoencoder.

D. Coordinate Prediction

1. Correlation

Signal correlation is a crucial aspect in signal research and analysis. In this study, a correlation system is used to compute and compare the input signal with an available fingerprint dataset. For two discrete signals $x[n]$ and $y[n]$, the calculation of their correlation, denoted as $C(x, y)$, is performed using the following formula:

$$C(x, y) = \sum_{n_1}^{n_2} x[n]y[n] \quad (8)$$

Where n_1 and n_2 represent specific time intervals for calculating the correlation between the two signals [12]. In a special case where the two signals are identical, it can be observed that in this case, the main correlation is the signal's energy:

$$C(x, x) = E(x) \quad (9)$$

2. Convolutional Autoencoder

The Convolutional Autoencoder (CAE) combines convolutional neural network principles with an autoencoder. It is often used for unsupervised learning tasks. Like an autoencoder, the CAE architecture consists of an Encoder, Code, and Decoder [10], [11]. The proposed CAE architecture in this study is illustrated in Figure 4.

The encoding part processes the input as a matrix using convolutional layers to produce lower-dimensional output than the input matrix. The decoding part takes the lower dimensional representation from the encoding part and transforms it back to the original matrix size using decoding layers. The training process of the Convolutional Autoencoder is similar to that of the Autoencoder, with the aim of minimizing the difference using Mean Squared Error (MSE) as the loss function.

2. Normalized Cross – Correlation

Normalized Cross-Correlation (NCC) is used in signal processing to measure the degree of similarity or correlation between two signals. NCC is typically employed to search for a specific signal pattern within a larger signal.

This research proposes using the NCC coefficient to compare the input signal with a pre-existing fingerprint database to determine the most accurate coordinates. NCC between two signals $x[n]$ and $y[n]$ is determined by the following formula [5]:

$$NCC(x, y) = \frac{\sum_{n_1}^{n_2} x[n]y[n]}{E(x)E(y)} \quad (10)$$

This formula normalizes the aggregate correlation by dividing the numerator by the product of the energy of two signals, $x[n]$ and $y[n]$. The result falls within the range of -1 to 1, indicating the level of similarity between the two signals. A value of 1 typically represents complete correlation, while -1 indicates complete inverse correlation. A value close to 0 generally indicates low or no correlation between the two signals.

Utilizing this approach involves the identification of k reference points exhibiting the closest distance. Eventually, the point coordinates to be determined are predicted as the centroid of these k reference points. Different values of k result in different predicted coordinates, calculated using formula (11):

$$(x, y) = \frac{1}{k} \sum_{i=1}^{k} (x_i, y_i) \quad (11)$$

III. EXPERIMENTS AND RESULTS

A. Data collection

The experiment was conducted on the 6th floor of the Ta Quang Buu Library at Hanoi University of Science and Technology, Vietnam. Six BLE beacons were placed at coordinates $(0,0), (0,4), (0,8), (8,0), (8,4)$, and $(8,0)$ within an $8m \times 8m$ area, as described in Figures 6 and 7. The beacons and Bluetooth signal strength receiving devices were on the same floor of the plane.

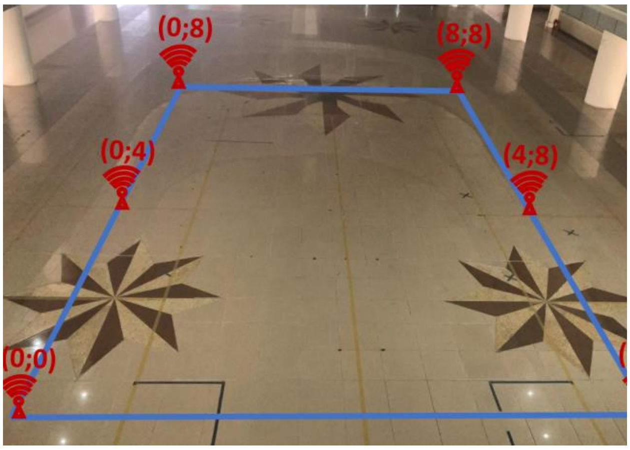

Figure 6. The experimental environment.

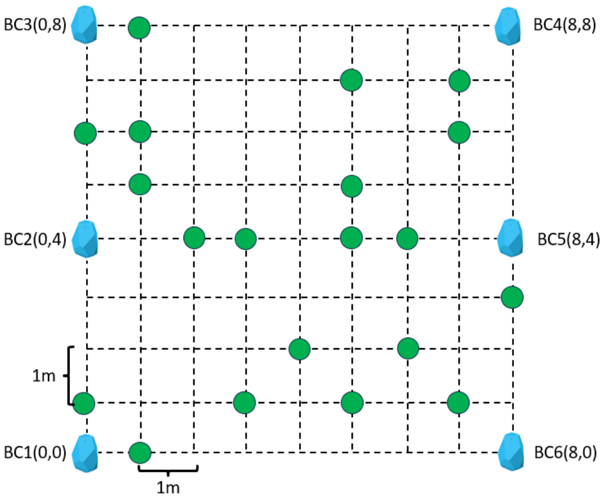

Figure 7. Arrange the experiment to collect RSSI values from beacons at each reference point.

There is a total of 75 reference points on the map. At each reference point, 200 RSSI value samples were gathered for a specific beacon. The reference points are placed one meter apart to ensure that the data density is not too dense and to avoid confusion between reference points during feature extraction. Additionally, 20 random test points were collected to assess the performance of the fingerprint feature extraction model, as depicted in Figure 7 and Figure 8.

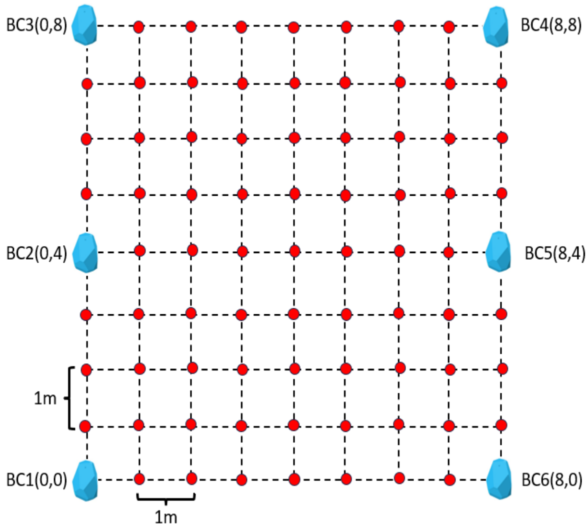

Figure 8. Test points are collected randomly.

Figure 9 presents a specific example of RSSI data from 200 samples recorded at two reference points (RP_1 and RP_2) for a specific beacon. Conversely, Figure 10 illustrates RSSI data from
200 samples obtained from two different beacons (BC_1 and BC_2) at a reference point. These data illustrate the uneven signal variations. This inconsistency may be due to the influence of the surrounding environment and factors causing random errors during the experimental process. This issue poses a significant challenge for indoor localization methods relying on BLE signals.

B. Utilizing Kalman Filter

As explained in the previous section, noise factors can significantly affect the process of fingerprint feature

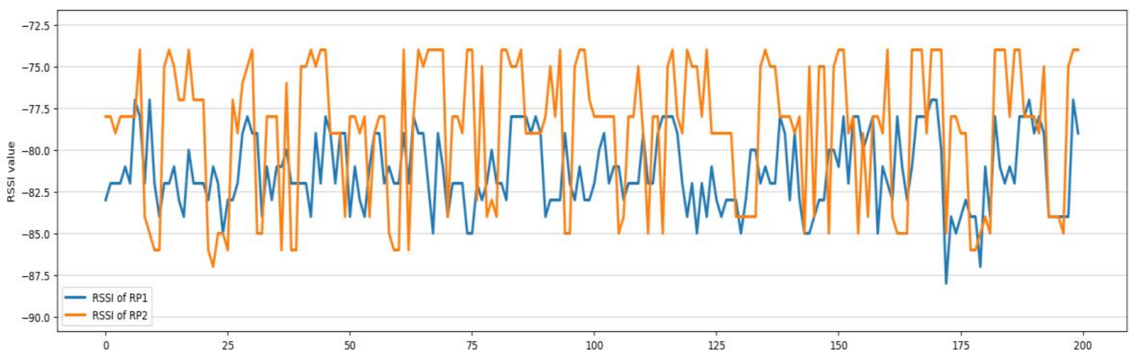

Figure 9. The RSSI values of the same beacon is obtained at different reference point.

extraction and BLE signal-based localization. Consequently, the collected database underwent Kalman filtering to partially reduce the noise in the aforementioned values. Moreover, it enhances the feature characteristics of RSSI values at each reference point. Figure 11 below illustrates the difference before and after employing Kalman filtering. It is evident that, after passing through the Kalman filter, the RSSI data eliminates noisy values, resulting in new, more stable data.

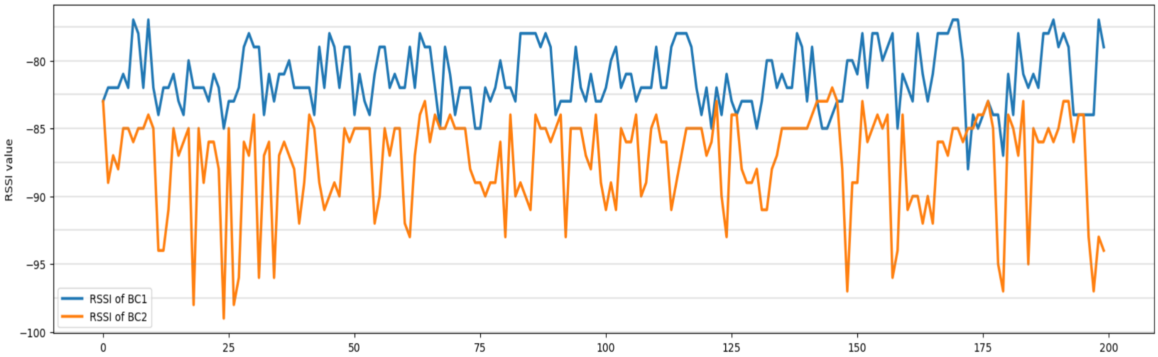

Figure 10. The RSSI values obtained from two different beacons at the same reference point.

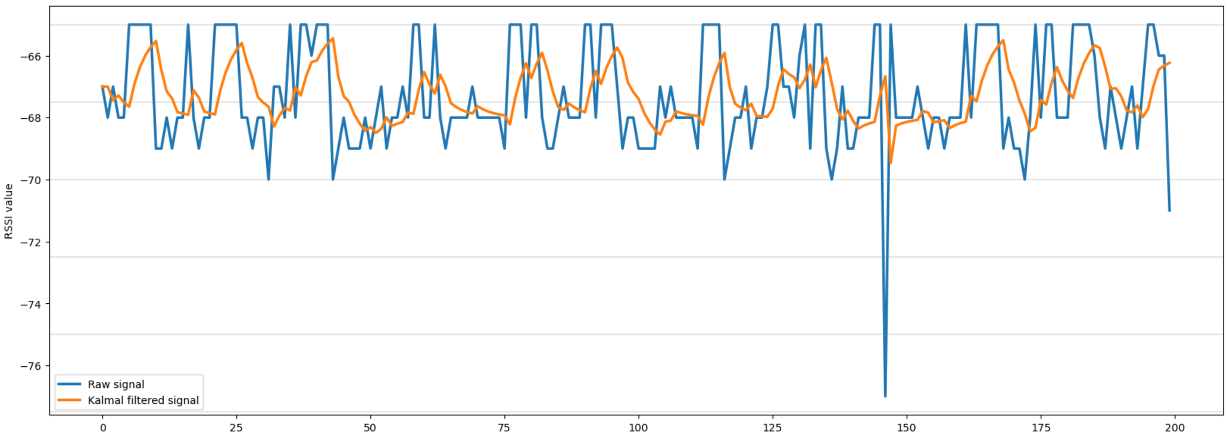

Figure 11. The raw RSSI values and after passing it through the Kalman Filter.

C. Experimental results

Table 1 displays the results using two methods, one incorporating the Kalman filter and the other without the filter, with different values of k ($k = 3,4,5,6,7$). Parameters in the table include the mean, median, maximum, and minimum error values. Initially, a comparison is made between two methods, AE and CAE, revealing that the average error values for different k values are notably smaller with the CAE method than with the AE method. The AE method provides the smallest average error of 2.60m with $k = 4$, while the CAE method yields the smallest average error of 1.07m with the same k value. When combined with the Kalman filter, it can be observed that the accuracy of the localization task improves. Specifically, with $k = 4$, the AE_Kalman method achieves the smallest average error of 1.16m, which is an improvement compared to AE (2.6m), and the CAE_Kalman method delivers the smallest average error of 0.98m compared to CAE's 1.07m. Of the four experimented methods, CAE_Kalman demonstrated the highest stability, showcasing a localization error ranging from 0.12m ($k = 4$) to 2.39m ($k = 6$). In contrast, the AE method shows a maximum localization error of 5.49m at $k = 3$.

Figures 12 and 13 illustrate cumulative distribution function (CDF) curves for the following methods: CAE_Kalman, CAE, AE_Kalman, and AE. It can be observed that CAE_Kalman and CAE have similar CDF curves, while AE_Kalman and AE exhibit similar curves. When the Kalman filter is applied, CAE_Kalman outperforms CAE, and AE_Kalman outperforms AE. CAE_Kalman and CAE have a lower error range of less than 2m, whereas AE_Kalman and AE have an error range of less than 4m. Using Kalman filtering improves the performance of fingerprint-based localization and reduces the error range.

Figure 14 illustrates the localization error box and whisker plots for the four methods employed in this study, specifically at a value of $k = 4$. It is evident that the CAE method generally outperforms the AE method, and the comparison between applying and not applying the Kalman filter in data processing shows a clear difference in efficiency.

The CAE method combined with the Kalman filter ($k = 4$) is compared to studies using native BLE fingerprint-based localization. The comparison is made on various aspects such as the number of beacons, used, the area size, and the minimum, average, and maximum, location errors. As explained in section 2, Mai et al [5] used fingerprinting combined with Pedestrian Dead Reckoning and Particle filter to achieve a minimum average error of 1.18m. Alvin Riady et al [6], with a larger localization scale and a greater number of beacons than our method, achieved minimum average and maximum errors of 1.1178m and 3.3601m, respectively. Li et al [4] used the ENTM method, developed by the KNN and WKNN methods, and achieved an average error of 1m. Table 4 compares the CAE method combined with the Kalman filter and other methods. The comparison table shows that the proposed CAE method combined with the Kalman filter achieved an average error of 0.98m, significantly outperforming the compared methods.

Table 1. Statistical parameters of the proposed methods with different k values (unit: m).

Methods	Statistics	k = 3	k = 4	k = 5	k = 6	k = 7
CAE_Kalman	Mean	1.19	0.98	1.24	1.37	1.41
	Min	0.33	0.12	0.20	0.37	0.52
	Max	2.33	1.60	2.24	2.39	2.33
	Median	1.05	1.02	1.22	1.20	1.42
	Var	0.31	0.21	0.28	0.26	0.26
	Std	0.55	0.46	0.53	0.51	0.51
CAE	Mean	1.12	1.07	1.21	1.18	1.37
	Min	0.23	0.2	0.27	0.33	0.40
	Max	2.57	2.15	2.41	2.27	2.59
	Median	1.05	1.02	1.22	1.12	1.25
	Var	0.41	0.28	0.32	0.28	0.46
	Std	0.64	0.53	0.56	0.53	0.68
AE_Kalman	Mean	1.25	1.16	1.21	1.37	1.46
	Min	0.33	0.25	0.28	0.47	0.87
	Max	3.07	2.85	2.61	2.69	3.03
	Median	1.05	1.09	1.09	1.31	1.38
	Var	0.44	0.29	0.25	0.24	0.26
	Std	0.66	0.54	0.50	0.49	0.51
AE	Mean	2.82	2.60	2.76	2.69	2.72
	Min	0.94	0.25	0.28	0.17	0.77
	Max	5.49	4.75	5.07	4.78	4.90
	Median	2.96	2.65	2.66	2.71	2.71
	Var	1.94	1.51	1.95	1.70	1.64
	Std	1.39	1.23	1.40	1.31	1.28

Table 2. Comparison of CAE incorporating Kalman filter with other fingerprint-based methods

Studies	Methods	Number of Becons	Area size (m x m)	Minimum Error (m)	Average Error (m)	Maximum Error (m)
Mai et al [5]	Pedestrian Dead Reckoning + Fingerprinting + Particle filter	8	35×25	---	1.18	---
Alvin Riady et al [6]	ANN	23	19×12	0.1055	1.1178	3.3601
Mingfeng Li et al [4]	ENTM	4	8×8	---	1	---
This study	CAE + Kalmam filter	6	8×8	0.10	0.98	1.77

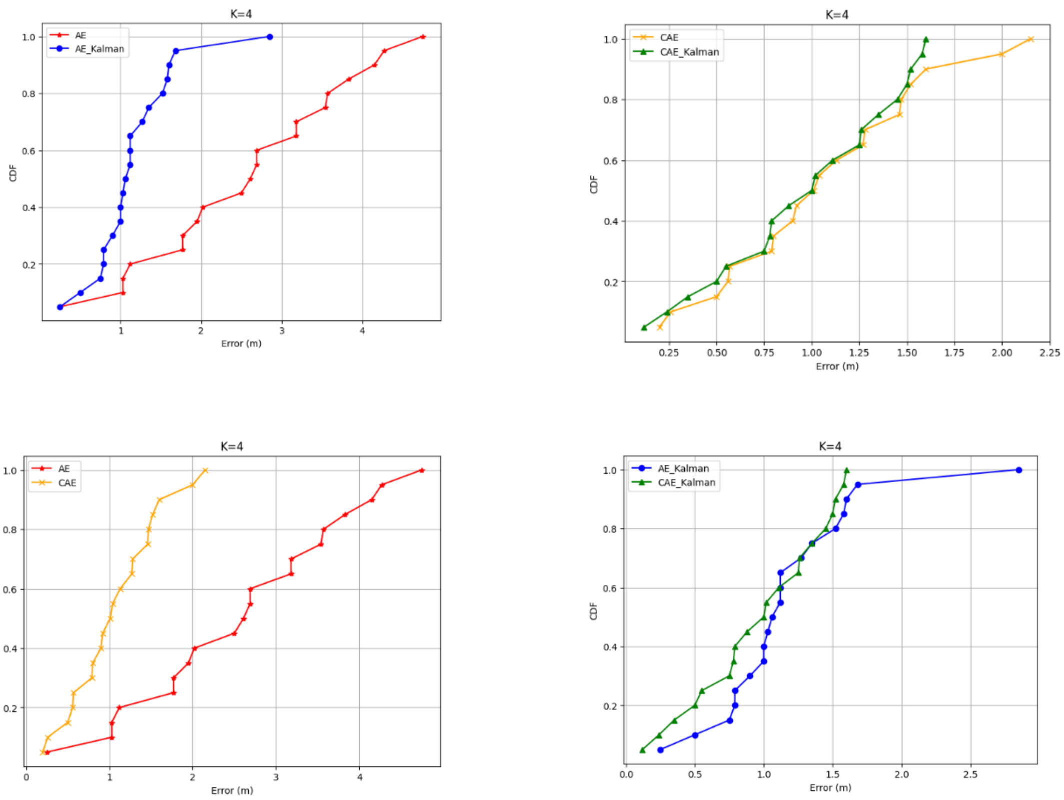

Figure 12. The localization error CDF curves, where $k = 4$.

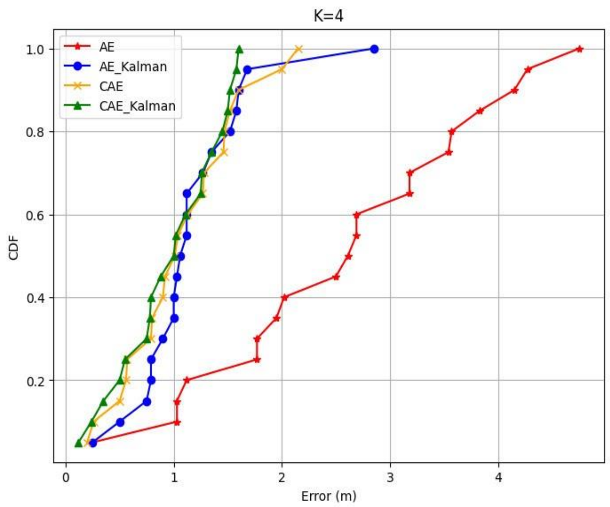

Figure 13. Comparison of the localization error CDF curves of four methods, where $k = 4$

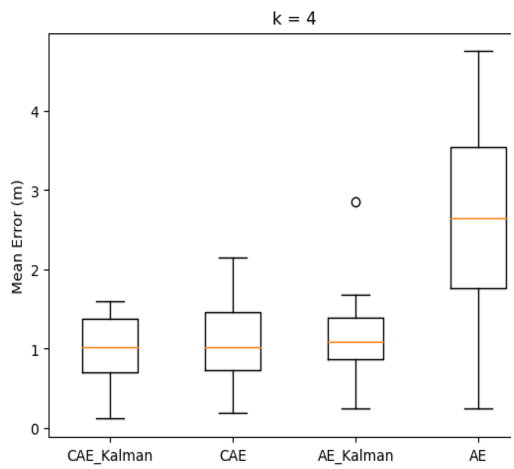

Figure 14. The localization error CDF curves box-whisper plots, where $k = 4$

IV. CONCLUSION

In this research, we employed four distinct methods to assess the performance of indoor localization: CAE_Kalman, CAE, AE_Kalman, and AE. Our study results reveal that the CAE model outperforms the AE model, highlighting the superiority of the CAE model in fingerprint feature extraction for indoor localization. Additionally, we examined the impact of applying the Kalman filter to both models. The results demonstrate that using the Kalman filter significantly enhances the performance of both models compared to not using the filter. This underscores the effectiveness of improving the stability and accuracy of RSSI values obtained from BLE beacon signal transmitters. In summary, this research has elucidated the excellence of the CAE model and the positive effects of the Kalman filter in enhancing the performance of fingerprint feature extraction for indoor localization. This study has some limitations such as the test scenarios have not been implemented comprehensively, the influence of obstacles in the experimental environment on positioning has not been evaluated. Besides, the error assessment only stops at static error, that is, the influence of movement has not been calculated in the positioning error results. This study experiments with positioning in 2D coordinate space, the application in 3D space requires additional factors to be determined such as height, angle and direction of incoming waves between the signal transmitter and receiver, ... In terms of feature extraction, this research direction can be applied, however, it is necessary to adjust and supplement more suitable approaches in each specific problem.

Improving the accuracy of indoor localization systems is an important issue. Therefore, more and more methods and algorithms are being proposed to reduce noise, increase stability and efficiency. Besides, designing an indoor localization system that operates in real time is the top goal to be achieved. There are many issues that need to be resolved with this orientation such as: hardware device delay in signal transmission between reference point and access point; propose prediction algorithms to improve speed and accuracy to match real-time conditions, etc. Finally, indoor positioning systems are needed to be integrated into applications and mobile devices for goods management or object tracking.

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PHƯƠNG PHÁP ĐỊNH VỊ TRONG NHÀ BẰNG BLE HIỆU QUẢ SỬ DỤNG ĐẶC TRƯNG DẤU VÂN TAY

Tóm tắt: Sự xuất hiện của công nghệ Bluetooth Low Energy (BLE) đã tạo ra nhiều cơ hội cho việc định vị trong nhà. Tuy nhiên, việc trích xuất các đặc trưng dấu vân tay từ các giá trị cường độ tín hiệu nhận được (RSSI) của tín hiệu Bluetooth thường mang lại kết quả có sai sót và mất ổn định. Nghiên cứu này sử dụng bộ lọc Kalman để ổn định các giá trị RSSI nhận được. Nó sử dụng các mô hình Bộ mã hóa tự động và Bộ mã hóa tự động tích chập để trích xuất các đặc trưng và so sánh các điểm kiểm tra ngẫu nhiên với các điểm tham chiếu trong cơ sở dữ liệu bằng cách sử dụng tương quan chéo được chuẩn hóa.

***Từ khóa* -** Indoor Localization, Fingerprint, Bluetooth Low Energy, Autoencoder.

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