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Trajectory mapping through channel state information by triangulation method and fine-tuning

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Abstract

Trajectory mapping techniques have widespread applications in diverse fields, including robotics, localization, smart environments, gaming, and tracking systems. However, existing free devices encounter challenges in representing trajectories, thereby limiting the effectiveness of applications such as robotics, localization, and tracking systems. The imprecise mappings generated by these methods lead to suboptimal performance and unreliable results. The proposed approach leverages WiFi sensing through channel state information (CSI), triangulation techniques, and a fine-tuning mechanism to enhance trajectory precision within indoor environment trajectory mapping. The proposed solution employs a domain adapter fine-tuning technique to enable location-independent tracking via CSI, minimizing errors. The use of CSI MIMO signals for trajectory mapping offers enhanced spatial resolution, robust multipath handling, and improved accuracy in tracking movement by leveraging multiple antenna channels and exploiting the rich information embedded in signal reflections and scattering, while triangulation aids in accurately determining the location of objects or targets. Furthermore, incorporating a fine-tuning mechanism refines the generated trajectories. The findings demonstrate substantial enhancements in mapping precision, with an accuracy of 95.5% in tracking 13 paths within the new domain. These results underscore the effectiveness of the proposed approach in overcoming the limitations of existing methods and achieving highly accurate trajectory mapping.

Keywords: WiFi sensing, Fine tuning, Channel state information, Trajectory tracking

Introduction

Device-free trajectory tracking and localization approaches enable various applications and services, facilitating seamless navigation, asset tracking, context-aware computing, and enhanced user experiences within indoor environments [1, 2]. With the burgeoning increase of smart devices, location-based service integration has become ubiquitous across diverse domains. Concurrently, there has been a concerted effort to enhance the precision of location recognition [3–6]. The requirement of location awareness is dichotomized into outdoor and indoor domains, and there has been a commensurate surge in demand for indoor location awareness, categorizing much research in this domain [7, 8]. Consequently, alternative methodologies utilizing indoor WiFi, Bluetooth, RFID, UWB, FMCW, and analogous technologies have been explored for indoor location recognition [9]. While conventional outdoor location recognition relies on the Global Positioning System (GPS), its efficacy diminishes indoors due to substantial position errors and signal obstructions by building structures [10]. The current localization systems face several challenges that hinder their effectiveness and reliability in indoor environments, including limited accuracy, high infrastructure requirements, signal interference sensitivity, complexity in multipath propagation handling, and difficulty scaling for large and complex indoor spaces[11, 12].

Trajectory mapping is the process of determining the path of movement of a target person by taking measurements from certain fixed landmarks. The pursuit of accurate trajectory tracking has been identified as an objective for the emerging applications of WiFi-based sensing [13]. The reason behind this is its potential to serve as a facilitator for ongoing and forthcoming industrial revolutions. The standard technique for achieving localization in an outdoor setting has been the use of a sensor that utilizes GPS, which uses satellites to determine the position of the receiver's node [14, 15]. Unfortunately, the signals used by GPS cannot penetrate the walls and roofs of buildings, and as such, they are not suitable for indoor localization. Furthermore, compared to the outdoor scenario, an indoor environment is very challenging owing to exacerbated multipath issues caused by the many reflections and obstructions that block the direct line-of-sight (LoS) link between the transmitter and the receiver. A closely related concept to localization uses measurements from the target device to generate a map to analyze the effects of the signal on the environment. One advantage of this approach is that it eliminates the need to program the details of the map into the application [16, 17]. Furthermore, the necessity for unrestricted device-free localization sensing arises from mapping trajectories without relying on handheld devices, enabling seamless tracking and positioning in various environments [18]. For applications in real-world settings, it is required to consider scalability, setup, and running costs before choosing a localization mechanism for installation.

Utilizing WiFi CSI for localization presents several challenges, such as the sensitivity of CSI to environmental changes, human movement, and structural variations, which lead to fluctuations in signal strength and multipath effects, affecting localization accuracy [4]. Additionally, non-line-of-sight (NLOS) conditions can introduce errors in estimating distances, impacting the precision of localization algorithms [5]. Moreover, the need for extensive calibration and fingerprinting processes to map CSI data to physical locations is labor-intensive and time-consuming, especially in dynamic environments [19]. Furthermore, processing and interpreting CSI data for localization requires modern algorithms and computational resources, posing a challenge for real-time implementation on resource-constrained devices.

This work proposes a design that incorporates the triangulation method based on channel state information (CSI) to achieve trajectory localization by capturing signal strength variations at different locations. Triangulation, which utilizes measured angles and known distances, offers notable advantages in enhancing WiFi-based unwearable trajectory localization. It provides heightened accuracy in indoor positioning by generating more precise location estimates compared to alternative methods. Additionally, triangulation mitigates the effects of signal fluctuations and multipath phenomena commonly encountered in WiFi-based localization systems, thereby reducing sensitivity to signal variations and environmental factors [20]. Furthermore, triangulation enhances the scalability and adaptability of unwearable trajectory localization, enabling position calculations using fixed points across diverse indoor environments. The proposed system design leverages WiFi and integrates domain adaptation techniques to address the challenges associated with WiFi-based unwearable trajectory localization and enhance the performance and applicability of indoor positioning systems. This integration enables fine-tuning learning, allowing for the seamless utilization of pre-trained models in new domains. This approach facilitates the easy adaptation of the localization system to different indoor environments, as depicted in Fig. 1.

The triangulation method enhances the effectiveness of location-independent positioning in indoor environments by capitalizing on the triangulation technique. It leverages measured angles and known distances to calculate precise position estimates, surpassing the accuracy of alternative methods. This methodology's reliance on angle and distance measurements contributes to its robustness against signal variations and environmental changes. Additionally, it alleviates common challenges encountered in WiFi-based localization systems, such as signal fluctuations and multipath effects. The principal contribution of this study resides in its comprehensive investigation of indoor localization technologies, with a specific emphasis on their practical implementation. The successful implementation of fine-tuning and domain adaptation techniques enables the application of transfer learning in the context of CSI localization. Integrating the triangulation method further augments this achievement, enhancing the precision and reliability of indoor localization. The combined utilization of fine-tuning, domain adaptation, and triangulation methodologies represents a noteworthy advancement in the field. It offers valuable insights into transferring CSI-based localization models across different domains. The justification for this work contributes to the field of indoor localization, as summarized here:

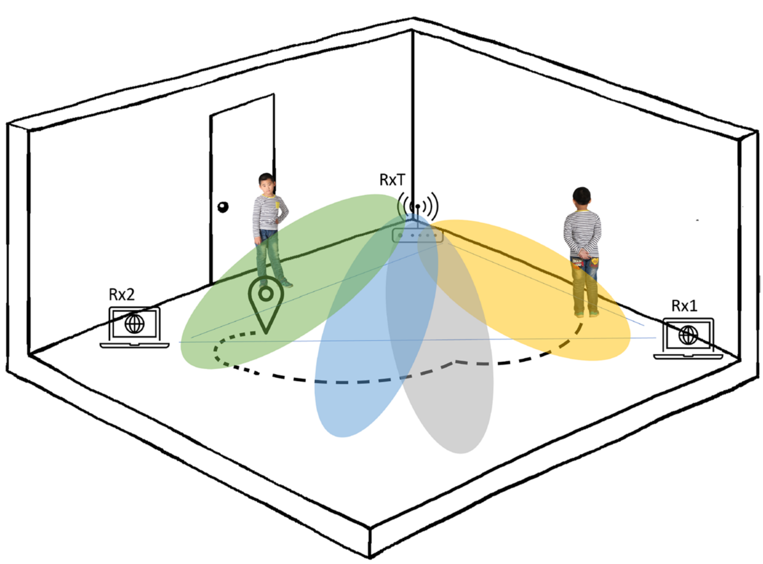

Fig. 1 Analyzing WiFi signal strength and connectivity patterns achieves trajectory mapping

1. To develop a new domain adaptation model that facilitates efficient transfer learning across diverse domains, thereby reducing the effort required for adapting WiFi-based trajectory mapping to new environments.
2. Implementing the triangulation method for free device trajectory tracking using CSI and enhancing precision.
3. To execute the compilation of a dataset and subsequent practical analyses, thereby generating dependable data and assessing the efficacy and real-world feasibility of the proposed methodologies.

These contributions collectively contribute to advancing the field of indoor localization by introducing novel techniques, addressing key challenges, and providing practical insights for implementation and evaluation

This work is organized into five key sections, beginning with the introduction, which outlines the scope, provides an overview of the challenges in existing techniques, and sets the stage for subsequent analysis. The second section engages with the current body of literature, examining state-of-the-art indoor localization techniques while identifying the research gaps the proposed methods aim to address. The third section presents a detailed account of the methodology, elaborating on developing a domain adaptation model and highlighting the advanced techniques employed to enable efficient transfer learning across diverse domains. The fourth section explains the experimental setup and evaluates the proposed methods using the triangulation approach and the domain adaptation model, applying a range of metrics. It also highlights the strengths, limitations, and practical implications of the proposed methods, identifying future directions for research and further refinement of indoor localization technologies. The final section synthesizes the experimental outcomes, concluding with their broader impact.

Related works

WiFi adopts wireless technologies for indoor trajectory mapping due to its widespread availability in existing infrastructure and cost-effectiveness [21]. WiFi-based localization systems leverage the presence of access points (APs) in indoor spaces to estimate the position of devices by measuring received signal strength (RSS), time of flight (ToF), or a combination of both. These systems offer broad coverage and minimal setup requirements, making them ideal for large-scale deployment. However, challenges such as signal interference, NLOS propagation, and multipath effects often introduce inaccuracies in localization estimates. WiFi-based localization leverages the ubiquitous presence of WiFi access points in indoor environments to estimate the location of a target device [20]. It utilizes RSS measurements, ToF calculations, or a combination of both to determine the distance between the target device and the WiFi access points. WiFi-based approaches offer advantages, including low infrastructure costs, wide coverage areas, and compatibility with existing WiFi networks, making them favorable for large-scale deployments [22]).

One of the primary challenges of WiFi-based sensing and localization is the NLOS propagation of WiFi signals, which results in errors in distance estimation. The presence of obstacles such as walls, furniture, and human bodies causes signal attenuation and multipath effects, leading to inaccuracies in position estimation [23, 24]. WiFi-based indoor positioning systems have garnered substantial attention due to the ubiquitous nature of WiFi signals in urban landscapes [25, 26]. Pioneering investigations have elucidated the efficacy of WiFi fingerprinting techniques in attaining elevated accuracy through meticulous exploitation of signal strength variations. Furthermore, the integration of Bluetooth Low Energy (BLE) has emerged as a strategic enhancement, as demonstrated in the research conducted by [27] utilizing BLE beacons for proximity-based localization, offering significant benefits in terms of energy efficiency and cost-effectiveness. Notably, ultra-wideband (UWB) technology, characterized by its ability to provide exceptionally fine-grained location information, has emerged as a promising contender for achieving high-precision indoor localization [28]. Noteworthy investigations have examined the applicability of UWB in contexts demanding unparalleled accuracy, such as asset tracking and virtual reality environments [20, 29].

To address the challenges posed by signal fluctuations and environmental factors, researchers have explored CSI for indoor localization [24, 30]. CSI provides detailed information about the wireless channel, including phase shifts, signal reflections, and multipath effects. Advancements in WiFi hardware have also contributed to indoor localization techniques. For instance, the emergence of multiple-input, multiple-output (MIMO) WiFi systems has enabled the utilization of spatial information for localization. MIMO systems employ multiple antennas to transmit and receive signals simultaneously, resulting in signal diversity and improved localization performance. By exploiting this fine-grained information, CSI-based approaches offer improved accuracy compared to RSS-based methods. [31] developed Widar 2.0, which uses a CSI-based indoor localization system that employs Doppler effects based on time of flight (ToF), achieving an average error of 1.5 m.

Recent studies have explored the integration of deep learning techniques with traditional WiFi-based localization methods. For instance, [7] proposed a novel approach that leverages deep learning representations of WiFi CSI fingerprints. By replacing original fingerprints with hidden layer representations from deep learning models, this method utilizes autoencoders, convolutional neural networks (CNNs), and long short-term memory (LSTM) networks to process bi-modal CSI data. Their work is replacing the original fingerprints with hidden layer representations from a deep learning model. CSI provides detailed channel information that can be extracted from readily available commodity WiFi network interface cards (NICs). The authors use deep learning methods like deep autoencoder networks, CNNs, and LSTM networks to get bi-modal CSI data that includes average amplitudes and estimated angles of arrival (AOAs). They then extract and calibrate this data. The performance of the deep learning model can vary depending on specific environmental factors and the availability of training samples, limiting the generalizability of the proposed method in specific indoor environments. Other studies have explored the integration of other sensors and technologies to enhance the reliability of indoor localization and tracking by combining different techniques such as RSSI and CSI [32] with inertial sensors.

The device-free localization approach, exemplified by WiTraj [2], utilizes commodity WiFi devices to track individuals without requiring personal devices. To address this concern, WiTraj proposes a novel DFS-based motion tracking system that extracts DFS and reconstructs walking trajectories using CSI. By doing so, the system provides robust indoor motion tracking, surpassing the challenges encountered by existing methods. However, the specific dataset and environment that WiTraj is limited to represent the performance of the proposed method only partially in different scenarios or under varying conditions. Experimental results show varying degrees of accuracy depending on the specific algorithm and the conditions of the environment. This system employs Doppler frequency shift (DFS) and CSI to reconstruct walking trajectories, providing robust indoor motion tracking. However, the method's performance can be influenced by specific datasets and environmental conditions, which may limit its applicability across diverse scenarios.

The work by Xue, J., et al. presents a novel approach to device-free localization by utilizing deep-learning representations of WiFi CSI fingerprints [7]. Their work is replacing the original fingerprints with hidden layer representations from a deep learning model. CSI provides detailed channel information that can be extracted from readily available commodity WiFi network interface cards (NICs). The authors use deep learning methods like deep autoencoder networks, CNNs, and LSTM networks to get bi-modal CSI data that includes average amplitudes and estimated angles of arrival (AOAs). They then extract and calibrate this data. The performance of the deep learning model can vary depending on specific environmental factors and the availability of training samples, limiting the generalizability of the proposed method in specific indoor environments. Other studies have explored the integration of other sensors and technologies to enhance the reliability of indoor localization and tracking by combining different techniques such as RSSI and CSI [32, 33] with inertial sensors.

In the context of scene recognition, Liu et al. introduced the scene-recognition indoor localization (SRIL) method, which uses a mutation particle swarm optimization-based neural network to distinguish between LOS and NLOS conditions [34]. This approach enhances localization accuracy by adapting to varying scene conditions. Despite its promising results, the SRIL method's accuracy are susceptible to environmental factors, which can impact its performance. The proposed method utilizes an MPSO-BP neural network with mutation particle swarm optimization to create the scene recognition model. This makes it possible to find LOS and NLOS areas. The work contributes to indoor localization and tracking systems by presenting device-free indoor localization through scene recognition. However, the available search results state the specific limitations. One significant limitation is the impact of environmental factors of the SRIL method. Shown in Table 1 is a phenomenon summary of methods used for localization-based and trajectory mapping based on the characteristics of CSI.

Triangulation method and adaptive free device approach

Deploying two WiFi sensors in conjunction with a single transmitter creates a triangulation system that allows for location determination and precise trajectory sensing over time. To refine the localization process, we harness the multipath phenomenon, in which signals take multiple paths between the transmitter and the receivers due to reflections and diffractions in the environment. Each WiFi sensor equipped to receive signals from the standard transmitter captures the multipath signals and exploits their unique geometrical characteristics. Multipath geometry mapping entails analyzing signal reflections and their associated delays in order to create a spatial representation.

Table 1 Recent studies on localization and fingerprinting using WiFi technology

Method	Ref	Algorithm	Data types	Location dependent	Performance	Limitations
CSI	[35]	PAIL (AdaBoost)	Amplitude, phase	✓	80% accuracy	Susceptible to significant environmental variations impacting CSI phase and amplitude
CSI	[36]	PCNB (naive Bayes)	Amplitude	✓	Up to 86% in specific locations	Requires extensive training; naive Bayes struggles with non-continuous features
CSI	[37]	BLS (KNN)	Amplitude	✓	75%, error below 2 m	Dependent on line-of-sight (LoS) and requires multiple access points (APs)
CSI	[38]	LCAF (naive Bayes)	Amplitude	✓	85%, error < 1.5 m	Ineffective in dynamic environments with amplitude-based mapping
RSSI CSI	[32]	Fussing RSSI and CSI	CSI Amp. and power strength	x	Up to 80% accuracy	Can be enhanced by employing machine learning models to improve accuracy
CSI	[31]	Doppler shift and AoA	Amplitude	✓	Error < 1.3 m	Limited accuracy due to small bandwidth constraints with Doppler shift
CSI	[7]	Multi-layer extreme machine learning	Amplitude	x	Avg. 1.4 m error	Requires large datasets for diverse environments
CSI	[2]	Doppler-MUSIC	Amplitude	✓	Avg. 1.6 m tracking error	Highly sensitive to noise and environmental factors, limiting bandwidth usage for stable accuracy
WIFI	[39]	KNN-based fingerprinting with vision fusion	Amplitude, phase	✓	1.24 m accuracy, 60% within 0.8 m	Low computational cost, but sensitive to interference and environmental changes
CSI	[40]	SVM-NB for NLOS/LOS detection	Amplitude, phase	✓	0.82 m (lab), 0.73 m (corridor), NLOS precision > 97%	Requires extensive empirical modeling, limited by NLOS signal reduction

Employing two WiFi sensors in pairing enhances the system's ability to discern the target's trajectory, enriching the triangulation method with additional data points. The triangulation algorithm calculates the distances and angles between the transmitter and each sensor, utilizing the multipath geometry information. The multipath reflections provide a nuanced understanding of the trajectory the target follows in real-time. Figure 2 displays the coordinates of AP1, AP2, and AP3 as (x1, y1), (x2, y2), and (x3, y3), respectively. We compute the distances from each AP using the Pythagorean theorem. To apply the Pythagorean theorem, we use the distances from AP1, AP2, and AP3, represented by d1, d2, and d3, in Eqs. 1, 2, and 3, respectively.

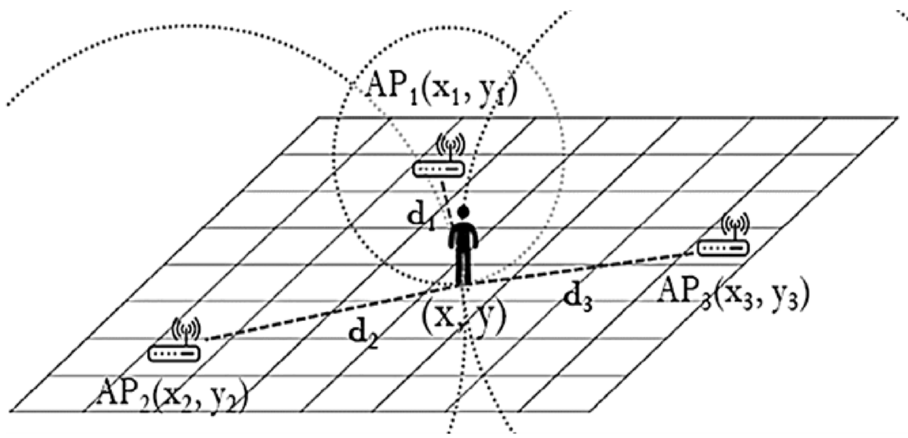

Fig. 2 The triangulation technique utilizes CSI for detecting the location of a target within the wireless coverage range

$$d_1 = \sqrt{(x - x_1)^2 + (y - y_1)^2} \tag{1}$$

$$d_2 = \sqrt{(x - x_2)^2 + (y - y_2)^2} \tag{2}$$

$$d_3 = \sqrt{(x - x_3)^2 + (y - y_3)^2} \tag{3}$$

The triangulation technique enables the entity's coordinates to be determined. (x, y), as shown in Fig. 2, provides a robust means of indoor location recognition that leverages the inherent characteristics of WiFi technology. Within the free space model, the Friis free space equation expresses the received power at a receiver antenna, situated at a distance from a transmitting antenna. The equation is characterized by the variables P_t for transmitted power, G_t for transmitter antenna gain, λ for wavelength in meters, and d for the distance from the transmitter to the receiver [41].

The algorithm computes the distance of target location using at least three access points on a circle centered at each access point, with a radius corresponding to the distance from that AP. The intersection point determines the target's coordinates, thereby allowing the system to estimate the position. The triangulation equations provided in Eqs. 1, 2, and 3 calculate distance using the Pythagorean theorem, in which the differences in x and y coordinates between the access points and the target are squared and summed to compute each distance.

The triangulation method for WiFi localization determines a person's position by measuring signal frequency changes between multiple WiFi nodes. By intersecting these distance estimates, the method pinpoints the location. Figure 3 illustrates this localization process based on frequency shifts between nodes, with subfigure (a) depicting the arrangement of the nodes and sub-figure (b) demonstrating how variations in frequency are utilized to enhance the accuracy of the location estimate.

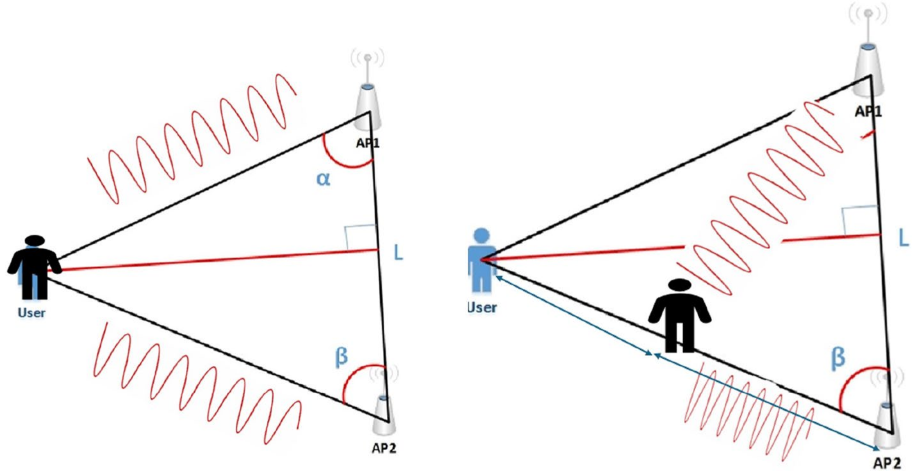

Fig. 3 Localization process using frequency changes between nodes to refine location estimates

Channel state information

Within the context of MIMO technology, CSI refers to the information collection that characterizes the state of the wireless channel between the transmitter and receiver [41]. This information includes the channel's amplitude, phase, and frequency response, collectively describing how the wireless signals propagate through the environment. Researchers widely recognize CSI as a prominent metric in Wi-Fi-based sensing technology because it offers valuable insights into the characteristics of wireless signal propagation from the transmitting device to the receiving device [29]. Analyzing CSI delivers a deeper understanding of the signal's behavior, enabling them to extract useful information about the surrounding environment, such as localization and tracking. Researchers obtain CSI by measuring and analyzing the received signals at the receiving end, considering the effects of multipath propagation, interference, and other environmental factors.

$$y_j(t) = \sum_{i=1}^{n_t} h_{i,j}(t) * x_i(t) + \eta_j(t), \quad i = 1, 2, \ldots, n_t; \quad j = 1, 2, \ldots, n_r \tag{4}$$

Considering certain variables simplifies Eq. (5) in a narrowband flat fading channel. The variable $H(i, j)$ represents the channel fading factor between the transmitted antenna i and the received antenna j. Meanwhile, $X(i)$ denotes the transmitted signal of antenna i, and y_i represents the received signal of antenna j.

$$y_j(t) = \sum_{i=1}^{n_t} h_{i,j} x_i(t) + \eta_j(t) \tag{5}$$

which is expressed in Eq. (6).

$$y(t) = Hx(t) + \eta(t) \tag{6}$$

The expressions for the MIMO system's transmit matrix, $x(t)$, receive matrix, $y(t)$, channel additive white Gaussian noise matrix, $n(t)$, and channel fading factor matrix, H, can be defined in Eq. (7):

$$H = \begin{bmatrix} h_{1,1} & h_{1,2} & \dots & h_{1,n_t} \\ h_{2,1} & h_{2,2} & \dots & h_{2,n_t} \\ \vdots & \vdots & \ddots & \vdots \\ h_{n_r,1} & h_{n_r,2} & \dots & h_{n_r,n_t} \end{bmatrix} \tag{7}$$

Figure 4 shows a MIMO equivalent model. The received signal of the j antenna can be defined as:

By combining distance measurements from multiple sensors and utilizing the geometric principles of triangulation, the system calculates the target's position in real-time. The benefit of using multiple WiFi sensors in pairs is that it improves the ability to track the target's movement across a space, reducing errors that might occur due to signal interference or environmental factors. In essence, the triangulation method transforms WiFi signal data into location sensing system suitable for a variety of indoor applications, from human tracking to object detection.

$$P_r = \frac{P_t G^2 \lambda^2}{(4\pi)^2 d^2} \tag{8}$$

$$G_r = \frac{\text{Power density directed}}{\text{Power density isotropic}} = \frac{A_{\text{sphere}}}{A_{\text{ont}}} = \frac{4\pi R^2}{A_{\text{ant}}} \tag{9}$$

$$A_{\text{ext}} \approx \theta_{\text{Az}} \cdot \theta_{\text{EL}} \approx \frac{R\lambda}{b} \cdot \frac{R\lambda}{h} \tag{10}$$

$$G_r = \frac{4\pi}{\frac{2}{2} \cdot \frac{\pi}{h}} \approx \frac{4\pi A}{\lambda^2} \Rightarrow A = \frac{G_r \lambda^2}{4\pi} \tag{11}$$

NLOS and LOS scenarios are considered in the propagation process by training the CSI database under both NLOS and LOS conditions. Leveraging NLOS detection allows for more precise localization in the online stage, narrowing the search area and improving match accuracy. The first step introduces a pre-processing method to extract subcarriers from CSI measurements and eliminate noise. We categorize the training data at each reference point into NLOS and LOS conditions for subsequent analysis.

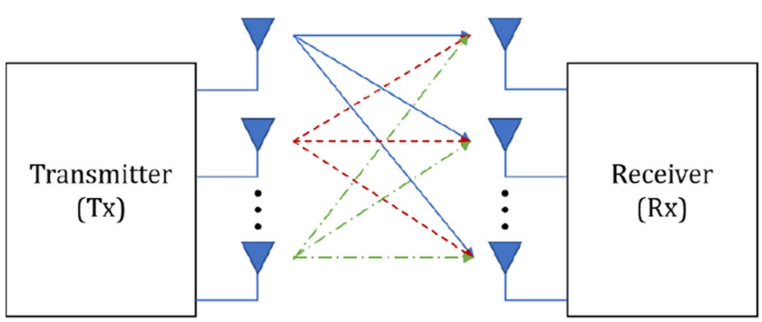

Fig. 4 A visual depiction of a MIMO system

$$P_{\text{floor}}(d) = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 \left(d^2 + 4h_2^2\right)} \tag{12}$$

During the subsequent phase, we collect and incorporate data about the indoors, linking the transmitter and receiver into a detection model as shown in Fig. 5. During the third stage, we gather random statistics at various locations within the room.

The CSI within the room undergoes refraction and diffraction, leading to deviations in the received data according to the physical model. Consequently, diverse placements yield varied outcomes due to this phenomenon.

$$P_{rLOS1} = \frac{P_t G^2 \lambda^2}{(4\pi)^2 (d^2 + 4h_1^2)} \tag{13}$$

$$P_{rLOS2} = \frac{P_t G^2 \lambda^2}{(4\pi)^2 (d^2 + 4h_2^2)} \tag{14}$$

Symbols h_1 and h_2 signify the vertical distances from the transmitter-receiver link to the ceiling and floor, respectively. P_t denotes the transmitted power, Gt represents the transmitter antenna gain, λ is the wavelength measured in meters, and d refers to the distance from the transmitter to the receiver. In this stationary scenario, the presence of the target introduces various signal transmission paths impeded by the

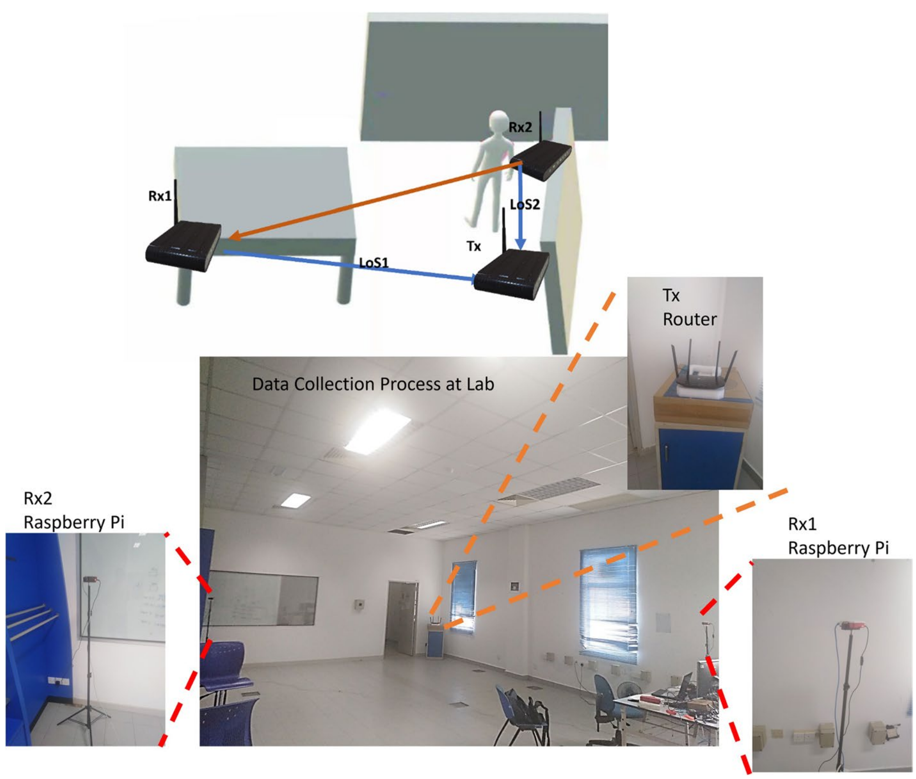

Fig. 5 Triangulation method with **a** LoS depicting the direct LoS between nodes and **b** data collection environment

human body. The effect of the target on the received power complying with the radar and equation is computed as given in Eq. (15).

$$P_{\text{sca}}(r_1, r_2) = \sum_{h_i} \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 (r_1^2 + h_i^2)(r_2^2 + h_i^2)} \quad h_i \in (0, h] \tag{15}$$

Here, r_1 represents the distance between the transmitter and the target, while r_2 denotes the distance between the receiver and the target within the horizontal plane.

Sequence flowchart

The designed system architecture incorporates a domain-adapting model. Figure 6 presents the flowchart, depicting the sequential steps and processes that the system follows. The architecture explicitly emphasizes the fine-tuning adapting model, incorporating BiLSTM classifier layers as a foundational component. We carefully describe and configure these BiLSTM classifier layers to optimize the system's performance within the fine-tuning adapting model. They enable the model to capture dependencies and patterns in the input data effectively. By processing the input data, extracting relevant features, and making predictions or classifications based on learned patterns and representations, these layers significantly contribute to the system's overall functionality.

The schematic design of the WiFi localization system is a multifaceted framework consisting of distinct components to achieve precise indoor location estimation, as shown in Fig. 7. The system integrates two WiFi receivers into a Raspberry Pi cluster strategically positioned for signal reception within the targeted environment. This receiver configuration ensures robust data collection, a fundamental requirement for subsequent localization processes. Following signal acquisition, the received WiFi signals undergo a meticulous preprocessing and filtering stage. This step involves noise reduction, signal normalization, and the application of appropriate filters to enhance data quality, laying the groundwork in subsequent stages of the system. The subsequent stage involves extracting CSI amplitude data from the preprocessed signals. This extraction process focuses on capturing and isolating features that distinctly characterize WiFi signals, providing a foundation for precise localization.

Preprocessing and feature extraction

The model employs a median filter as part of its signal preprocessing stage to enhance the quality of the input CSI data. The median filter replaces each data point with the median value within a specified window. This filtering technique effectively reduces the impact of outliers and noise in the CSI signal, resulting in a smoother and more reliable dataset. The model utilizes a BiLSTM network to extract features from the pre-processed CSI data in conjunction with the median filter. The BiLSTM architecture captures sequential dependencies in the input data by design. It processes the CSI data forward and backward, allowing it to learn and encode relevant patterns and relationships between consecutive CSI samples. The BiLSTM network captures temporal dependencies and extracts meaningful features that contribute to leverage the sequential nature of the CSI data. This ability to analyze CSI data in sequence enables the model to capture dynamic changes and variations in wireless signal propagation. This ability to analyze

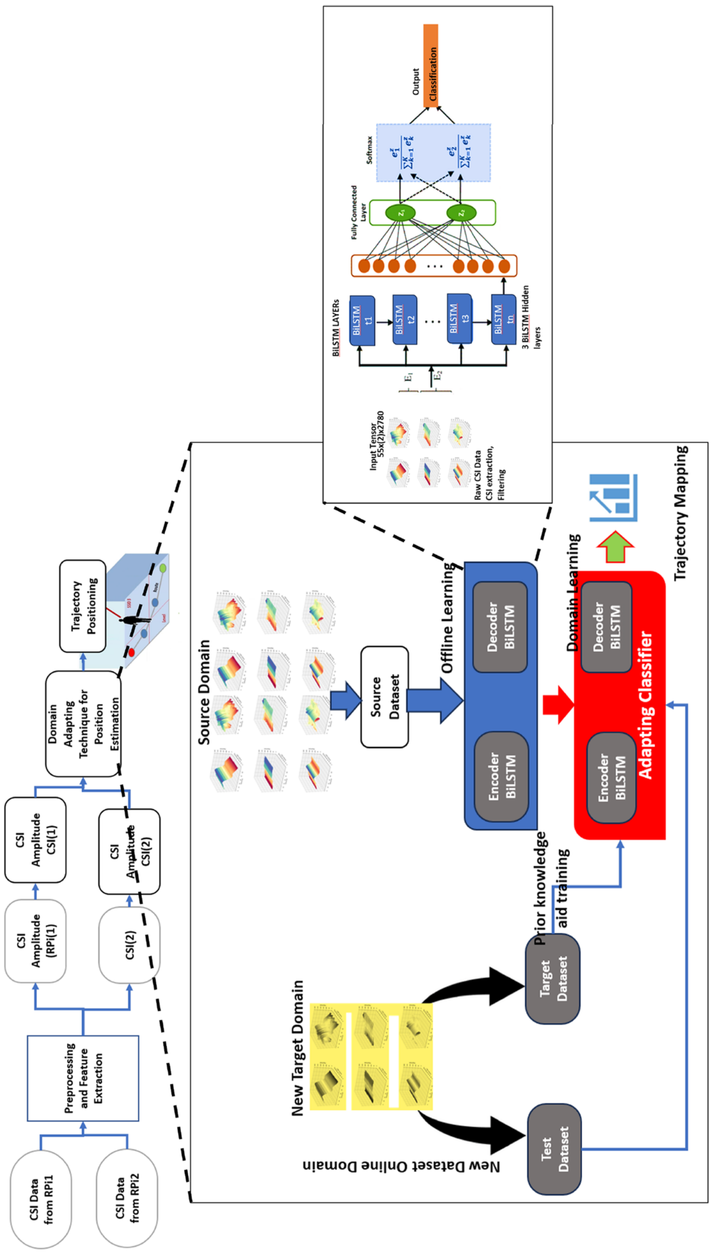

Fig. 6 The system architecture representation of domain adaptation

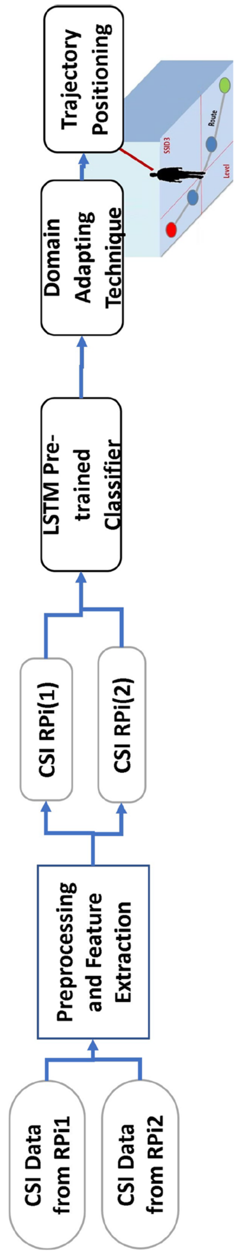

Fig. 7 Indoor localization framework

CSI data in sequence enables the model to capture dynamic changes and variations in wireless signal propagation and enhances its performance in applications such as object detection, localization, and tracking in Wi-Fi-based sensing systems.

Bilstm network

BiLSTM networks classify the sequence of the input CSI dataset within the domain of adapting the fine-tuning model. The BiLSTM layers play an important role in capturing the temporal dependencies and patterns within the CSI data. The network architecture of the BiLSTM layers includes several key components, including BiLSTM layers, dropout, fully connected layers, and a SoftMax function. The BiLSTM layers are responsible for processing the sequential input CSI data in both forward and backward directions. This bidirectional processing enables the network to capture past and future dependencies, allowing it to effectively model the temporal dynamics in the data. The network architecture that processes the input CSI dataset, as shown in Fig. 8, includes BiLSTM layers, dropout layers, fully connected layers, and a SoftMax function.

Dropout layers mitigate overfitting and improve generalization. Dropout randomly sets a fraction of the input units to zero during training, reducing the reliance on specific features and preventing the network from becoming overly specialized to the training data. After the BiLSTM layers and dropout, the network employs fully connected layers to extract and transform the learned features. These layers connect each neuron to every neuron in the previous layer. This dense connectivity facilitates the extraction of higher-level representations from the input data. Finally, the output layer applies a softmax function to obtain probability distributions over the different class labels. The softmax function normalizes the output scores, ensuring that they sum up to one and can be interpreted as probabilities.

Domain adapting classifier

The domain-adapting model employs a fine-tuning approach that incorporates both online learning and domain learning. During the online learning phase, the model trains using the provided online training data to adapt the pre-trained encoder and decoder layers specifically to the online domain. This process aims to update the model using new data from the online domain and fine-tune it for improved performance in that specific domain. In the domain learning phase, the model trains using the provided domain training data to adapt the pre-trained encoder and decoder layers to the target domain. The goal of domain learning is to leverage the knowledge gained from the source domain to adjust the model, which was initially pre-trained on a different domain, to the target domain.

By training separate models for online learning and domain learning, it becomes possible to adapt the encoder and decoder layers for each scenario independently. This approach provides flexibility and allows for a focused adaptation of different aspects based on specific requirements. Leveraging the pre-trained model enables the training of the latter decoder layers' weights while utilizing the trained features and weights from the previous location, which reduces the training effort in the target domain. The domain-adapting model Fig. 9 illustrates the integration of a pre-trained model from the

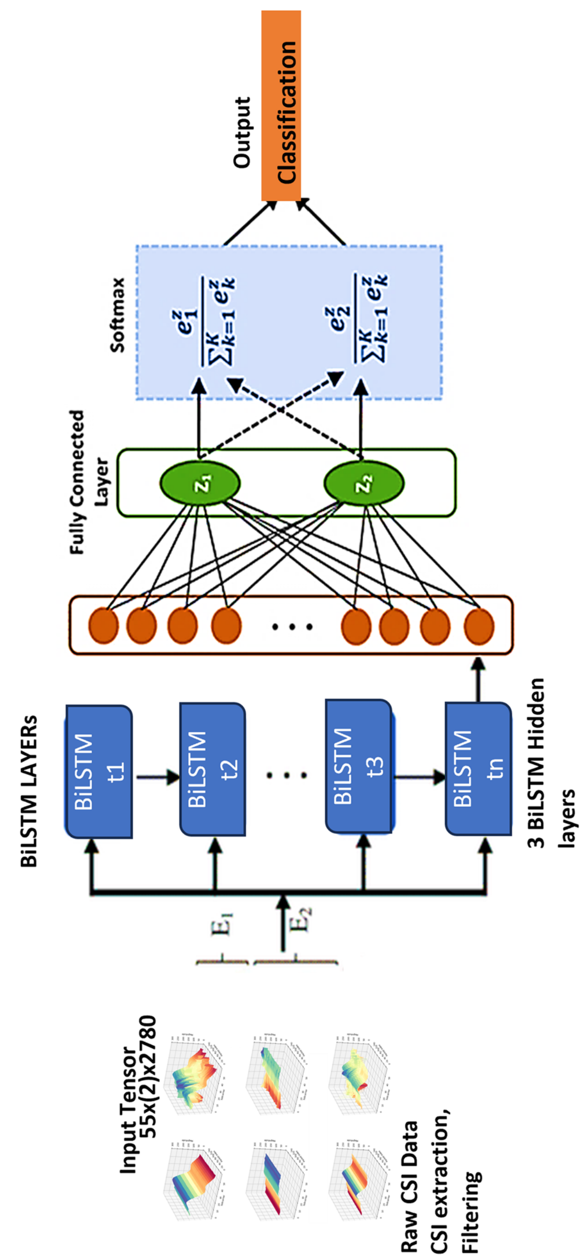

Fig. 8 BiLSTM network architecture

source domain with a new target domain, showcasing the process of adapting the model to the target domain using domain-specific training data.

Algorithm 1 outlines an adaptation algorithm for the Fine-tuning Adaptation Method. This method aims to adapt a pre-trained classifier model using CSI data from a source domain to perform classification on new target data. Fine-tuning the model's encoder and decoder layers allows for better generalization and improved classification performance in the target domain. Transferring knowledge from one domain (source) to another (target) with limited direct training data is known as domain adaptation using CSI for trajectory mapping. By leveraging CSI, which captures detailed signal characteristics between nodes, the model adapts to the target domain's unique conditions and variations in signal behavior. This approach enhances the accuracy of trajectory mapping by fine-tuning the model to better align with the target environment's specific signal patterns and dynamics.

Algorithm 1 Fine-tuning adaptation method

Require: Source domain data, labeled data, new target data
Ensure: Classified target data
Train and load the pre-trained classifier model
Freeze all layers of the pre-trained model except the last encoder and decoder layers
Read source domain data and target domain data
Extract features from the target domain data using the modified encoder of the pre-trained model
Initialize a new classifier model:
    with the same architecture as the pre-trained model
    with the last encoder and decoder layers modified for the target domain
Fine-tune the new classifier model using the labeled data from the source domain:
    Define the source domain loss function:
        $L_{\text{source}}(\theta) = \sum_i L(y_i, f(x_i; \theta))$
        where L is a chosen loss function (e.g., cross-entropy),
        y_i is the true label for sample x_i, and f is the classifier model parameterized by θ
    Define the optimizer O and learning rate η
    Update parameters of the last encoder and decoder layers by minimizing L_{source}:
        $\theta_{\text{fine-tuned}} = \arg\min_\theta L_{\text{source}}(\theta)$
    Repeat steps 6.1 to 6.3 for a specified number of epochs or until convergence
Combine labeled data from the source domain and the target domain:
    Shuffle and batch the combined dataset D_{combined} into mini-batches
Perform further fine-tuning on the new classifier model using the combined dataset:
    Adjust learning rate η_{adapted}
    Continue training on D_{combined}
    Gradually unfreeze more layers of the model
    Update parameters of unfrozen layers by minimizing the combined loss:
        $\theta_{\text{adapted}} = \arg\min_\theta L_{\text{combined}}(\theta)$
Evaluate the fine-tuned model on the new target data:
    Predict labels for the new target data
    Assess performance of the fine-tuned model

The advantage of having a fine-tuning domain adapting model lies in its ability to leverage a pre-trained model from the source domain to expedite the adaptation process in the target domain. By utilizing the pre-trained model, the encoder and decoder layers in the target domain benefit from the knowledge and features extracted during the offline phase, reducing the effort required for training. The encoder and decoder layers in the

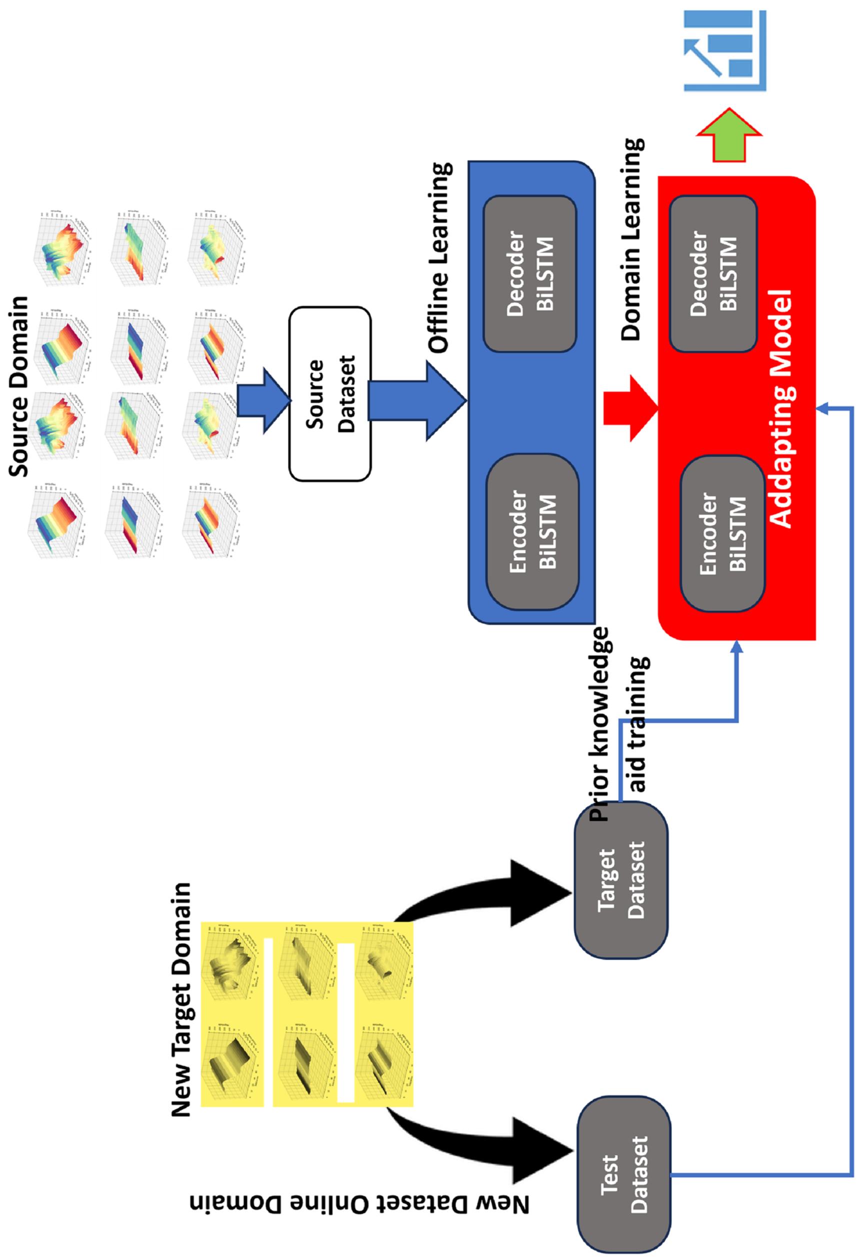

Fig. 9 The layout of the fine-tuning domain adapting process

target domain take advantage of the pre-trained model's learned representations, allowing them to encode the input data more effectively. Training the encoder layers from scratch in the target domain is time-consuming and requires significant computational resources. Similarly, the decoder layers leverage these weights to decode the encoded representations and generate outputs. The process reduces the training effort needed for the decoder layers, as they can build upon the pre-trained model's knowledge to refine their performance in the target domain.

The localization process combines the domain adapting module with the triangulation method to estimate the target's location. The triangulation method utilizes the extracted CSI amplitude data from two WiFi receivers. By calculating the distances between each receiver and the target location, the triangulation algorithm leverages the geometric relationships among these distances to estimate the target coordinates with high precision. The algorithm discerns and classifies the target within the localized space by computing features that enhance user interaction and interpretability. By visually representing the movement of the tracked entity over time, this feature provides dynamic insights into the path traversed within the environment. The trajectory mapping augments the system's capabilities by offering a comprehensive and intuitive visualization of the target's trajectory, aiding in understanding their movement patterns and behavior within the space.

Results and discussion

Experiment setup

The experimental setup in this work used clustered Raspberry Pi 4B units interconnected via a D-Link switch (model No. DES-1008A). Two Raspberry Pi units are receivers, while a TP-Link AC1350 router is the transmitter. The Raspberry Pi devices operated on Linux version 5.10.92 firmware and were equipped with Nexmon, a firmware modification framework, for extracting CSI. The receiver and transmitter components adhered to the IEEE 802.11n/ac standard, enabling multi-user functionality. Furthermore, they were compatible with the dual-band spectrum's frequency bands of 20 MHz, 40 MHz, and 80 MHz. The process used the 20 MHz bandwidth for the 2.4 GHz frequency and the 80 MHz bandwidth for the 5 GHz frequency range. Each transmitted packet encapsulated information for 64 or 256 subcarriers, depending on the configuration. The selected hardware and settings ensured compatibility with the desired frequency bands, MIMO capabilities, and subcarrier information encapsulation.

Utilizing a clustered system of interconnected Raspberry Pi devices to improve computational scalability and availability underscores the commitment to robust and efficient data processing. The Nexmon firmware configures the Raspberry Pi devices into monitor mode to facilitate packet capture and acquisition of packets using TCP-DUMP on a Raspberry Pi. The router is injected using a Laptop Nitro an515-58 featuring an Intel® Core™ i5-12500H processor and an NVIDIA® GeForce® RTX3050 CPU @ 3.30GHz processor. Subsequently, the data captured is imported into MATLAB for real-time analysis using a Secure Shell (SSH) link between the Raspberry Pi and MATLAB. We have made the dataset collected in this work publicly available through the provided

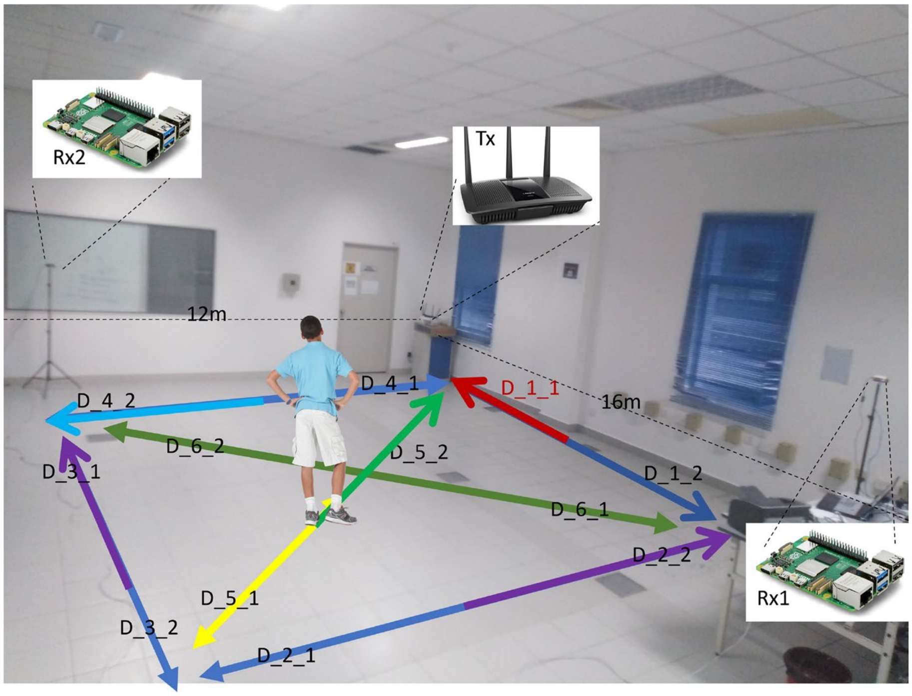

Fig. 10 The experimental layout and trajectory paths capture and analyze CSI amplitude changes

linked[1] and *Github*[2] repository, facilitating future enhancements and advancements in the field.

The need to collect our dataset stems from the scarcity of existing datasets that specifically address trajectory mapping. We collected the dataset in a specific location, which included 12 distinct paths and an empty environment. Two Raspberry Pi (RPi) units captured the necessary data as receivers, while a router served as the transmitter device. Simultaneously, the laptop injected data into the network, contributing to the comprehensive dataset collection. This dataset collection process allowed for subsequent analysis and evaluation of various aspects of network performance, signal quality, and other relevant parameters within the specified location. The dataset uniquely identified each path using the notation D_{1_2}, representing "Path 1, Direction 1," indicating the specific route in one direction. Similarly, D_{1_2} denoted the same path but in the opposite direction. The layout of the experimental location in Fig. 10 provides a representation of the spatial arrangement of the environment. It includes the positioning of WiFi receivers, transmitters, and other relevant elements within the experimental setup. Figure 10 illustrates the layout of the experimental location, providing a visual representation of the spatial arrangement of the environment. The diagram showcases the precise placement of WiFi receivers, transmitters, and other pertinent elements within the experimental setup. The dataset was collected from two distinct environments to analyze and improve the robustness of the results. The lab and home environments vary in terms of spacing and furniture, as shown in Fig. 11. This provides data that better reflects real-world

[1] https://data.mendeley.com/preview/d7442jp8b7?a=0f0eefac-efe9-4113-b3cf-88ba08400171
[2] https://github.com/FahdSaadA/Domain_Adapting_CSI_WiFi_Mapping/tree/main

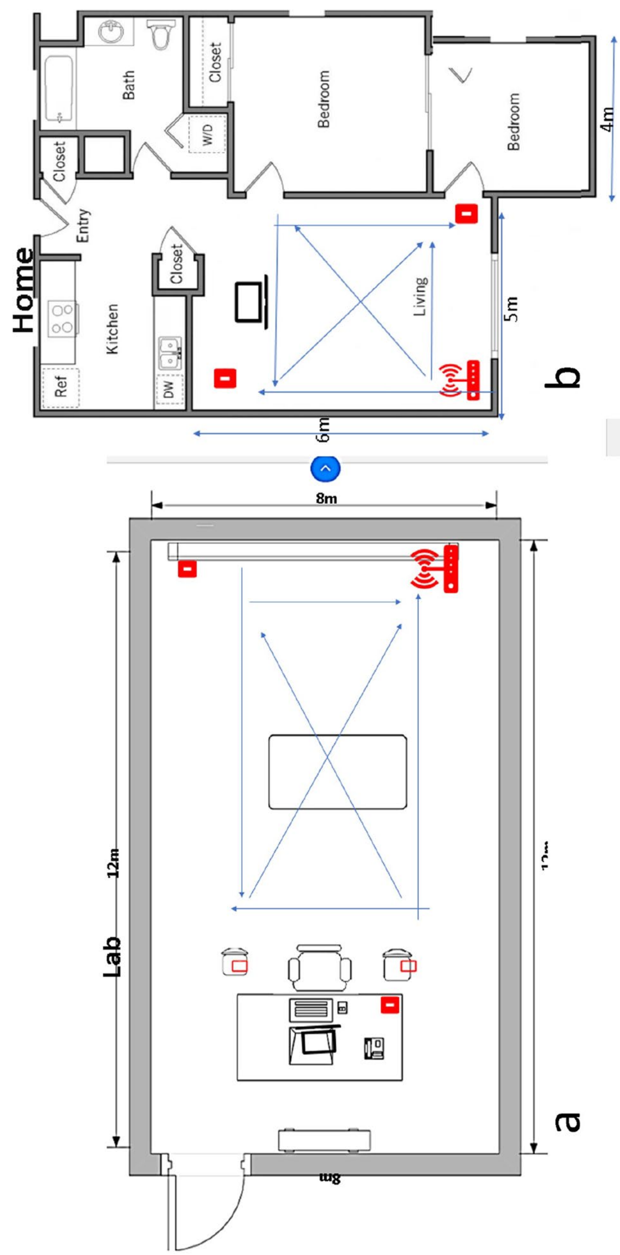

Fig. 11 The experimental layout and trajectory paths capture and analyze CSI amplitude changes

conditions, enhancing the robustness of the dataset. The dataset captures a wide range of scenarios, facilitating a more thorough understanding of patterns and behaviors in both stable and unpredictable conditions.

Line-of-sight analysis

The LoS analysis involves analyzing the CSI data for localization purposes using the triangulation method in conjunction with the domain adapting module. This analysis will enhance localization by leveraging the direct path information between WiFi transmitters and receivers. The triangulation method utilizes the extracted CSI amplitude data from multiple WiFi receivers to estimate the real-time coordinates of the target. The triangulation algorithm exploits the geometric relationships among these distances to determine the precise position. The module fine-tunes the localization model using the collected CSI data to improve localization performance, allowing the model to adapt to the specific characteristics of the target environment. By incorporating the LoS analysis into the triangulation method and domain adapting module, the localization system utilizes direct path information and dynamically adjusts to the target environment's characteristics. As a result, the system achieves enhanced precision and resilience in estimating coordinates. The process of capturing data within the trajectory paths, as depicted in the layout in Fig. 12, involves the meticulous utilization of a 20 MHz bandwidth while moving within the labeled trajectories.

When two CSI sensor nodes are used, the sensing amplitude changes depending on the direction of movement. This is shown in Fig. 13 with subplots (a–f), which map and estimate the trajectory. Each subplot in the figure corresponds to a specific trajectory signal variance, providing a nuanced analysis of the signals captured during a person's movement. The discernible variations in these trajectory signals provide valuable insights into the diverse movement patterns, allowing for mapping and estimating the traversed trajectories. Visualizing signal variances across different bandwidths and frequencies enhances the system's capacity to discern subtle nuances in trajectory paths. The intricate examination of trajectory signals in various scenarios, as presented in Fig. 13, underscores the system's efficacy in capturing and interpreting dynamic movement patterns for robust trajectory mapping and estimation applications.

For instance, Fig. 13a provides a clear illustration of the signals captured by two sensors. Figure 13a illustrates the signals captured by two sensors corresponding to the trajectory (1) shown in Fig. 12. In the first sensor's signal, we observe a constant value, indicating that the person's movement remains stationary or unchanged during this portion of the trajectory. However, in the second sensor's signal, we notice increasing changes in amplitude as the person moves forward, signifying a progressive movement in that direction. Conversely, when the person starts moving backward in the first trajectory, the second sensor's signal exhibits decreasing amplitude changes. This observation highlights the ability of the system to capture and represent the varying signal patterns associated with different directions of movement within a given trajectory. Figure 13b shows the impacts of the sensors, with the captured signal showing the second trajectory at path 2. The figure illustrates the changes in signals 1 and 2 as the individual moves along the trajectory in both forward and backward directions. Signal 2 undergoes continuous changes when the person is not near RPi2, whereas significant fluctuations occur in sensor 1 (RPi1). In

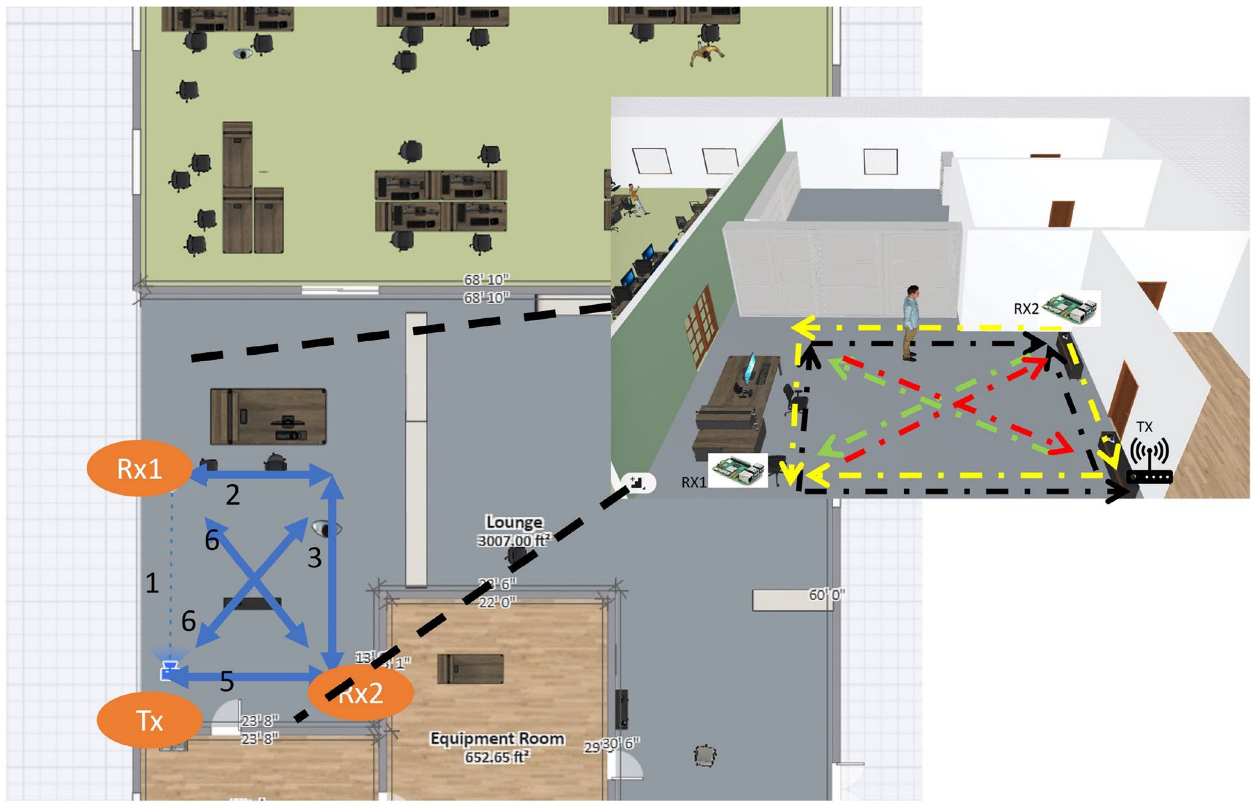

Fig. 12 The outline of the trajectory path during the experiment and the corresponding triangulation nodes involved in the analysis

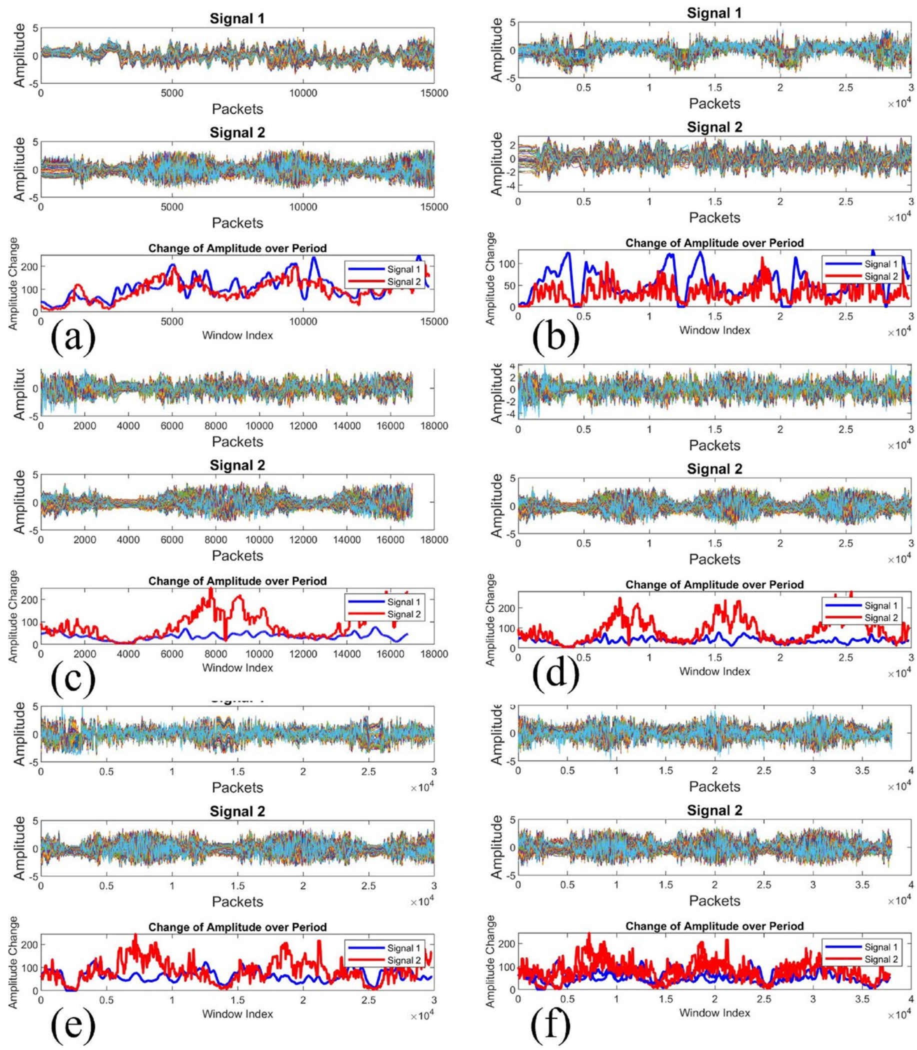

Fig. 13 Trajectory signal variance across the different directions of movement shows the system's capability to map and estimate trajectories based on CSI amplitude changes

RPi1, the signal transitions from low to high and vice versa, depending on the direction the person follows. The mapping enables identifying the characteristics associated with the trajectory the individual follows. At the same time, when the first sensor moves forward and backward from its position, changes occur. This mapping of signals enables the determination of the direction of movement by analyzing the changes in signals between the two sensors. Such an advanced trajectory mapping technique allows for detailed representation of the movement patterns.

Through wall evaluation

In the experimental evaluation, we positioned one of the sensors behind a wall to introduce an investigative dimension to the impact of physical barriers on trajectory mapping. As illustrated in Fig. 14, the layout configuration entails placing one sensor behind a wall while the other remains in the open space. This method has potential for continued tracking and plotting trajectories through walls, opening up possibilities for applications in surveillance, security, and location-based services. The experimental layout and results depicted in Fig. 14 exemplify the system's resilience in scenarios with physical barriers, substantiating the viability of trajectory mapping through walls based on CSI amplitude changes.

The results of the through-wall trajectory analysis, as demonstrated in Fig. 15, underscore the system's notable capability to sense and delineate trajectory paths even when confronted with physical barriers. Figure 15 illustrates how the system robustly captures and interprets trajectory data in real-world scenarios, even when physical obstructions exist. This outcome holds substantial implications for indoor tracking applications, showcasing the potential of utilizing CSI amplitude changes for trajectory sensing through obstacles such as walls. The sensory signals of CSI amplitude, plotted for trajectory paths from directions 1 to 6, provide valuable insights into the movement patterns. Each direction represents a specific trajectory path, indicating forward and backward movements. Figure 15 shows $D1_1$, representing the first trajectory path in the forward direction, while Fig. 14 shows $D1_2$, signifying the backward movement through a wall. Remarkably, the signal plots demonstrate the sensory ability to perceive through-wall information, akin to LoS sensing. Through-wall sensing enables predicting an individual's trajectory path despite obstacles due to its distinguishable features. These findings highlight the potential of through-wall sensing in mapping trajectory paths and offer promising opportunities for various applications in areas such as indoor tracking, surveillance, and behavior analysis.

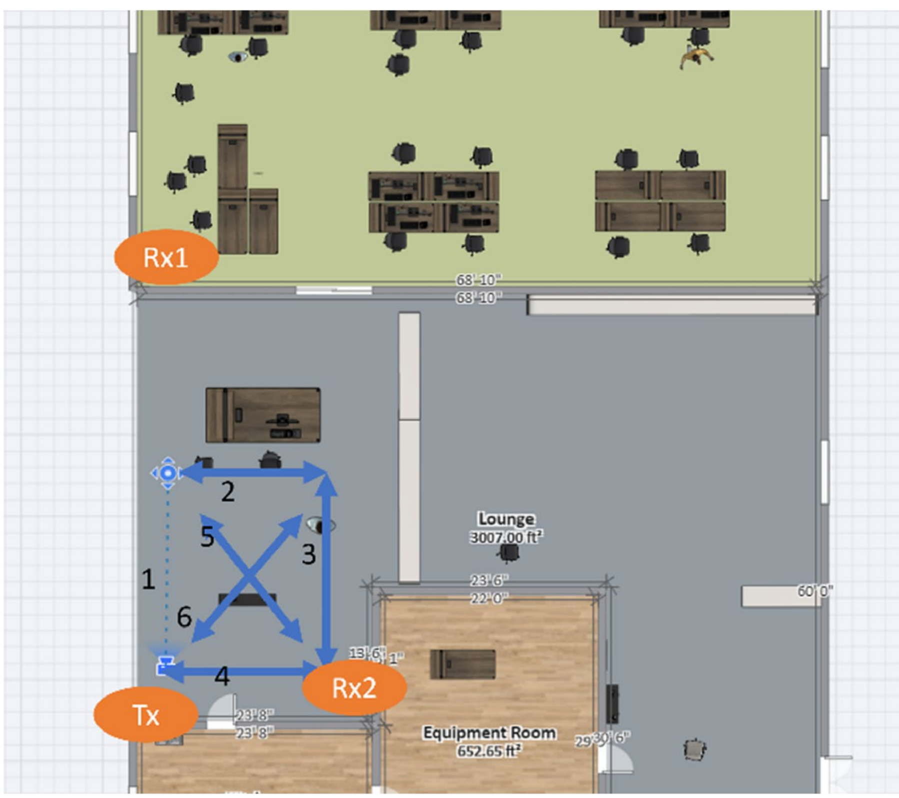

Fig. 14 The through-wall experimental layout depicts location analysis and trajectory, with arrows indicating the directional flow

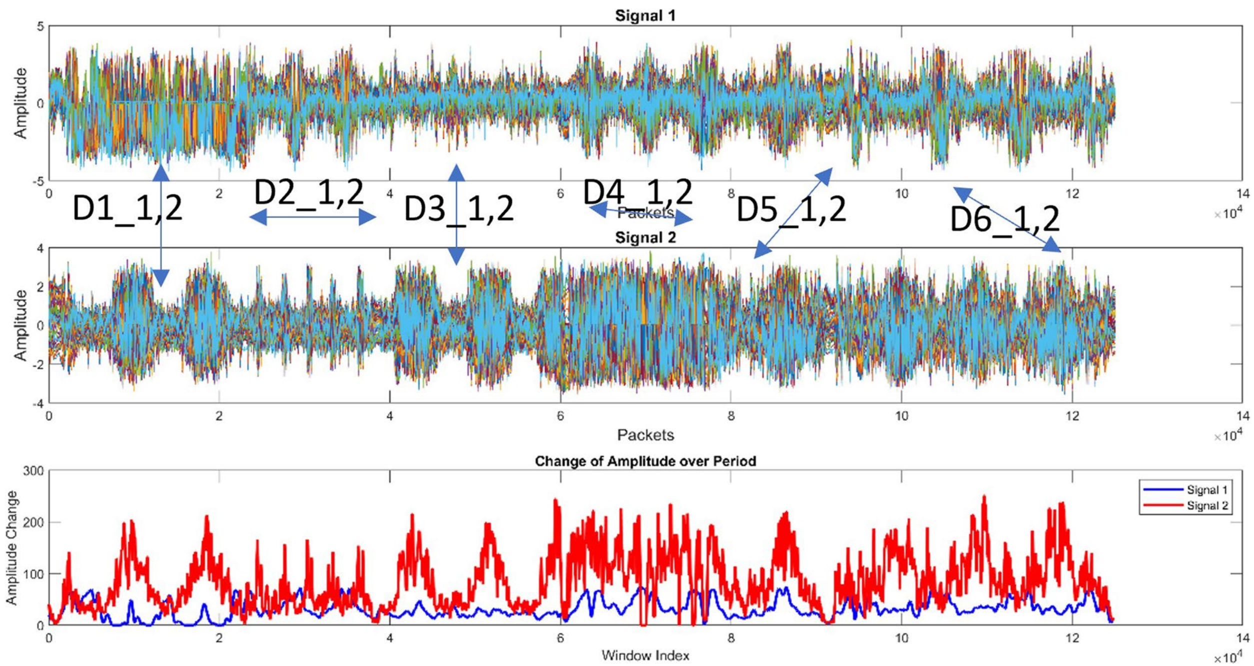

Fig. 15 Through-wall trajectory using the triangulation method affirms the effectiveness of the triangulation method in capturing and interpreting trajectory data through physical barriers

Distance tracking effects

The distance inspection of the triangulation method for WiFi trajectory heatmapping involves a comprehensive examination of the system's ability to measure distances based on CSI amplitude changes. By employing triangulation techniques, the system gauges the distances between the WiFi sensors and the target, providing data for trajectory mapping. The resulting heatmap reflects variations in signal strength and distance across the monitored space, yielding valuable insights into the spatial dynamics of movement. The triangulation method enables the generation of precise distance measurements, contributing to the creation of detailed trajectory heatmaps.

Figure 16 illustrates a decline in localization accuracy with increasing distance despite fluctuations in location errors' minimum, maximum, median, and mean values. The median and mean location errors did not exhibit a monotonic increase, and estimations at distances of 15 m or 20 m displayed slightly higher location errors than those at 5 and 10 m. This phenomenon cannot be solely attributed to measurement deviations; rather, it predominantly arises from the overlooked consideration that the target and access points (APs) exist in a three-dimensional space rather than on a two-dimensional plane. It is essential to recognize that the APs provide Angle of Arrival (AoA) measurements in a three-dimensional space, encompassing both azimuth and elevation. In our calculations, these measurements were treated as fixed angles. From a mathematical standpoint, as the distance between the target and APs increases, the error diminishes when approximating three points of varying heights to lie on the XY plane.

State-of-the-art analysis

The accuracy of various models for a given task can provide insights into their performance and effectiveness. In the context of the specific task at hand, the accuracy values achieved by different models are as follows: SVM attained an accuracy of 67%, NB

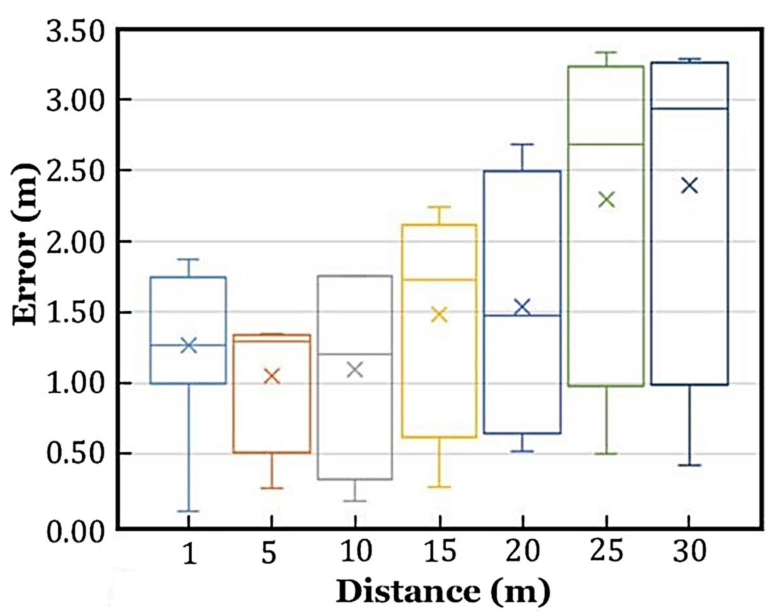

Fig. 16 Distance error based on the separation distance between triangulations nodes

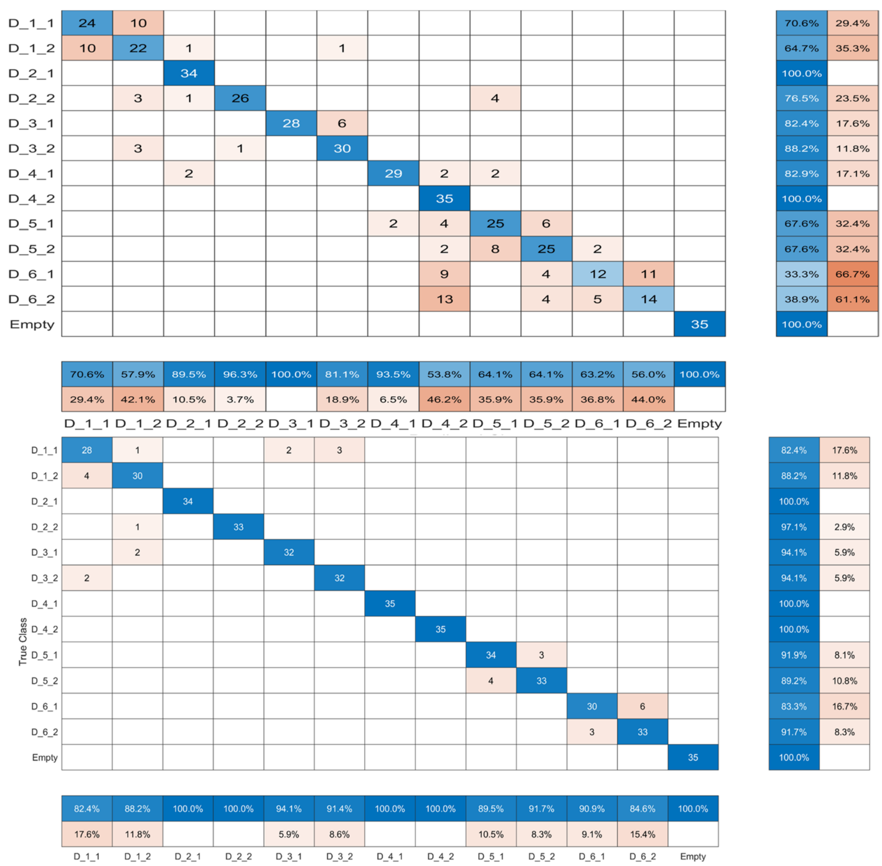

Fig. 17 Performance of LSTM classifier and fine-tuning adapting model classifier for the 13 classes

gained 59%, LSTM achieved 75%, GRU reached 73%, and the adapting domain classifier achieved an impressive accuracy of 91%. These accuracy measurements serve as quantitative indicators of the models' abilities to classify or predict the target variable correctly. Therefore, based on these accuracy values, the SVM, LSTM, GRU, and adapting domain classifier models demonstrate relatively favorable performance compared to the NB model. However, it is essential to consider other evaluation metrics and conduct further analysis to gain a comprehensive understanding of the models' overall effectiveness and suitability for the specific task. Figure 17 demonstrates the effectiveness of the LSTM classifier and fine-tuning adapting model classifier for the 13 classes in classifying the data into multiple categories.

The adapter model enhances classification in a new domain by improving classification accuracy compared to traditional approaches. It introduces domain-specific adapters, which are small additional layers attached to the pre-trained model. The model adapts and learns domain-specific information while preserving the knowledge learned from the source domain through the use of these adapters. By fine-tuning the adapter model on the target domain data, it captures domain-specific features, leading to improved classification accuracy in the new domain. Table 2 outlines recent advancements in trajectory and fingerprinting techniques for indoor localization. It summarizes the methods employed, highlights the limitations encountered, and identifies potential challenges

Table 2 Recent developments in fingerprinting-based indoor localization: methods, limitations, and potential challenges

Ref.	Method	Classifier	Tool	Freq GHz	BW MHz	Localization	Mapping	Acc. error	Perf. and limitations
[42]	CSI-amplitude	AdaBoost	Intel NIC	5	20	✓	×	1.1 m	Limitations in highly dynamic environments
[43]	CSI phase	Meta-learning	Intel NIC	x	x	✓	×	1.3 m	Requires extensive offline training
[44]	CSI-phase calibration	SSIM-based augmentation	x	x	x	✓	×	2.4 m	Location-dependent limitations and requires training
[4]	CSI amp. and phase	AdaptDNN	Intel 5300 NIC	5	20	✓	×	0.61 m	Location-dependent limitations and requires training
(Xue et al., 2023)	CSI amp. and phase	ML-ELM	Intel 5300 NIC	5	20	✓	×	1.1	Requires large training data and may vary by location
[32]	CSI -RSSI amp.	LoS effects	Raspberry pi 4B	5	80	✓	✓	0.9 m	Sensitive to environment and complexity of human activities.
[1]	(mmWave)	Hungarian algorithm	TI IWR6843ISK	60 - 64	4	✓	✓	0.2 m	Higher cost, and power consumption, with a complex algorithm.
[7]	CSI amp.	ML-ELM	Intel 5300 NICs	2.4	20	✓	×	1 m	Location-dependent and requires intensive training.
[2]	CSI amp.	Doppler-MUSIC	Intel 5300 NICs	2.4	20	✓	×	0.3 m	Limited bandwidth leads to difficulty in achieving accurate sensing using Doppler based on CSI
This work	Triangulation	Fine-tuning algorithm	RPi 4B	2.4,5	20/80	✓	✓	5–10%	Requires having at least small dataset for the domain

in this field. The analysis of recent works offers valuable insights and serves as a foundation for evaluating the effectiveness and applicability of different approaches in indoor localization research.

Existing approaches leveraging WiFi CSI for localization within indoor environments have demonstrated improvement in indoor positioning, such as those employing CSI amplitude, phase, and hybrid methods. For example, the use of AdaBoost classifiers with CSI amplitude data, as explored by [42], achieves competitive accuracy but is highly sensitive to dynamic environments. Similarly, Wei et al. [43] implemented a meta-learning approach using CSI phase information, achieving reliable results but requiring substantial offline training, which limits its scalability across diverse environments. These methods face limitations in environments with signal fluctuations due to NLOS propagation and multipath effects.

The triangulation-based approach integrated with a fine-tuning algorithm, which demonstrates computational efficiency and scalability when compared to state-of-the-art fingerprinting-based indoor localization methods. As highlighted in Table 1, The method achieves a localization accuracy improvement of 5-10% compared to traditional approaches that rely on CSI amplitude or phase-based techniques. Notably, the approach offers a low-cost and energy-efficient solution, while supporting dual-frequency (2.4 GHz and 5 GHz) with bandwidths of up to 80 MHz. Unlike other methods, such as those relying on complex algorithms like Doppler-MUSIC or Hungarian algorithms, which are resource-intensive and constrained by limited bandwidth, our system benefits from the flexibility of domain adaptation [1, 2]. By incorporating fine-tuning techniques, the approach reduces the need for extensive offline training, a key limitation in several existing systems [7]. Additionally, the method reacquires small dataset for domain adaptation.

Impact of numbers of nodes

The number of nodes in trajectory-sensing systems plays a role in determining their accuracy and effectiveness. Increasing the number of nodes leads to improved trajectory-sensing capabilities and enhanced spatial coverage of the sensing area, resulting in better tracking and capture of individuals' movement patterns. This increased coverage allows for tracking of individuals within the monitored environment. Moreover, a higher number of nodes provides a denser network of sensing points, which enables finer-grained trajectory sensing. That means the system captures more detailed and precise information about an individual's movement, including subtle changes in direction, speed, or acceleration. The system captures more detailed and precise information about an individual's movement, including subtle changes in direction, speed, or acceleration, resulting in more accurate and reliable trajectory-sensing outcomes.

However, it is essential to consider the trade-off between the number of nodes and the associated costs and complexity. Deploying and maintaining a greater number of nodes requires additional resources, including hardware, power supplies, and communication infrastructure. Moreover, a higher number of nodes can introduce challenges in terms of data processing and management. Therefore, one must strike a balance between the number of nodes and the desired level of trajectory sensing accuracy, taking into account the practical constraints and requirements of the specific application or environment.

Impact of different environments and orientation

The evaluation of the trajectory mapping using the proposed module reveals promising results in tracking the direction of movement. In such cases, the model effectively localizes the real-time position of individuals and predicts their movement direction. However, the model's performance diminishes when confronted with untrained trajectories or non-linear paths that could improve, as depicted in the trajectory depicted in Fig. 18. This is evident when the trajectory deviates from the patterns observed in the training data. The model struggles to estimate the real-time position of the person along the non-linear trajectory.

Despite these limitations, it is noteworthy that the module still achieves a commendable 90% accuracy in identifying the path direction and the general direction of movement. While the model may not precisely localize the person's position along non-linear trajectories, it still provides valuable insights into the overall movement patterns. Additional training is required to improve the trajectory mapping module's accuracy for non-linear trajectories. Further iterations of training sessions should encompass a diverse range of non-linear paths, capturing various complexities and variations. By incorporating such training data, the model can learn to understand and predict individuals' real-time positions within non-linear trajectories, leading to improved accuracy in localizing positions along these paths.

Impact of sampling rates

Data packets are captured or measured within a network at a frequency known as the sampling rate. By conducting an experimental evaluation, we observe how the sampling rate affects the packet rate measurements' accuracy, reliability, and responsiveness. The evaluation reveals that a higher sampling rate provides more detailed information about packet rates, enabling better detection of network congestion, identifying potential bottlenecks, and facilitating effective network management. Conversely, a lower sampling rate may lead to coarser measurements, potentially missing essential variations in packet rates and hindering the ability to monitor and analyze network performance. Figure 19 shows the relationship between sampling rate in trajectory mapping.

Limitations and future works

The methods provide groundbreaking trajectory mapping approaches by combining CSI triangulation with domain adapting learning techniques. Integrating transfer learning into the trajectory mapping process proved to be a paradigm shift, enabling the system to learn and adapt to complex patterns in signal data. Using CSI data with transfer learning algorithms enhanced the system's ability to discern intricate details, resulting in a more nuanced trajectory mapping. The synergy between CSI-triangulation and deep learning improved the accuracy of trajectory predictions and demonstrated resilience

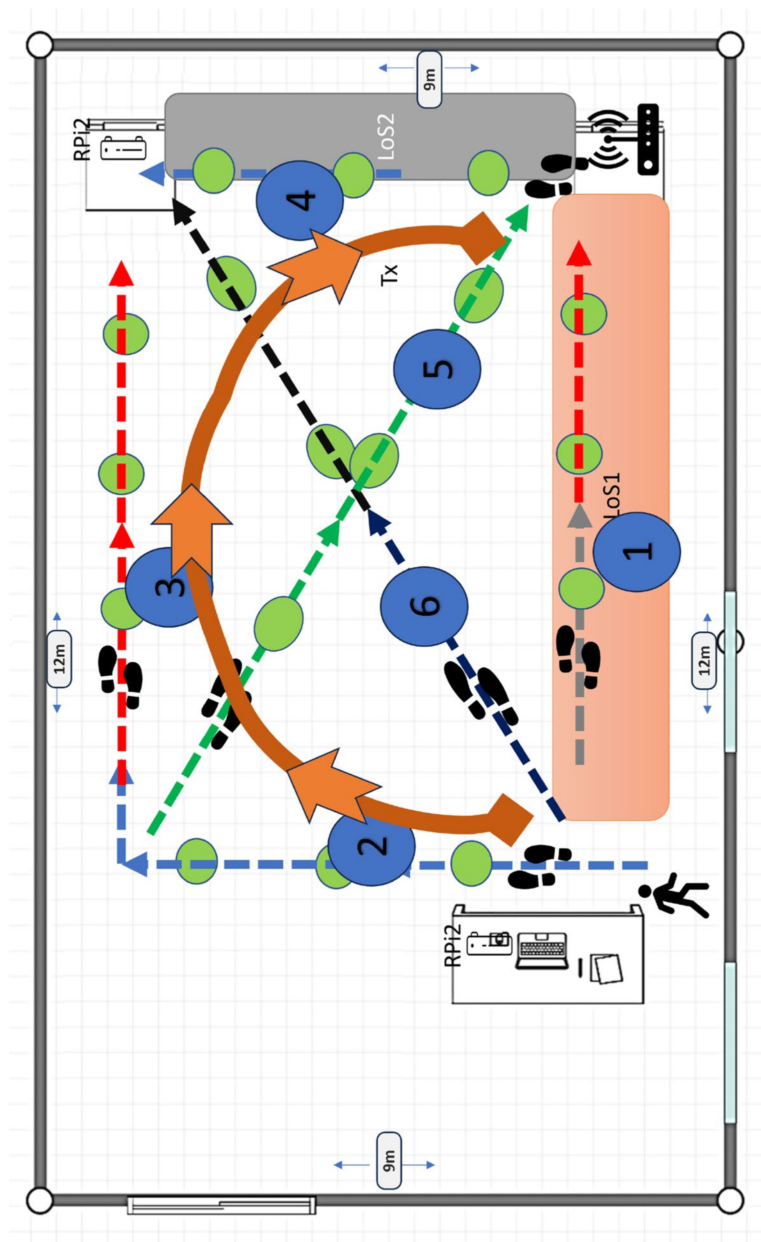

Fig. 18 Trajectory mapping and localizing positions along untrained or non-linear paths

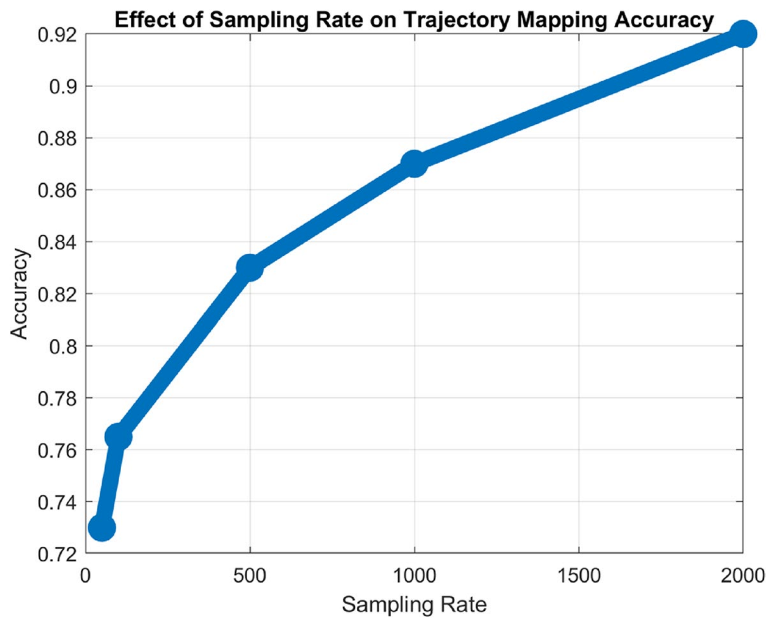

Fig. 19 Relationship between sampling rate and accuracy in trajectory mapping

to environmental changes. The adaptability of the deep learning model allowed for real-time adjustments, making it a robust solution for trajectory mapping in dynamic settings.

The proposed model for indoor localization using clustered RPi has its limitations and challenges. The study proposed an innovative localization method to enhance sensing precision without the necessary training samples and achieve resilience to environmental conditions. Nonetheless, using transfer learning for WiFi-based localization provided the potential for improving the accuracy of WiFi-based localization, and this could be a natural progression of this study in the future.

The challenge of tracking multiple people with a free device remains considerable. Although advanced techniques such as beamforming can improve the accuracy of the sensing system, the challenge of designing a robust wireless sensing system that can detect and track multiple people in dynamic environments remains considerable. Further research in this area could address these challenges and contribute to develop reliable indoor localization systems. This capability will enhance the practicality and scalability of localization in large-scale deployment scenarios. To this end, there is potential to develop multi-person tracking methods that leverage DL architectures and innovative signal processing techniques.

Conclusions

In conclusion, using CSI signals in conjunction with a domain-adapting algorithm has proven to be effective for trajectory mapping. The localization system successfully achieves robust system by leveraging the fine-tuning capabilities of the domain-adapting algorithm. The CSI signals provide valuable insights into the environment's wireless channel characteristics and signal propagation. By extracting and analyzing these signals, the system gains a comprehensive understanding of the spatial relationships between WiFi transmitters and receivers, thereby enabling precise trajectory mapping. The domain-adapting algorithm further enhances the system's performance by customizing the localization model to the specific characteristics of the target environment, resulting in improved accuracy in trajectory estimation. Integrating CSI signals and the domain-adapting algorithm presents promising opportunities across various domains, including indoor tracking, surveillance, and behavior analysis, where accurate trajectory mapping plays a vital role in comprehending human movement patterns and spatial behavior. Overall, the proposed trajectory mapping approach demonstrates effective potential as a robust foundation for conducting in-depth analyses of human indoor tracking and behavioral patterns, as evidenced by practical investigations and the resulting findings.

Abbreviations

BiLSTM	Bi-directional long short-term memory
CNN	Convolutional neural network
CWT	Continuous wavelet transform
CSI	Channel state information
LOS	Line-of-sight
LSTM	Long short-term memory
mmWave	Millimeter wave
NIC	Network interface card
Non-LOS	Non-line-of-sight
RSSI	Received signal strength indicator
HAR	Human activity recognition
MIMO	Multiple-input multiple-output

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Authors' contributions
Fahd Abuhoureyah played a key role in the project by implementing the proposed method, overseeing the data collection process, and conducting a thorough analysis of the gathered data.
Yan Chiew Wong provided invaluable supervision and leadership throughout the work, provided insights, and ensured the project remained on track to meet its goals.
Dr. Ahmad Sadhiqin contributes to the project by introducing and incorporating technical methods, enhancing the project's technical aspects, and expanding its methodological scope.

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Availability of data and materials
The data and tools used in this work description are made available at the following links: ***linked*** (https://data.mendeley.com/preview/d7442jp8b7?a=0f0eefac-efe9-4113-b3cf-88ba08400171) and ***Github*** (https://github.com/FahdSaadA/Domain_Adapting_CSI_WiFi_Mapping/tree/main).

Declarations

Competing interests
The authors declare no competing interests.

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