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REVIEW ARTICLE - ENGINEERING

Device-Free Localization Techniques: A Review

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Abstract

Device-free localization (DFL) has emerged as a transformative technology for tracking objects and individuals without requiring them to carry electronic devices. This paper reviews two pivotal techniques of DFL: Link Quality Measurement and Link Scattering techniques. Link Quality Measurement focuses on evaluating the quality of wireless links through metrics like Received-Signal-Strength and Channel-State-Information, offering simplicity and reliability. Meanwhile, Link Scattering harnesses signal reflections and diffractions caused by environmental obstacles to estimate device-free target positions. This review provides insights of Link Quality Measurement, Link Scattering methods and highlighting DFL metrics. By shedding light on these critical aspects, it offers valuable insights into the current state of DFL technology and its potential in diverse domains, ranging from smart environments to security systems.

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Keywords: Indoor Localization; Indoor Tracking; Device-Free; Radio Tomography; Fingerprinting; Passive-Localization.

1. Introduction

Localization holds immense significance across multiple fields, including healthcare [1], safety [2], smart homes [3], and retail analytics [4]. Traditional localization methods, such as Global Positioning System (GPS) or camera-based surveillance, possess limitations and may not be suitable for certain situations due to concerns regarding privacy or infrastructure requirements. In such cases, DFL emerges as an invaluable solution. By enabling the tracking and localization of individuals without the necessity of electronic devices, DFL presents notable advantages. It offers convenience, upholds privacy, and boasts a wide array of applications. For instance, within healthcare, DFL empowers healthcare professionals to remotely monitor patients' movements and activities, thereby enhancing personalized care and facilitating prompt responses during emergencies. In smart homes, DFL enables context-aware automation, thereby enriching user experiences and supporting energy efficiency. Retailers can capitalize on DFL to scrutinize customer behavior and optimize marketing strategies. By obviating the need for individuals to carry dedicated devices, DFL not only enhances convenience but also addresses privacy concerns, underlining its value and potential as a technology across diverse domains. Numerous investigations have concentrated on utilizing wireless signals, such as Wi-Fi [5-7], Bluetooth [8], Zigbee [3],[9-11], Ultra-Wide-Band (UWB) [12,13] and infrared [14-16], for the purpose of DFL. These signals can be employed to analyze variations in parameters like Received Signal Strength (RSS)[17-20], Channel-State-Information (CSI) [21-24], Angle of Arrival (AoA) [25, 26] and Time of Arrival (ToA) [27, 28] in order to estimate the position of individuals. In particular, RSS-based techniques have been extensively explored, leveraging the decay of wireless signals to ascertain the proximity of individuals to access points.

Regarding methodologies, researchers have put forth diverse algorithms and approaches to accomplish precise DFL. These encompass machine learning techniques, such as Support Vector Machines (SVM) [29] and neural networks [30], as well as statistical methods like Kalman filtering [31-34] and particle filtering [35-37]. Additionally, scholars have developed localization algorithms based on signal fingerprinting [19, 24, 29,38], and probabilistic models to amplify the accuracy and dependability of DFL systems. The assessment of performance metrics for DFL systems has also received significant attention. Metrics including localization error, tracking precision, and resilience to environmental dynamics have been utilized to gauge the efficacy of distinct techniques and algorithms. These metrics play a pivotal role in establishing benchmarks and facilitating comparisons among different DFL approaches.

Despite its promising applications, DFL encounters various challenges. One major hurdle arises from the presence of multiple individuals within the tracking area [6], [39-41], which gives rise to ambiguity in sensor measurements and target identification. Tackling this issue necessitates the development of sophisticated algorithms capable of accurately distinguishing and tracking individual targets. Moreover, signal attenuation caused by obstacles, interference from other wireless devices, and environmental dynamics pose additional impediments to achieving reliable and precise localization.

Nomenclature & Symbols

AoA	Angle of Arrival	MDE	Mean Distance Error
CDF	Cumulative Distribution Function	MIMO	Multiple Input and Multiple Output
CdRTI	Channel Diversity Radio Tomographic Imaging	MIC	Maximum Independent Column
CSI	Channel-State Information	DFL	Device-Free Localization
COTS	Commercial off-the-Shelf	ELM	Extreme Learning Machine
ESD	Electronical Switched Directional	ER	Exponential Rayleigh
GMM	Gaussian Mixture Model	GPS	Global Positioning System
GSM	Global System for Mobile	HMM	Hidden Markvo Model
ISAR	Inverse Synthetic Aperture Radar	KLD	Kullback-Leibler Divergence
KNN	K-Nearest Neighbors	LoS	Line-of-Sight
PGFE	Parameterized Geometrical Feature Extraction	RF	Radio Frequency
RFID	Radio Frequency Identification	RIP	Restricted Isometry Property
PRR	Packet Reception Rate	RSS	Received Signal Strength
RSVD	Regularised Singular Value Decomposition	RTI	Radio Tomographic Imaging
SMC	Sequential Monte Carlo	SVM	Support Vector Machines
ToA	Time of Arrival	UWB	Ultra-Wide Band
VRTI	Variance Radio Tomographic Imaging		

In conclusion, the goal of this research is to present a thorough understanding of DFL methods, including their classification, metrics for evaluation, uses, and difficulties. We may learn more about the state of the industry today, spot knowledge gaps, and pave the road for improvements in DFL technology by looking into these important topics.

2. Letrature Review

Wang et al [7] implemented DFL system using commercial off-the-shelf (COTS) Wi-Fi devices and DFL works on model-based technique. The algorithm enables target localization with no prior offline training. Using CSI as localization metric and since CSI is location-sensitive, the target site can be identified by modelling the CSI measurements of various wireless networks as a set of power fading-based equations. However, due to the abundant multipath propagation indoors, it is difficult to represent RSS or even the fine-grained CSI. A pre-processing strategy is used in an effort to pinpoint the subcarriers that are unaffected by multipath. Thus, accurate localization can be achieved by using CSIs on the "clean" subcarriers. In cases involving line-of-sight (LoS) and non-line-of-sight, the method achieves median accuracy of 0.5 m and 1.1 m, respectively. Kaltiokallio et al [42] explains how Bayesian filters are better at localization than imaging techniques since they directly connect measurements to a person's position. However, divergence problems with Bayesian filters are possible. In order to solve this, the paper offers a novel Bayesian filter that incorporates measurement data from imaging technologies. This filter combines the accuracy of Bayesian filtering with the resilience of imaging, providing a solution to the problem. With errors of 0.11 m in a 75 m^2 indoor deployment and 0.29 m in an 82 m^2 residential trial. Shengxin et al [43] discusses cost-effective indoor positioning using Radio Tomographic Imaging (RTI). Instead of using the unstable RSS, it suggests using fine-grained CSI and employs multiple input and multiple output (MIMO) techniques to create a CSI-MIMO attenuation model, benefiting from frequency and spatial diversity. Additionally, the paper suggests using a higher signal frequency for better shadowing loss. Experimental results confirm that this CSI-MIMO approach significantly improves localization accuracy compared to RSS-based RTI methods. Zhou et al [29] introduces a device-free presence detection and localization method using Wi-Fi CSI and SVM. It detects human presence by analyzing changes in Wi-Fi signals within a specific area and utilizes SVM for classification. The algorithm also estimates object locations based on CSI fingerprint patterns and SVM regression. To handle noisy Wi-Fi signals, it employs density-based spatial clustering to reduce noise and principal component analysis to extract key features and reduce dimensionality. In two scenarios, the method achieves a presence detection precision of over 97% and localization accuracy of approximately 1.22 to 1.39 meters. Ruan et al [44] introduces a device-free passive localization and tracking system using cost-effective RFID tags. It tackles localization as a classification task, comparing methods like K Nearest Neighbor (KNN), Multivariate Gaussian Mixture Model (GMM), SVM. For tracking, it suggests two Hidden Markov Model (HMM)-based approaches: GMM-based HMM and KNN-based HMM, which extends KNN into a probabilistic style. These methods are adaptable to other fingerprint-based tracking systems. Extensive experiments show their effectiveness, achieving up to 98% localization accuracy and an average tracking error of 0.7 m. Guo et al [35] addresses a common challenge in device-free localization and tracking using wireless sensor networks, where changes in RSS become unpredictable due to multipath interferences. To tackle this issue, the researchers propose a new RSS model called the Exponential-Rayleigh (ER) model. This model comprises two components: a large-scale exponential attenuation part and a small-scale Rayleigh enhancement part, which helps depict target-induced multipath components. They then apply the ER model with a particle filter for multi-target localization and tracking, demonstrating its superiority over existing models in experimental tests. Overall, the ER model, especially its use of the Rayleigh model, proves effective in mitigating multipath interferences and enhancing device-free localization and tracking performance.

Wang et al [18] implemented D-Watch, a device-free localization system using low-cost RFID technology. Unlike previous approaches that consider multipath interference a problem, D-Watch utilizes multipaths to achieve precise localization (within decimeters) without the need for offline training. It uses AoA information from RFID tags' backscatter signals and a novel P-MUSIC algorithm to accurately detect signal power drops caused by target blockages. Importantly, D-Watch's wireless phase calibration doesn't disrupt ongoing communication. Real-world tests show D-Watch's effectiveness: in a multipath-rich environment, it achieves a median accuracy of 16.5 cm for human target localization and 5.8 cm for tracking a user's fist in a 2m x 2m area. It can also localize multiple targets, a challenging task in passive localization.

3. Device-Free Localization Techniques

This section describes popular techniques used in DFL as stated in [45]. With the widespread use of wireless radio frequency signals such as Global System for Mobile (GSM), Wi-Fi, and FM, it is feasible to construct a system for ubiquitous localization. These DFL techniques are typically denoted as radio monitoring. These techniques use link readings to determine the position of an object. RSS and CSI are the fundamental properties of wireless connections used in radio sensing. There are two categories of approaches that take measured properties into consideration for position approximation: 1) Link Quality Measurement, and 2) Link Scattering. Consequently, the methodologies are similarly classified as 1) Radio-Vision approach (using shadowing or link quality measurement) and 2) Radar-based approach (using link reflection or diffraction). Vision-based approach is further subdivided into A) Propagation based Model, B) Statistical Methods Estimation, C) Training Approach.

3.1. Propagation model techniques

3.1.1. Shadowing

The shadowing model uses the radio link's RSS attenuation. After removing the localizing object, all radio connections' RSSs are measured. In real-time positioning, the receiving node estimates the difference between the empty environment's average RSS and shadowing loss's RSS. Link shadowing is modeled as a linear mixture of signal attenuation. The signal's spatial effect model and relationship influence various attenuation models in the literature. [32], [46] revised the spatial effect model and built an ellipse-based geometrical model with nodes at the foci. For objects inside the ellipsoid, the RSS is either zero or inversely proportional to the square root of the radio connection length. This model quantifies each link's attenuation. Real-time monitoring compares RSS between humans and the target item. The GMM, a stochastic model known for shrinking positioning error, describes ambient noise. Tracking the moving item uses regularization. The shadowing approach also reduced error when localizing and tracking one or more people. The active sensor nodes in this approach consume a lot of power.

3.1.2. Channel Diversity

Multiple channel communication between sensor nodes increased Radio Frequency (RF) sensor network shadowing [47]. The author shows that RSS measurements from several frequency channels better indicate signal shadowing probability in sensor node links. Packet Reception Rate (PRR) and link fade level determine the two-channel selection criteria. PRR maximizes communication reliability and fade level [36] maximizes connection fade. The researcher confirms that the diversity of channels used in positioning network enhances localization accuracy over single RF frequency channel. Human localization was tested indoors with 70 m^2 ground area and 30 sensor node elements. Mean errors did not exceed 0.1m. This method exclusively localizes non-moving objects and humans. The author also does not describe the localization methods for moving objects.

3.1.3. Ambient Radio Imaging

Since sensor nodes are not constantly powered, energy efficiency is as important as positioning accuracy in DFL systems. Energy saving is essential for outdoor and indoor localization procedures but often overlooked. Khaledi et al. [48] considered energy efficiency and accuracy in device-free localization. This technique divides the monitoring region into smaller segments and turns off partitions with ineffective link RSS fluctuation. They also proposed radius- and ellipse-based connection estimates near the target.

They also compared energy-efficient and localization-accurate methods with shadowing [49] and variance [32] methods. Three scenarios office, indoor, and bookstore were tested for the proposal. The radius-based approach is more accurate but the ellipse-based approach is more energy efficient. The technique only tracks one target.

3.1.4. Exponential Rayleigh Model

[35] suggested an ER RSS based model for DFL that includes superior performance. Fig. 1 shows how Bayesian inference estimates state posterior distribution. The state space model shows time-dependent state transitions and prior state probability distribution. The constant velocity block shows target movement. Monte Carlo-based particle filters calculate the state posterior distribution. HAC algorithms were used to identify several targets. ER model blocks are.

- Motion Model: Physical processes can model object movement. A first-order Markov process human movement model tracks activities. The Markov chain model predicts the next system state according to its prior states. Thus, using the last state, the target motion can be estimated. ER model generates object mobility using state-space models.
- Particle Filtering: The Monte Carlo approach [50] extends filtering to particle filters in non-Gaussian and nonlinear systems. State probability distribution is stated using random position particles for best solution. Re-sampling solves particle degeneracy. Device-free object localization in the ER model uses the SIR particle filter.
- Hierarchical clustering localizes several objects. HAC [51] clustering is promising. Each particle is initially autonomous, and each iteration passes, clusters are linked under linkage rules and discontinued when cluster number matches objects. Target state information is in the cluster centers.
- Multiple Particle Filter: Closas et al. [52] proposed the Multiple Particle filter to boost performance in high-dimensional targets. Tracking is better than the particle filter.

3.1.5. Directional radio imaging

Most device-free localization methods use radiation-omnidirectional antennas. Wei et al. [53] proposed that an antenna with directional orientation enables improvement in radio link quality for device-free localization accuracy. The author used an ESD based antenna that relies an energy-efficient and cost-effective positioning. ESD antennas provide dynamic electronic direction control more efficiently than standard antennas. This directional antenna controls multipath fading by directing and collecting signals in the desired direction, enhancing link quality. The authors proposed 36 transmitter-receiver pairs for a radio network. These were direction-pattern pairs. This approach outperformed [46], Variance Radio Tomographic Imaging (VRTI) [32], and Channel Diversity Radio Tomographic Imaging (cdRTI) [47] in localization accuracy under LoS and non-LoS circumstances.

3.1.6. Compressive sensing

Compressive Sensing allows multiple item localization and counting [54, 55]. Researchers suggest dense sensor node deployment for excellent localization accuracy. However, Wang et al. [54] demonstrated high localization in sparse deployment conditions using Compressive sensing.

Modern device-free WSN techniques use RSS-based metrics. This localization method relies on RSS link interference. Wang et al. [92] utilizing Compressive sensing object position was rebuilt in form of sparse signal. This method was chosen for sparse recovery. The device-free localization problem's Restricted Isometry Property (RIP) was mathematically demonstrated to be satisfied. Fig. 2 shows that the sensing matrix-position vector product follows RIP with high likelihood. The author performed Compressive analysis on the optimal grid size, unlike existing grid dimensions design for small positioning error. They also verified localization and target counts in large-scale settings.

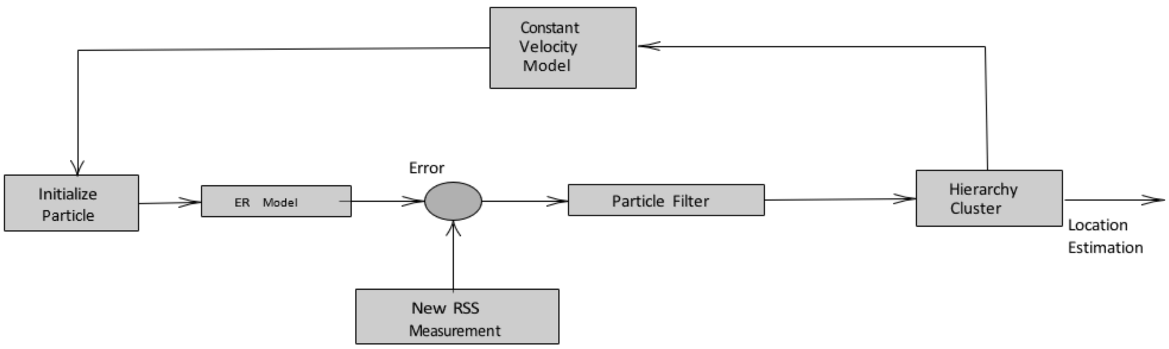

Fig. 1. ER Model Diagram[45]

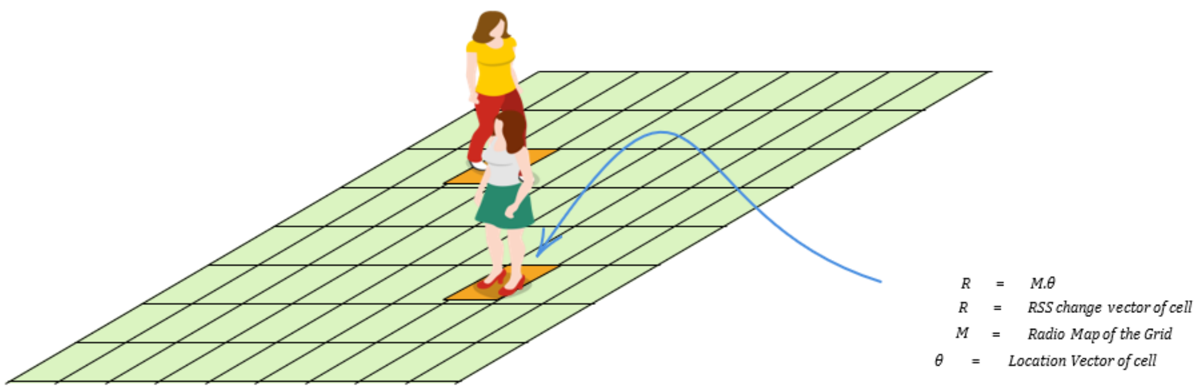

Fig. 2. Compressive Sensing: The target is located by utilizing compressive sensing theory and the real-time RSS of the cell, which is illustrated by the colored cell [45]

3.2. Statistical estimation techniques

3.2.1. Sequence Montecarlo

By using WSN movement detection. RSS measurements use a Gaussian Mixture Model communication connection. Sequential Monte Carlo (SMC) followed foreground detection. Foreground detection models the likelihood of influenced link by subject's presence as a classification issue, then estimates it using RSS measurement and takes the mean. SMC provides a good solution for nonlinear and non-Gaussian scenarios. The author evaluates system performance in a building with 24 wireless sensor nodes. They showed that connection structure might estimate individual location. This approach obtained a 0.2m root mean squared localization error in the dynamic environment without offline training. This approach works well in LoS and non-LoS situations [56].

3.2.2. Variance based model

The propagation radio model-based approach calibrates the environment without the target. Environment changes cause localization errors and recalibration. Wilson et al. [32] proposed variance-based DFL. Their method divides the localization zone into voxels. However, a vector of RSS variance [57] represents the links' shadowing region and can be utilized to locate the target in physical space. This method does not calibrate the empty environment before object localization and includes environmental variances. Link shadowing or attenuation is demonstrated using the normalized ellipse weight model. Kalman filter application in pixel space and regularization localizes moving targets [46]. The author tested 34 sensors in indoor dwelling situations and found a positioning error of 1.03m. They lowered the Kalman filter delay and improved localization error to 0.45m. Since all wireless devices are continuously active, the approach is power inefficient and fails to pinpoint static objects due to RSS changes.

3.2.3. Histogram distance

Traditional DFL systems require device pre-calibration in an empty environment. Zhao et al. [58] use Histogram Distance-based DFL to address this problem. It localizes motionless and mobile subjects without the need for calibration period. This histogram difference value quantifies RSS change and estimate's location. Lower node density benefit from this strategy. An object near a link's LoS temporarily deviates the RSS histogram from the calibrated one. The RSS histogram is long-term, while the deviated histogram is short-term. Kullback-Leiber divergence is used to compare these two histograms based on a metric [59]. Kernel-based approaches simplify the computationally intensive metric definition and calculation. From this histogram, different metrics estimate the location. Zhao et al. [60] add histogram difference and online calibration to the reasoning. The suggested model was experimentally confirmed with 16 nodes in a 16 m^2 area, attaining a 0.7m root-mean squared localization error, better than all Variance Based DFL models. [32], [46].

3.2.4. Kernel distance

Histogram distance based DFL systems are computationally costly because to a low-complexity calculation issue [58]. Zhao et al. [60] upgraded the network with kernel distance technique and found stationary and mobile objects in LoS and non-LoS scenarios. This approach measures RSS histogram difference. The author examined histograms with other values including Kullback-Leibler Divergence (KLD) and kernel distance and discovered that kernel-based technique outperforms others. Five experiments utilizing Wilson et al. [36] data confirmed the kernel-based technique. Finally, the kernel approach was compared to other DFL methods [32], [56], [61] and found to be solely appropriate to real-time localization in LoS and non-LoS settings without training.

3.2.5. Three-State RSS

A three-state RSS model was proposed where electronic noise, reflection, or shadowing determine measurements depending on the object to be localized or tracked. Fig. 3 shows the state-specific statistical and spatial model obtained from this model. A link monitoring program estimates target object and propagation model states. Even with larger sensor node sensing regions, this model provides better localization accuracy than the other empirical models, according to the author. This three-state RSS model adds a state to the time-varying two-state channel model. Human-induced temporal fading in the two states lets this model estimate human position. The human-induced effect shadows the received signal and creates a new multipath component by reflection The model works indoors. Coherent receiver architectures make it easy to determine RSS changes and temporal variation. RSS measurement changes depend on LOS signal since the receiver is synced to it [47]. The goal was to record minor channel changes at all frequencies. An indoor 48 m^2 experiment with localization error between 0.07m and 0.46m validated this model [62].

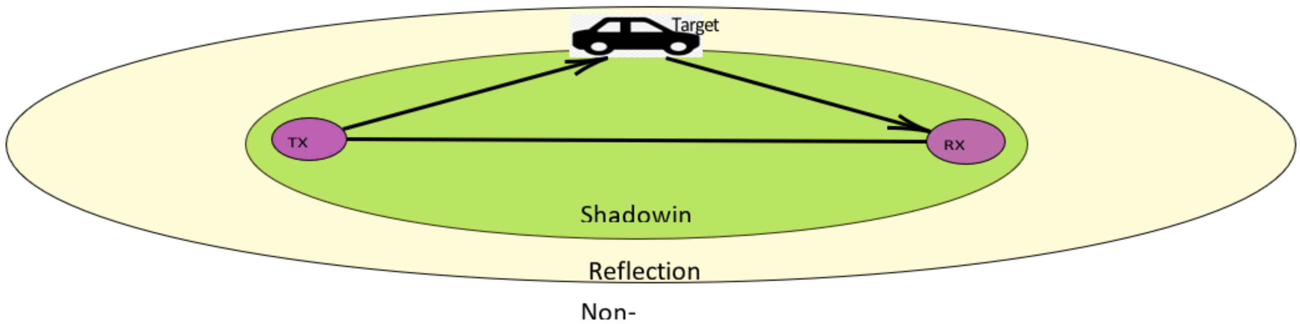

Fig. 3. Three State RSS Technique [45]

3.3. Training based techniques

3.3.1. Channel selection with regression

DFL systems need recalibration to maintain accuracy due to environmental changes. In this dynamic context, Lei et al. [63] used better channel selection and logistic regression to improve localization accuracy. The author suggested a frequency channel selection approach that selects two correlated channels with greater Pearson correlation coefficient for RSS training and testing in resilient environments. Logistic regression classifier enhances DFL localization accuracy without database rebuild. Logistic regression was employed for position estimation after two correlated channels were trained and tested [64, 65]. This approach has the lowest localization error, according to the author's experiments.

3.3.2. Markov model

A human body motion sensing, body localisation, and fall detection was implemented. HMM method leverages RF signal properties from a sensor network in a workplace. This machine-to-machine communication system monitors 2.4 GHz ISM band RF waves. RSS footprint analysis and Markov model-based prediction aid body localization with RF signal monitoring and human-induced diffraction and multipath effect. The technology locates motion, position, and health-critical posture. This strategy can also protect industrial workers. The source is combined with sensor data for monitoring. The author tested this approach for sensitivity and specificity. The 14 m^2 model with 12 sensor nodes obtained 0.198m average localization error [66].

3.3.3. Extreme learning machine

The RF-based DFL system measures RSS and fuses these values to determine position. Zhang et al. [67] presented an Extreme Learning Machine (ELM) [68]-based DFL strategy to improve efficiency and localization accuracy. The damaged connection is parameterized geometrically in this paper. Geometrical intercepts and differential RSS measurement form this depiction. ELM inputs Parameterized Geometrical Feature Extraction (PGFE) features from damaged links. Fig. 4 shows the ELM training and testing PGFE-ELM for DFL. Due to unpredictable wireless propagation, the approach is resilient to uncertain wireless link combinations. This algorithm outperformed WKNN, BPNN, SVM, and RTI DFL in experiments. BPNN and SVM [69] become stuck at the local minimum and require a long training period. This technique outperforms typical machine learning algorithms [70-72]. Due to classic advantages like unified learning, binary classification, and multiclass classification, it is applicable to many DFL-based systems like face recognition [73, 74], industrial production [75, 76], human physical activity recognition [77, 78], landmark recognition [79, 80], and leukocyte image segmentation [81].

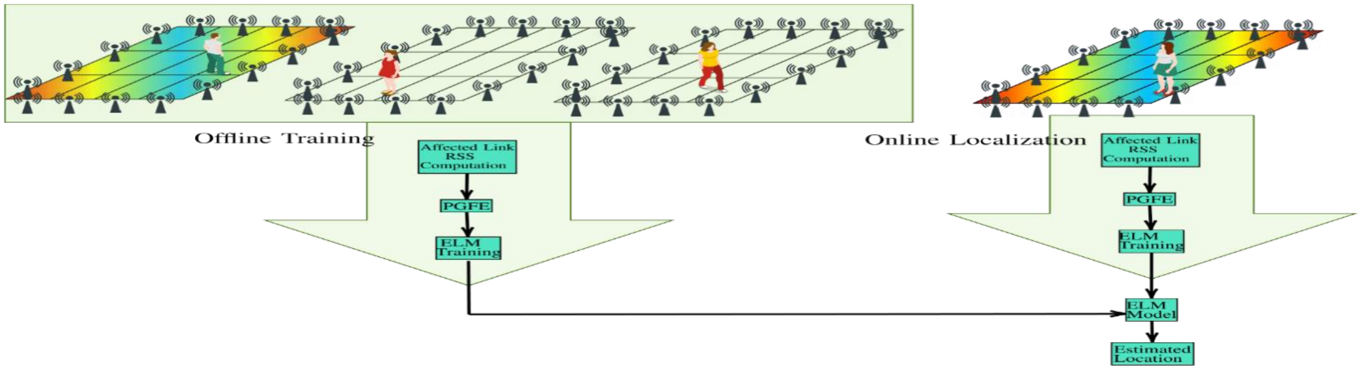

Fig. 4. PGFE Machine-Based Extreme Learning Device-Free Localization [45]

3.3.4. iUpdator

Fingerprinting-based DFL systems are popular due to low deployment cost and accuracy. Chang et al. [116] created iUpdator, a DFL system that augments fingerprint database sparse characteristics using Self-augmented Regularised Singular Value Decomposition (RSVD). iUpdator updates the entire RSS fingerprinting database at reference locations. This algorithm detects RSS difference variation and neighboring wireless link similarities to overcome short-term RSS variation.

Fig. 5. shows the four modules of iUpdator: intrinsic correction acquisition, reconstruction data collecting, fingerprint matrix reconstruction, and localization. In inherent correlation module, iUpdator harvests fingerprint matrix Maximum Independent Column (MIC) vectors and forms inherent correlation matrix. The inherent correlation matrix constrains reconstruction fingerprint matrix. Reconstruction data collection module collects RSS measurements at a minimal number of reference locations to generate the reference matrix. No-decrease matrix also acquires distant points from direct links. Self-augmentation RSVD creates fingerprint matrix from correlation matrix, reference matrix, and no decrease matrix. Reconstructed fingerprint matrix and non-linear optimization algorithm estimate object location in localization module. This technique yielded 0.5–1m localization accuracy in 108 m^2 office, 88 m^2 library, and 100 m^2 hall with 8 WiFi access points.

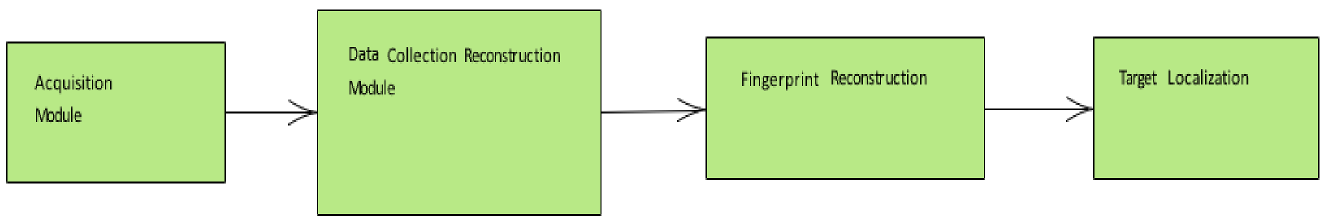

Fig. 5. iUpdator Technique Diagram [45]

3.4. Scattering based techniques

3.4.1. Wi-Fi Scattering

Wi-Fi-based scattering employs DFL infrastructure. Cost-effective approaches. Wi-Fi-based DFL systems require motion detection [82]. Motion detection uses feature extraction and moving variance. Moussa et al. [19] suggested DFL system Maximum Likelihood estimator for smart settings. RSS feature extraction from environmental changes or CSI from physical temporal variation improves detection. Multipath propagation extends link detection range in Wi-Fi CSI-based human detection [83, 84]. Wu et al. [85] proposed breadth-based human localisation. CSI methods are environmental change-resistant. Wi-Fi-enabled WiVi [86] detects moving objects across walls and doors.

WiVi uses Inverse Synthetic Aperture Radar (ISAR) to locate and track several objects. WiDeo [87] backscatters Wi-Fi infrastructure. Backscatter sensor: access point. The RF sensor uses three primary properties of the reflected signal to locate things. Amplitude, ToF, and AoA. WiDeo emulates SDR radar [88]. WiDeo was found to locate five things more accurately than previous methods.

3.4.2. Radio frequency identification (rfid) based

RFID-based DFL systems place RFID tags in the deployed area. RFID readers send the signal, which things scatter to RFID tags. The tags modify the RF signal to indicate whether the object is in the region. This diffused signal helps an RFID reader locate the object. Scattering detects moving things. RFID scattering systems have a ten-meter communication range that can be improved by RFID reader sensitivity [18]. Ruan et al.'s RSS fluctuation-based RFID tracking system TagTrack [44] predicts target objects with 98% accuracy using a Hidden Markov Model. Yang et al. propose RF backscattering through walls using an antenna array of RFID tags dubbed Tadar [89]. A Hidden Markov Model and Viterbi algorithm estimate object motion. Indoor localization error was 7.8-20 cm. Kuska et al. [90] used RFID reader and tag tiling for geometric DFL human location. For minimal maintenance, cost, scalability, and deployment, Shi et al. [91] switched to passive RFID.

3.4.3. mTrack

DFL systems use RF signal reflection for scattering. The object's wavelength blocks the signal. This attribute maximizes reflection but does not improve scattering-based localisation in the typical ISM range 2.4–5GHz. Wei et al. [92] proposed mTrack, a 60GHz IEEE 802.11ad-based tracking system. mTrack tracks the slightest object location change using an electronically steerable high-directional beam. With one transmitter and two receivers, it measures RSS and phase from the scattered signal. This approach estimates reflected signals from relative angle to locate the target. Due to high frequency, the author achieved a localization error below 8mm at a range of 1m. Thus, this technique can locate minuscule items, biomedical in-body tumors, and wireless transcription.

4. Device-Free Systems Metrics

This section describes metrics used to assess the performance of DFL system which contain: 1) accuracy, 2) cost, 3) complexity, 4) precision, 5) scalability, and 6) robustness as stated in [93].

4.1. Accuracy

The Mean Distance Error (MDE) and the position error rate are frequently used accuracy measures for positioning and tracking. For a two-dimensional position, the accuracy is measured using the first metric. The Euclidean distance of the anticipated coordinates and the real coordinates is averaged to determine the MDE. In the latter, discrete position estimation is the principal application. It is determined by dividing the total number of places by the number of right locations. The identification rate, which is determined by the ratio of the corrected identification over the total number of real values, is the generally used statistic for measuring target identification. The identification results can also be examined using a confusion matrix. The difference between the estimated and actual targets is used to determine how accurate person counting is. The counting percentage, which can be achieved by dividing the predicated count by the real number of people, can then be used to determine the accuracy of target counting.

4.2. Cost

The adoption of the suggested solution may be impacted by the cost. Hardware price, energy consumption cost, and human labor fees make up the typical three components of the cost. Ideal solutions should be reasonably priced in terms of hardware. Less time and labor should also be needed to mount and adjust the solutions. The solution must use little electricity in order to lower the cost of energy. Analyzing and comprehending the requirements of the positioning and tracking system, such as the size of the area, the precision of the positioning and tracking outcome, and the number of residents, can lead to a cost-effective solution.

4.3. Complexity

The speed at which a DFL and tracking system analyzes data and finds an object (person) in real time manner is referred to as system complexity. the study revealed that the majority of works measure the total time needed to compute estimates in seconds or milliseconds before reporting the system latency.

4.4. Precision

In addition to providing precise position estimates, DFL and tracking systems must also function consistently, that is, show minimal variance in their results over a number of trials. The consistency of position estimation is assessed using a statistic called precision. It frequently goes hand in hand with accuracy. DFL and tracking system precision can be evaluated using cumulative probability functions (CDF) of a distance error. It provides the inaccuracy in the distance between the estimated and real locations' distributions. If, for instance, one system's CDF is 90% within 2.3 m and the other system's CDF is 50% within 2.3 m, it is preferable to choose the system of 90% since it is more reliable than the system of 50%.

4.5. Scalability

Scalability refers to a system's ability to adapt to various area sizes. For a system to be scalable, it must maintain its performance across a wide deployment region. In most cases, the accuracy and scalability are compared. The experiments in the articles under consideration are typically carried out on a few testbeds of various sizes. When the dimensions of positioning area are changed, the results of these trials are compared to see how precise each system is. The density of wireless devices can be used to gauge scalability. It speaks of the quantity of sensor nodes within a given area, such as nodes per square meter. Not only can the density of wireless devices be used to calculate scalability, but also the density of people.

4.5. Robustness

A DFL and tracking system must be robust in order to function successfully even in the presence of irregular or insufficient measurements brought on by broken sensors, harsh environmental conditions, or various deployment environments. By conducting studies in testbeds with a variety of graphical and furniture configurations, robustness can be assessed. For instance, a broad hallway might have less multipath issues than a packed workplace space. The accuracy of different testbeds is then contrasted. These outcomes can be contrasted using the MDE and the CDF of a distance error as metrics. Additionally, the resilience could be measured using a sensitivity investigation, which assesses each output to find its influence on an output uncertainty.

5. Conclusion

This review has provided a concise overview of DFL techniques. DFL has emerged as a promising and versatile technology, leveraging existing wireless signals to locate objects without the need for additional hardware. The review has explored various DFL methods, including propagation models, statistical estimations, training-based approaches, and scattering-based techniques, highlighting their strengths and limitations.

Furthermore, we introduced essential metrics for evaluating DFL systems, emphasizing accuracy, cost, complexity, precision, scalability, and robustness as critical factors in assessing their performance.

As DFL continues to evolve, it holds significant promise for applications across multiple domains, from smart environments and healthcare to security and industrial automation. By understanding the diverse methodologies and metrics discussed in this review, researchers and practitioners are better equipped to harness the potential of DFL and drive innovation in this dynamic field.

6. Future Work

This section highlights some future works intended for DFL as state in [45].

Systems for localization are created, calibrated, and tested in a typical setting. Major aberrations in overall accuracy might result from abrupt changes in the environment. By simulating the object's motion and using Doppler shifts [94] for localization and activity detection, these environmental effects can be overcome. Future work will likely involve modelling environmental effects on precise DFL systems. The CSI-based DFL systems are well-liked because of their design and use. This technique makes use of the link's channel frequency response. Due to frequency selective fading, different frequencies are vulnerable to differing levels of attenuation. In order to filter the poor frequency carriers that are fading-prone and determine object position in DFL systems, Wang et al. [7] presented a LiFS model. For the purpose of resolving the frequency-selective fading issue in DFL units, dimensionality reduction approaches [95], [96] like PCA and kPCA methods are efficient in extracting features from CSI measurements. For better localization, activity recognition, and detection-based applications for the coming Smart World, this device-free systems method can be developed. It is difficult to estimate the correct carrier channel frequency, and this might reduce the unpredictability of received signals, which limits the precision of localization, as well as the Doppler shift of received signals. A frequency synchronization technique for the sensor nodes was put out by Luong et al. [97] to improve carrier channel frequency estimation. an innovative approach uses accurate feature selection and the formulation of rules for better location prediction using a deep learning approach in DFL. The majority of data modelling problems were resolved using deep learning, which is undoubtedly relevant to a wide range of situations, including speech recognition and computer vision. In situations without devices, it can even be extended to human senses [98]. Only a few works on RFID technologies have been documented in device-based frameworks [99] that can be used in device-free localization settings. There are numerous techniques used to locate people or things based on their motion patterns. The vital sign can be used to expand this further. Future technologies that localize people based on their vital signs, such as their heartbeats [100], breathing [101], [102], etc., have a lot of promise.

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