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Passive Localization Utilizing Wireless RSSI: A Review

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***Abstract*: *Localization is the process of determining the location of an object or device in an environment, and it can be achieved using radio frequency signals in wireless communication systems. Localization can be achieved using active or passive localization methods. Active localization is the most accurate but power-intensive, while passive localization is used in an environment where a targeted object does not have any devices. Consequently, this review paper is centred on the passive localization technique using radio tomography images, wherein object location is estimated using received signal strength measurements. The review paper presents passive localization as an improvement over active localization methods, problems, and limitations of tomography for Received Signal Strength Indicator* (*RSSI*)*, recent contributions, and possible research directions. This review paper provides a broad and generic perspective of the ongoing research on passive localization, which might benefit researchers and professionals in wireless communications, localization, and signal processing.*

***Keywords*: *Active localization, Fingerprinting, Passive localization, Radio tomography images, Wi-Fi.*

1. Introduction

Internet of Things (IoT) applications within interior spaces include real-time locations, assets, and service personalization. In these applications, localization remains of superior significance since it offers detailed data concerning the relative location of objects, people, or assets within a specified enclosed area [1, 2, 3]. As applied to wireless communication, localization denotes the procedure for identifying the geographical location of wireless devices or nodes in the network [4, 5, 6]. This can be done by signal strength measurements, time-of-flight measurements, angle-of-arrival measurements, and signal propagation modeling [3, 7]. Wireless localization has applications in various contexts, including asset management, navigation, service delivery, and emergency response. In an indoor navigation system, wireless localization is used to determine the position of a user's mobile device and to guide them to a particular place in a specific building [7]. The principles of wireless localization vary depending on the wireless technology used. In Wi-Fi, location is found using signal strength measurement, which approximates the distance between a device and the APs, while cellular Localization involves the use of triangulation on the signal strengths of the base stations to locate a mobile phone [8]. A significant problem arises from applying the wireless localization task due to the variability of signal strength in different environments, signal attenuation, and interference. However, a large number of research works aim at raising the efficiency and robustness of wireless positioning approaches, signal processing algorithms, and machine learning techniques, integration of new kinds of antennas, and simple clustering for wireless device networks [9, 5, 10, 11].

Typically, triangulation or trilateration techniques, Wang, Yihitler, Jintti, and Huang [12, 6] have been used in traditional localization approaches. In triangulation, an estimate of the location of a transmitter is made with the help of the Angle of Arrival (AoA) of a signal. Trilateration, on the other hand, estimates the transmitter's position based on the distance between the transmitter and the receiver. In triangulation, the receiver uses other antennas to estimate the signals' AoA. The transmitter's location can be determined when AoA lines are approximately crossed from different antennas. This strategy is normally applied in Line-Of-Sight (LOS) circumstances, whereby the signal is transmitted directly from the transmitter to the receiver [12, 13]. On the other hand, trilateration estimates the distance between transmitter and receiver, whereby either the Time of Flight (ToF) or the strength of the received signal is considered. When there are several receiving antennas and receivers, the distance from the emitter to each of the receivers can be estimated. The circles formed around each receiver intersect to give an approximate location of the transmitter [14]. This method is most commonly employed in Non-Line-Of-Sight (NLOS) conditions where a signal may be obstructed, reflected, or scattered [15]. An improvement has been made in trilateration techniques is the use of the quadrilateral series location method along with DV-Hop for the localization in the agriculture domain [16]. However, BAD-Hop is proposed to minimize the error caused by the average distance formula used per hop. BAD algorithm is an intelligent optimization method that was used along with the DV-Hop Algorithm for localization [17]. Another traditional localization approach is fingerprinting, where a database with signal features of various locations is made and used to match and predict the transmitter's position. The second method is the centroid, based on the location of the center of gravity of the received signals from multiple receivers to estimate the transmitter's position [18].

In different applications, several wireless technologies are used as follows: Bluetooth [19-21], wireless local area networks [22-25], wireless personal area networks [26, 27], radio frequency identification [20, 28-31], magnetic fields [32-36]. Every technology has some benefits and drawbacks, and the sort of technology to be adopted largely depends on the needs of the software application [6, 31]. Bluetooth and Wi-Fi are used because they are common in smartphones and are deployed significantly in buildings. Some of these technologies can use Received Signal Strength Indicator (RSSI), AoA, or ToF methods for the localization based on the deployment [37, 38]. Bluetooth Low Energy (BLE) beacons, if placed at known locations, can be used for proximity-based localization of devices [39], while access points for more localized tracking [6]. Some of the industrial uses of ZigBee, a widely used low-power wireless communication protocol, include the field of localization. ZigBee is based on a wireless mesh network, where devices can communicate with each other at low energy levels. Localization algorithms can be applied over ZigBee, such as RSSI [40, 41], ToF, and AoA [42]. These methods enable ZigBee-based systems to achieve accurate position estimation in indoor spaces and find their applications in asset tracking, smart manufacturing, and industrial automation. The Radio Frequency Identification (RFID) tag can be placed on the object, and the reader can find its distance from the tag by either reflected signal strength or phase shift, thus allowing for its localization. Magnetic field-based localization is another technique suitable for localization in indoor environments. Magnetic fields are less obstructed than radio waves; they go through walls. This technology can be implemented through magnetic sensors mounted in a known pattern to receive the changes in the magnetic field due to the influence of magnetic materials. All these technologies feature unique strengths and weaknesses, and the choice of the technology to be employed depends on parameters such as precision, reach, energy consumption, and setting [42].

Wireless localization has emerged as one of the most important research topics for different applications, including indoor navigation, asset tracking, and environmental monitoring. RSSIs are stated to be among the many commonly implemented methods of wireless localization [43-45]. RSSI is an efficient technique used to calculate the distance between the transmitter and the receiver because the intensity of the signals reduces with the increase in distance between the transmitter and the receiver. Tomography is a process of reconstructing a cross-sectional view of an object or material by taking several measurements using multiple directions or angles. The term tomography comes from the Greek terms tomos ("slice" or "section") and graphia ("description" or "drawing"). In diagnostic medicine, it is well known in Computed Tomography (CT), wherein several X-ray images are combined to generate detailed cross-sectional images of internal organs [42]. RTI differs in that it does not reconstruct internal anatomical slices. Instead, it calculates an attenuation map of the observed region according to variations in RSSI measurements at GHz frequencies. As the human body absorbs or reflects radio waves at these frequencies, the reconstructed images show space variations in signal propagation instead of biological structure. Though the application of the term tomography in RTI is figurative and not literal, it underscores the analogy in reconstructing the image from indirect measurements [5, 12]. Consequently, in the case of passive localization using tomography RSSI, the method involves carrying out many measurements of received signal strengths at numerous locations to create a three-dimensional map of signal strength, which may then be used to calculate the position of the wireless device or target [12, 14, 15]. The tomographical RSSI-based passive localization technique involves estimating the position of the wireless device without transmitting any signals actively. The method is based on acquiring the information on the RSSI of already existing networks, for example, Wi-Fi or Bluetooth, and then using this data to construct a 3D signal strength map. The location of a wireless device can be estimated to an appreciable extent based on analyzing variations of signal strength of the same signal at different places [46].

Localization methods are generally classified into device-based and device-free methods. Such a classification serves to illustrate the range of methods conceived in the discipline. Device-based methods have been the traditional mainstay in research and industrial installations, as they take advantage of pre-existing wireless technology and allow for easy tracking solutions. In recent times, device-free methods have been receiving more attention because of their non-intrusive nature and the fact that they are appropriate for use in scenarios where it is inconvenient to carry or wear a device. Both types include a vast range of techniques that go from traditional statistical approaches to contemporary machine learning-based solutions, and each has strengths and limitations. Distinguishing this wide category enables researchers to place particular methods within a broader context and emphasizes the complementary relationship of the two methodologies in serving different requirements for applications.

1.1. The active positioning system

Device-based/active localization utilizes at least one active device transmitting signals that are to be received by many receivers for the device's localization. Some of the significant techniques include Global Navigation Satellite System (GNSS) [39], cellular networks [47, 29], and BLE. In this context, the Active RSSI-based localization [48]. The process entails using a transmitter and receiver where the former sends a signal picked by the latter. This distance is then derived by estimating the strength of the received signal by the receiver from the transmitter. Active localization is preferred for applications where the coordinates of the transmitter can be identified or are already known. Many research works have proposed active localization systems using RSSI and wireless technologies such as Bluetooth, ZigBee, and Wi-Fi. Based on the RSSI signals, a real-time people and assets tracking system using a Wi-Fi module and Raspberry Pi was established [12, 49]. These systems illustrate low-cost and scalable solutions but tend to be environmentally sensitive, such as multipath fading, shadowing, and interference. As a result, while active RSSI-based localization represents a workable and accessible solution for many IoT applications, its shortfalls in terms of accuracy and robustness have spurred the study of other techniques, such as passive localization and hybrid methods. Some of the main challenges in an active RSSI-based localization system are:

- **Non-linearity.** The trends in RSSI are non-linear with distance because there are many scatters in the range and strength measurements caused by environmental effects like obstacles, reflection, and interference around the transmitter and receiver nodes.
- **Multi-path** fading happens when objects repeat or diffuse the signals and reach the receiver along different routes. This causes an inexact estimation of distance and eventually impacts the degree of localization [50].
- **Signal attenuation.** Signal loss is the reduction in the signal power system as the signal travels through a given environment, absorbing, scattering, or

diffracting. This results in weaker signals, and estimating the distance between the anchor and mobile nodes becomes challenging.

- **Anchor node placement.** The position of the anchor nodes can greatly affect the localization result. In the best-case scenario, the locations of the anchor nodes should provide adequate signal coverage of the region of interest while reducing the impact of fading and attenuation.
- **Mobility.** In the mobile scenario, the mobile node's position varies over time, affecting the localization process. However, the mobile node may migrate, so it is challenging to have robust connectivity with the anchor nodes.
- **Calibration.** In the RSSI approach, it is critical to calibrate the RSSI measurements for proper localization to occur. RSSI calibration is the process through which the path loss is determined and most often entails calculating the RSSI or average at different, distinct distances apart from the anchor nodes.

1.2. Passive positioning system

Device-Free Localization (DFL) refers to a fundamentally distinct paradigm, in which there is no transmitter or tag on board the target, and localization is performed by processing the effect of the target on the wireless signal field [51]. Techniques common in passive localization include received signal strength index fingerprinting, time difference of arrival, angle of arrival, and radio frequency identification. The advantages and disadvantages of each technique include accuracy, cost, coverage area, and power required. The pace at which the schemes are updated depends on the method selected, which in turn depends on the application's requirements. To overcome these limitations, researchers are working on certain passive localization techniques for enhancing location estimation accuracy and rate [52].

Table 1. Merits and demerits of localization technologies

Localization technologies	Merits	Demerits
RSSI fingerprinting [53]	Simple, low-cost, and accurate in small indoor environments	Need for frequent calibration due to environmental changes and limited coverage area
Wi-Fi fingerprinting [9]	Easy to implement, works with existing Wi-Fi infrastructure, and can work without line-of-sight	Affected by changes in Wi-Fi signals due to environmental factors, may require continuous calibration, and may be affected by interference from other Wi-Fi devices
TDOA [54]	High accuracy with low computational cost. Works well in indoor and outdoor environments, and under non-line-of-sight conditions. No need for source power calibration	Performance can be impaired by multipath effects and reflections. Requires accurate time synchronization, and complex hardware is required
AOA [55]	High accuracy can be achieved in Line of sight, with fewer anchor nodes required; strict time synchronization is not essential	Accuracy degrades in non-line-of-sight due to reflection and multipath fading. Computational overhead and specialized hardware are required
RFID [56]	Low cost, low power consumption, accuracy in small areas	Need for proximity between the mobile node and the reader, interference from nearby metallic or electronic objects
Long Range communication (LORA) [57]	Low power consumption, long-range, scalable, and efficient tracking	Accuracy limitation, barrier, and multipath can limit the precision

A few studies on the subject are given in Table 1 regarding passive localization techniques, along with their merits and demerits.

The fingerprinting scheme does not need the line of sight. Still, the coverage can be affected by multipath interference and noise compared to radio tomography, which requires line-of-sight but is not greatly sensitive to the noise. Last, fingerprinting is mostly applied to indoor positioning, while radio tomography can be used both for indoor and outdoor positioning [25]. Here, we tabulate a comparison of radio tomography algorithms for device-free localization Table 2.

Table 2. Comparison of Radio Tomography image algorithms

Technique	Through wall	Online calibration	Stationary target	Channel diversity	Antenna circulation	Major contribution
RTI [58]	Yes	No	No	Yes	No	Accurate ranging
KRTRI [59]	Yes	Yes	No	No	Yes	Improved accuracy
SUBVRTI [60]	No	Yes	Yes	Yes	No	Robustness to noise
CDRTI [61]	Yes	Yes	No	Yes	No	Improved precision
ARTI [62]	Yes	No	Yes	No	Yes	High accuracy

Deep learning techniques have been increasingly used in radio tomography images to improve the accuracy and robustness of passive localization [63]. In radio tomography, the RSS or phase measurements are used to build a tomographic image of the environment. Deep learning techniques can be used in various tasks in radio communication systems, including signal classification, modulation recognition, channel estimation, and signal denoising. Some popular deep learning techniques used in radio communication systems are “Convolutional Neural Networks (CNNs)”, “Recurrent Neural Networks (RNNs)”, and autoencoders [64]. These techniques require large amounts of labeled data for training and significant computational resources for image processing. The interpretability and generalizability of deep learning models in radio tomography applications are still areas of active research. Still, they can potentially improve the performance and efficiency of these systems in noisy or complex environments. Hybrid techniques that combine machine learning and optimization-based approaches have also been proposed for localization in WSNs. These techniques aim to combine the advantages of both approaches while mitigating their limitations[39]. PSO-ANN, ACO-SVM, and GA-DT are familiar hybrid techniques used in range-based and range-free localization [65, 66]. They have also been applied to both static and dynamic contexts of WSNs. The advantages of the indicated forms of hybrid techniques are high accuracy and relative insensitivity to noise and errors. However, they can be very costly from the computational aspect and could need many training samples [65, 66]. It should be noted that both methods (device-based and device-free localizations) are based on intrinsically different localization techniques and must not be regarded as the same technique in variations. Although a preliminary overview is given here, detailed descriptions of each approach can be read in formal surveys [67]. Although considerable advances have been made, researchers are still left with a number of open challenges in localization systems. Indoor and dense deployments are plagued by environmental dynamics like multipath fading, shadowing, and interference, which cause accuracy to deteriorate.

Scalability can also be an issue since increasing the number of nodes results in greater computational complexity and communication overhead. Energy efficiency is a principal problem in the case of large-scale IoT and WSN applications, where nodes are battery-operated. Privacy issues also exist, as certain technologies (e.g., Wi-Fi CSI or camera-based techniques) can expose sensitive user data. Lastly, mobility robustness and real-time processing call for new algorithms that will optimize accuracy, computational complexity, and resource usage. All of these challenges call for the use of hybrid solutions that combine multiple modalities and sophisticated machine learning paradigms in order to provide robust and privacy-friendly localization.

The review article is organized into 5 sections: Section 2 is an overview of the related work done on passive localization based on wireless communication technologies with granularity, passive and active, and free device localization, and a comparison of techniques. Section 3 then discusses our approach to conducting a deep analysis for passive localization review and selection criteria for conducting a deep review. In Section 4, we have derived a comparison analysis, a review of different machine learning and deep learning methods used for passive localization techniques, and future directions. Lastly, Section 5 concludes with recommendations for future research work.

2. Literature review

This literature review provides an overview of RSSI-based localization using radio tomography, including free, passive, and active localization. Localization in wireless networks is a challenging problem that has been extensively studied in the literature [1-3]. While there have been significant advances in this field, several weaknesses have been identified that can limit the accuracy and reliability of localization techniques [68]. Here are some of the weaknesses identified from the literature [66, 69]:

- **Signal propagation and environmental factors.** Localization techniques are influenced by signal propagation behaviour, which consists of multipath fading, shadowing, and interference. Such factors might distort calculated distance values for localization and lead to moderate inaccuracy of the estimated position.
- **Hardware limitations.** The physical specifications of the wireless apparatuses that comprise the system may also need to be revised to ensure the accuracy of the localization phenomena. For instance, the transmitter's low power and the receiver's low sensitivity limit the transmission range of the wireless signals, affecting the correct distance measurement.
- **Scalability.** Some localization techniques are not applicable in large networks when the number of nodes is large. This, in turn, leads to increased computation time and communication overhead, which can reduce the real-time capability of the localization system.
- **Security and privacy concerns.** Some localization techniques may pose security and privacy issues because they involve transferring location-related

information between devices. Attackers can especially utilize this for voyeurism and surveillance of the users.

- **Robustness.** In some other cases, localization techniques depend much on the environment of deployment or other conditions and are, therefore, less immune to any changes in those areas. For example, a shift in the position or number of beacons in the environment may pose difficulties in assessing the position and orientation of the robots, and the placement of wireless devices in new formations may call for new localization algorithms to be designed.
- **Cost.** Finally, there are certain costs that companies must account for when running localization techniques; these costs may include the costs of the software that will implement the localization techniques in industries that have many industries. The additional hardware, e.g., anchor nodes, may be expensive, or the computing and transmission of location information may need to be more practical.

Another method used in WSNs to detect the position of objects or individuals without carrying a wireless device is called DFL [15]. DFL has received much attention in different sectors, including healthcare, security, and smart homes, because of its versatility. It is used to locate an object or person by considering the impact of wireless signals such as WIFI or Bluetooth. Thus, according to the tests, DFL has been shown to work in indoor and outdoor environments [70]. According to DFL techniques, the RSS, ToF, and CSI methods have accordingly been identified [40]. Great efforts have been devoted to investigating various benefits of DFL and confirming its practicability and efficiency. It has been implemented for indoor positioning in healthcare facilities, person tracking in security systems, and smart homes for occupancy and activity detection . The studies done in DFL in recent years aimed to improve the system's accuracy, robustness, and expansiveness. Questions, challenges, and the security implications of DFL have also been explored in the latest experiments. The current and future works of the researchers have tried to identify the objectives of enhancing the accuracy of the model DFL and making it more efficient and less sensitive to various conditions. Moreover, they are also studying the applicability of DFL techniques and identifying the threats to security associated with this localization methodology [71].

A novel method called DFL is widely considered one of the most promising approaches with much potential for changing some fields and contexts. It allows tracking objects and persons in WSNs without wearing any tag or beacon device. Because it has the potential to be applied in various industries, including health care, security, and smart homes, the area of DFL has received more attention. An important feature of DFL in WSNs is its capability to offer location information, and it does not need additional equipment or structures [72]. This makes DFL particularly suitable for situations where it is cumbersome or inadvisable for people or objects to have additional devices. For example, in health care, people can be tracked based on DFL when patients navigate without being fitted with any equipment. DFL also enhances the accuracy and reliability of location estimation, especially in indoor environments, where radio wave signals can easily be received and interfered with through barriers such as walls and furniture. Moreover, by considering the effects of these barriers on radio waves, DFL improves the accuracy of the location estimation process.

Additionally, DFL finds its use in security applications in that it identifies an intruder and pinpoints their location. Because WSNs with DFL capabilities can detect the existence of people in given places and further estimate their position or location [66], it is possible to develop tools for the use of cameras or other surveillance devices.

The application of DFL in Wireless Sensor Networks (WSNs) offers a trustworthy method for object position estimation that does not need extra infrastructure or devices to be carried by the target. Although most papers focus on applications in healthcare, security, and home automation, the potential applications of DFL are much broader. Typically, DFL may be classified into various modalities based on the kind of signals utilized to deduce the presence and position of a target. For example, Wi-Fi-based systems identify changes in signal strength to decide on the presence or absence of individuals or objects in an observed area. In the same spirit, RFID may be used, wherein RFID readers recognize and find tags affixed to objects or individuals [73]. Magnetic field-based methods allow the detection of metal objects by alterations created in the ambient magnetic field [74]. An acoustic signal is another modality with which a target's presence changes sound wave propagation [75]. Infrared-based approaches make use of variations in infrared radiation to deduce the presence of humans or object location [65]. Besides, video cameras can be applied to identify people or objects in the room, analyzing the video stream to define their movement. These modalities are incorporated into device-free localization, and their implementation can improve the precision and consistency of the method [76].

Radio Frequency (RF) sensor networks are an efficient technology for remote sensing and monitoring applications, including environmental, health, and security [28]. In recent years, the application of RF sensor networks for DFL has attracted interest because they allow a distributed approach to training a model while preserving the local non-shared raw data [77, 53]. DFL has many advantages over centralized machine learning approaches, as it increases security and privacy and permits the use of distributed computing facilities. In general, for RF sensor networks, the DFL can be applied to enhance the machine learning-based estimators created from the gathered data by sensors because these are noisy and influenced by interference. Challenges associated with the safety and control of RF sensor networks-based DFL have restricted communication bandwidth and energy, and the availability of algorithms for large amounts of data [53]. The main technologies applicable to generating RF sensor networks through the application of DFL include federated averaging, compression, and quantization to enhance the amount of information transmitted between devices. This work indicates that the new DFL based on RF sensor networks can open a new range of wireless remote sensing and monitoring applications and offset many of the significant disadvantages of the traditional centralized ML paradigms. However, more in-depth studies are required to enhance the efficiency of DFL-based RF sensor networks and algorithms and look into the potential security vulnerabilities raised by information sharing from sensors.

We found that Davidson and Piche [78] presented an active device-free localization approach based on Wi-Fi signals and multitask learning. Their approach uses a multitask learning framework to learn the position of the device given RSSI measurements. Finally, the authors describe how they test their method and prove it is highly accurate in various cases. In the same vein, Wang et al. [25] proposed a multi-modal deep learning that comprises channel and spatial domains for device-free localization in a Wi-Fi network. It suggests using a deep Convolutional Neural Network (CNN) with raw RSSI and CSI as feature inputs for the RSSI and CSI-based network, respectively, coupled with a spatial-domain network for positioning the device. They demonstrate the efficiency of their method, which is allegedly higher than that of other known methods. To this end, a DFL system is presented by Wu et al. [79] that deploys several WSNs to improve the precision and reliability of location tracking. To ensure high accuracy and reliability of the determined positions, the system exploits RSS and PDoA measurements to work efficiently indoors. Likewise, Ouyang and Abed-Meraim [32] proposed a DFL system using a WSN to detect a person's location indoors. RSS and TDoA measurements are used in the system to decode the position of tags with precision.

Zhang, Zhang and Cao [1] presented a comprehensive overview of techniques for indoor positioning via radio frequency signals for both active and passive location solutions. The authors also focus on the limitations and present an extensive performance comparison regarding accuracy, complexity, and cost. A promising passive localization method is presented as tomography RSSI.

Indoor positioning is discussed by Fouskas et al. in [2], where it presents a solution of tomography RSSI for Wi-Fi signal, a practical approach. The authors propose a system in which several access points are used to identify the RSSI of Wi-Fi signals at various points. They utilize tomography algorithms to locate a mobile device. Numerous tests carried out in various indoor scenarios demonstrate the system's efficiency.

Zafari, Gkelias and Leung [3] a novel passive RFID localization technique based on tomography for estimating the position of RFID tags using the RSSI of signals obtained from the readers is described. The authors offer a new algorithm to address NLOS impacts and interferences, and they conduct experiments in various scenarios.

A comprehensive review of indoor localization in wireless networks employing Time of arrival, Time difference of arrival, and RSSI for both range-based and range-free localization is covered in [80]. However, another detailed review of various passive location methods employing RSSI using a tomography RSSI approach and utilizing Wi-Fi devices offer is provided in the study [4]. The authors describe the difficulties related to the objective, review the limitations, and explain the state of the current research in the field. They also outline areas for further research investigations and call for more accurate and reliable localization algorithms. Real-time indoor localization based on a tomography-based approach using terahertz signals is suggested in [7]. In addition, multiple antennas use signal strength at several locations, and tomography algorithms predict the target device's location; this has been demonstrated in a wide range of indoor environments.

Oguntala et al. [8] presented a cooperative localization technique for WSNs employing RSSI tomography. The authors disclose a system that involves scanning for the same signals at different locations using several sensors and then applying tomography techniques to determine the location.

The passive localization of wireless devices using Expected Transmission Count (ETX) based on tomography RSSI is presented by Zheng, Li and Zhang [9] as a technique, in this case, the authors devised a simple method where they measured the ETX of packets at various locations to approximate the device's position. The system's performance is analysed using simulation experiments in a highly dense wireless sensor network.

Yihitler et al. [12] proposed a novel concept in the application of indoor passive localization utilizing radio tomographic imaging employing RSSI. RSSI is sensed at multiple locations, and distance is computed using imaging algorithms and tested in indoor scenarios. Passive localization is where objects or people do not have to carry special equipment. Radio Tomography Imaging (RTI) is used to detect and locate people and objects based on RSSI variation between nodes to form an area image, getting attention for indoor localization.

Many related research works have presented different approaches to passive localization using RTI information based on RSSI. For instance, Anderson et al. [14] developed a localization technique based on the inverse covariance of the Reference Signal Strength Indicator for target position estimation. The algorithm improves heading angle estimation and overall navigation performance by using magnetic data and correcting the attitude angle during Kalman filtering. It effectively removes non-Gaussian magnetic data, resulting in significantly higher accuracy. Adopting the DT + Kalman method reduces pedestrian positioning error in indoor navigation from 4.61 meters to 1.17 meters.

One flaw with RTI-based passive localization is that the received signal strength indicator may contain noise and interference that may affect the results obtained. To address this issue, several papers have offered recommendations for noise minimization and Interference cancellation, for example, in Yang et al. [70], where the authors proposed a noise reduction technique based on PCA, where a sparsity-promoting algorithm for interference was presented.

Yet another problem of employing RTI-based passive localization is the complexity of calculating the received signal strength indicators. To solve this problem, several studies have suggested approaches for simplifying the computational cost of the RTI-based localization algorithms. For instance, in Wang et al. [6], a method was presented to minimize the RSSI data dimensions by singular value decomposition, while He and Ma [81] a compressive sensing approach to acquiring and processing RSSI data was presented.

Patra et al. [48], a device-free passive localization technique employed by the interference of ambient signals is presented. The approach is founded on the concept that variation of the interference patterns of ambient signals results from the human body's presence. The authors also prove that it is accurate in indoor environments and is resistant to environmental changes.

Ganz et al. [20] present an active RFID-based indoor localization technique that uses RSSI and the phase difference is presented. The approach employs the emission of a signal from an active RFID tag and the calculation of the distance and angle of arrival of the signal at a reader based on only the RSSI and phase difference. The experimental assessments show that it has a high level of accuracy when used inside buildings.

Lee, Ahn and Han [35] presented a passive device-free localization technique that relies on deep learning with Wi-Fi signals. The method employs a CNN model to map RSSI signal data into relevant features and an SVR model to estimate the device's position. Measurable assessments confirm its precision in countless situations according to experimental evaluations. A passive device-free localization technique is presented.

Hamzeh and Elnagar [47] presented a passive localization technique that employs deep learning with the characteristics of channels in Wi-Fi networks. It uses IEEE 802.11n signals and comprises an RSSI and CSI feature extraction model based on a CNN and a location prediction model using a 2D-SVR. Various experiments authenticate the enhanced efficiency resulting from the use of this framework as compared to the traditional approaches.

Fusco and Coughlan [82] a passive device-free localization method based on CNNs and GANs with Wi-Fi signals is proposed. This approach uses CNN for feature extraction from the RSSI data while using GAN for creating new training datasets. The experimental evaluations highlighted spare ability in numerous situations its high accuracy was demonstrated.

A passive device-free localization technique was employed by Jung, Hann and Park [83] based on deep learning with residual attention in W-Fi networks. The approach uses a CNN for feature extraction from RSSI signatures and residual attention based on CNN to increase network discriminability.

Wu et al. [79] an active RFID indoor localization technique based on deep learning with a selective sampling scheme is presented. It adapts DNN to predict device location using RSSI measurements with an optimized sampling approach. Furthermore, the quantitative assessment of experimental analysis proves its reliability in different situations. Getting and shortening an adequate number of indoor localization samples may pose a great challenge.

3. Proposed methodology

The study has been conducted as literature review-based research papers relevant to the study topic to understand and identify approaches, techniques, challenges, benefits, levels, barriers, and attributes of Passive Localization Utilizing Wireless RSSI, thereby identifying, evaluating, and interpreting all research (ninety-four research papers out of two hundred forty-five papers) relevant to this particular research.

3.1. Research questions

- **Research Question 1.** What are the Current State-of-the-Art Techniques for Passive Localization Using Wireless RSSI?
- **Research Question 2.** What are the Prospects and Challenges of Integrating Machine Learning with Passive Localization Using Wireless RSSI?

- **Research Question 3.** What Factors Affect the Accuracy of Passive Localization with RSSI?

Meta-analysis is a statistical technique that has been used in this research to combine and analyse the results of multiple independent studies on this specific topic. Here we gather and analyse the data from existing studies to draw more robust and generalizable conclusions. This method is very effective in our case, particularly useful when individual studies may have produced varying or inconclusive results. Brief answers have been made in Section 4.

3.2. Selection criteria

We established specific criteria to determine which research articles would be included in this study. Research papers were included based on deliberate inclusion criteria, while others were excluded due to well-defined exclusion criteria. Articles that included Systematic Reviews (SR) as a distinct component were eligible for inclusion.

3.2.1. Inclusion criteria considered for this review

The following inclusion criteria were considered for this review paper:

3.2.1.1. Articles that discuss Systematic Reviews on Passive Localization Using Wireless RSSI.

3.2.1.2. Articles that mention the terms “Passive Localization”, “Wireless”, and “RSSI” and have content related to these concepts and their synonyms.

3.2.1.3. All articles that have been published in recognized journals and conferences, as well as those accepted in workshops. This includes peer-reviewed articles, technical reports, and book chapters.

3.2.1.4. All articles that are written in the English language.

3.2.2. Exclusion criteria considered

The following exclusion criteria were considered:

3.2.2.1. All types of theses (both master’s and doctoral theses).

3.2.2.2. Articles published in journals on Beall’s List related to active publications.

3.2.2.3. All forms of informal literature reviews.

3.2.2.4. Articles that discuss Systematic Reviews but do not present a report containing original SR results.

3.2.2.5. Articles that pertain only to teaching or education and do not present the results of a conducted review.

3.2.2.6. Literary materials such as editorials, extensive introductions, and comprehensive workshop summaries, which do not provide original review content, are also excluded.

3.3. Conduct of search process

We began our research by searching electronic databases for primary and relevant studies on Passive localization using wireless RSSI, including well-reputed journals, workshops, and conference proceedings. Our search utilized major keywords such as

Passive localization, Wireless RSSI, Received Signal Strength Indicator, Indoor localization, Location estimation, Radio frequency-based localization, Localization algorithms, Trilateration, Fingerprinting, Machine learning localization, Environmental factors in localization, Location tracking, RF-based positioning, Wireless sensor networks, Location-based services, Localization accuracy, Multipath effects, Interference in localization, Signal propagation and Localization techniques review. Boolean AND & OR operators created an initial pilot search string. We also reviewed the titles of international conferences on the relevant titles from 2000 to 2023 as a primary source for publishing SRs. The repositories used for our search were ACM Digital Library, Web of Science, IEEE Xplore, Science Direct, Springer, and Scopus, thereby formulating a quality assessment criterion.

QA1: Was the research design appropriate for addressing passive localization using Wireless RSSI?

QA2: Were the data collection methods well-defined and suitable for the research objectives?

QA3: Were clear procedures provided for collecting Wireless RSSI data?

QA4: Were the passive localization algorithms or techniques well-explained and appropriate for utilizing Wireless RSSI data?

QA5: Were details of the experimental setup (e.g., environment, equipment, scenarios) sufficiently provided?

QA6: Was there a comprehensive validation process to assess the accuracy and reliability of passive localization results?

QA7: Were appropriate statistical or computational methods used to analyze Wireless RSSI data?

QA8: Did the study discuss limitations and potential sources of error in the passive localization process?

QA9: Did the study compare its results with existing literature or known benchmarks?

QA10: Did the study provide novel insights, advancements, or improvements in passive localization utilizing Wireless RSSI data?

These questions cover a range of critical aspects for assessing the quality of studies related to passive localization using Wireless RSSI.

We scored questions as below:

QA1: This question evaluated whether the chosen research design was suitable and well-suited for addressing passive localization using Wireless RSSI. It aims to assess whether the study's design effectively addresses the research objectives and is aligned with the nature of the problem being investigated. Details in this respect are:

a. Studies fulfilling criteria = 67 (83.75%)
b. Studies partially fulfilling criteria 13 (16.25%)
c. Studies not fulfilling criteria=0 (0%)

QA2: This question assesses whether the data collection methods employed in the study were clearly outlined, appropriate, and aligned with the research objectives of investigating passive localization using Wireless RSSI. It aims to determine if the methods used to gather Wireless RSSI data were well-suited for achieving the study's goals:

a. Studies fulfilling criteria = 68 (85%)
b. Studies partially fulfilling criteria = 8 (10%)
c. Studies not fulfilling criteria = 4 (5%)

QA3: This question assesses the extent to which the study named and described the processes and procedures of Wireless RSSI (Received Signal Strength Indicator) data collection. Procedures that would be followed must be clear and well-documented to ensure that the process of collecting data is clear, well documented, and can easily be repeated. The effectiveness of Wireless RSSI data collection procedures require complete clarity to support the study results. Scientists should be able to conduct the described procedures to obtain the same results as those in the given work to confirm the findings of the study:

a. Studies fulfilling criteria = 69 (86.25%)
b. Studies partially fulfilling criteria = 9 (11.25%)
c. Studies not fulfilling criteria = 2 (2.50%)

QA4: An overview of passive localization algorithms or techniques and when it is suitable to use Wireless RSSI data is crucial in appreciating how the study tackled the issue of location estimation concerning wireless signals. It allows the readers to judge the methodological quality of the conducted study:

a. Studies fulfilling criteria = 68 (85%)
b. Studies partially fulfilling criteria = 9 (11.25%)
c. Studies not fulfilling criteria = 3 (3.75%)

QA5: Requiring detailed information about the experimental setup is prudent since it enables the users of the published work to judge the soundness of the conclusions published. It enables other researchers to conduct identical experiments and, therefore, to test if the same conclusions can be obtained:

a. Studies fulfilling criteria = 63 (78.75%)
b. Studies partially fulfilling criteria = 11 (54%)
c. Studies not fulfilling criteria = 6 (7.50%)

QA6: The credibility and reliability of the passive localization results should be validated using a rigorous validation procedure. By rigorously evaluating the accuracy and reliability of the estimated locations, researchers can determine the practical applicability of the localization approach and its potential limitations:

a. Studies fulfilling criteria = 71 (88.75%)
b. Studies partially fulfilling criteria = 7 (7.50%)
c. Studies not fulfilling criteria =2(2.50%)

QA7: Using appropriate statistical or computational methods is essential for extracting meaningful insights from Wireless RSSI data and drawing valid conclusions about passive localization. The choice of methods should align with the research goals and contribute to a robust and rigorous analysis:

a. Studies fulfilling criteria = 75 (77%)
b. Studies partially fulfilling criteria = 5 (14.5%)
c. Studies not fulfilling criteria =0 (%)

QA8: It is critical to identify limitations in the passive localization results and potential sources of error in all aspects of the results to ensure that errors and strengths are described as accurately as possible. It demonstrates the study's awareness of challenges and uncertainties and adds credibility to the conclusions drawn from the research:

a. Studies fulfilling criteria = 59 (73.75%)
b. Studies partially fulfilling criteria = 11 (13.75%)
c. Studies not fulfilling criteria = 10 (12.50%)

QA9: Comparing results with existing literature or benchmarks is essential for placing the study's findings in context, validating the research approach, and demonstrating the study's contribution to the field of passive localization using Wireless RSSI data. It allows readers to assess the novelty, significance, and potential practical implications of the study's outcomes.

a. Studies fulfilling criteria = 73 (91.25%)
b. Studies partially fulfilling criteria = 5 (6.25%)
c. Studies not fulfilling criteria = 2 (2.50%)

QA10: Demonstrating novel insights, advancements, or improvements is a key indicator of the research's significance and potential to advance knowledge and technology in the field. It highlights the study's potential to address challenges or open new opportunities for passive localization research.

a. Studies fulfilling criteria = 65 (81.25%)
b. Studies partially fulfilling criteria = 12 (15%)
c. Studies not fulfilling criteria = 3 (3.75%)

3.4. Quality matrix for selected research papers

Assessment of selected research studies is placed below in matrix form based on studies and questions along with responses as Yes denoted as "Y", Partial denoted as "P", and No as "N".

4. Results and discussion

- **Search results**

A total of 374 papers were initially identified. 150 studies were chosen as the final set of pertinent research papers after the inclusion and exclusion criteria were applied in compliance with the supervisor's instructions. On further scrutiny of the introduction and conclusion of these papers, 123 papers remained. 27 were further excluded. The process is shown below. Further details of selected papers are evaluated in Table 3 below, indicating that 83.75% of the coverage of QA1 is Yes. In QA2, 85% were Yes, 10% were Partial, and 5% were No. For QA3: 86.25% Yes, 11.25% Partial and 2.50% No. In QA4: 85% Yes, 11.25% Partial, and 3.75% No. In QA5: The reliability of the primary studies remains Yes 78.75%, 13.75% as Partial, and 7.50% as No. QA6: 88.75% Yes, 7.50% Partial, and 2.50% as No. QA7: Studies fulfilling criteria is 93.75% Yes and 6.35% as Partial. QA8: Studies fulfilling the criteria as Yes are 73.75%, Partial is 13.75%, and 12.50% are No. QA9: Studies fulfilling the criteria as Yes are 91.25%, Partial is 6.25%, and 2.50% are No. QA10: Studies fulfilling the criteria as Yes are 81.25%, Partial is 15.50%, and 3.25% are No.

Table 3. Search results analysis

Studies	QA1	QA2	QA3	QA4	QA5	QA6	QA7	QA8	QA9	QA10
S-1	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-2	Y	Y	Y	Y	P	Y	P	Y	Y	Y
S-3	Y	Y	Y	Y	Y	Y	Y	Y	Y	N
S-4	Y	P	Y	Y	Y	Y	Y	Y	Y	Y
S-5	Y	Y	Y	Y	N	Y	Y	Y	P	Y
S-6	Y	Y	Y	Y	P	Y	Y	Y	Y	P
S-7	Y	P	Y	Y	Y	Y	Y	Y	Y	Y
S-8	Y	Y	Y	Y	N	Y	Y	Y	Y	Y
S-9	Y	Y	Y	Y	Y	Y	Y	Y	Y	N
S-10	P	Y	P	Y	P	Y	P	Y	Y	Y
S-11	Y	Y	Y	Y	Y	Y	Y	P	Y	Y
S-12	Y	Y	Y	Y	Y	Y	Y	N	Y	P
S-13	P	P	P	P	P	P	Y	P	Y	Y
S-14	Y	Y	Y	Y	Y	Y	Y	N	Y	Y
S-15	Y	Y	Y	Y	P	Y	Y	Y	P	Y
S-16	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-17	Y	Y	Y	Y	Y	Y	Y	N	Y	Y
S-18	P	P	Y	Y	P	Y	Y	Y	Y	Y
S-19	Y	Y	Y	Y	Y	Y	Y	P	Y	Y
S-20	Y	Y	Y	Y	Y	Y	Y	N	Y	P
S-21	P	P	P	P	P	Y	P	Y	Y	Y
S-22	Y	Y	Y	Y	Y	Y	Y	P	Y	Y
S-23	Y	Y	Y	Y	P	Y	Y	N	Y	Y
S-24	Y	Y	Y	Y	Y	P	Y	Y	Y	P
S-25	P	P	P	P	P	N	Y	Y	Y	Y
S-26	Y	Y	Y	Y	N	Y	Y	P	Y	Y
S-27	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-28	P	P	P	P	P	P	Y	N	Y	Y
S-29	Y	Y	Y	Y	Y	Y	Y	Y	Y	P
S-30	Y	Y	Y	Y	P	Y	Y	Y	Y	Y
S-31	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-32	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-33	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-34	Y	Y	Y	Y	Y	Y	Y	Y	Y	P
S-35	Y	P	Y	Y	Y	Y	Y	Y	Y	Y
S-36	Y	Y	N	Y	Y	Y	Y	Y	Y	Y
S-37	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-38	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-39	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-40	P	Y	P	P	Y	P	Y	Y	Y	Y
S-41	Y	Y	Y	Y	N	Y	Y	Y	N	Y
S-42	Y	Y	Y	Y	N	Y	Y	Y	Y	Y
S-43	Y	Y	Y	Y	Y	Y	Y	Y	P	P
S-44	Y	Y	Y	Y	N	Y	Y	Y	Y	Y
S-45	Y	Y	Y	Y	N	Y	Y	Y	Y	Y
S-46	P	N	P	P	Y	P	Y	Y	Y	Y
S-47	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-48	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-49	Y	Y	Y	Y	N	Y	Y	Y	Y	P
S-50	Y	Y	Y	Y	P	Y	Y	Y	P	Y
S-51	Y	Y	Y	Y	Y	Y	Y	P	Y	Y
S-52	Y	Y	N	N	Y	Y	Y	Y	Y	Y
S-53	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-54	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-55	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-56	Y	Y	Y	Y	Y	Y	Y	Y	Y	P
S-57	Y	Y	Y	Y	Y	Y	Y	Y	P	Y
S-58	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-59	Y	Y	Y	Y	Y	Y	Y	P	Y	Y
S-60	P	N	P	P	Y	P	Y	N	Y	Y
S-61	Y	Y	Y	Y	Y	Y	Y	P	Y	Y
S-62	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-63	Y	Y	Y	Y	Y	Y	Y	P	Y	Y
S-64	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-65	Y	Y	Y	Y	Y	Y	Y	Y	Y	P
S-66	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 3 (c o n t i n u e d)

Studies	QA1	QA2	QA3	QA4	QA5	QA6	QA7	QA8	QA9	QA10
S-67	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-68	P	N	P	P	Y	P	Y	N	Y	Y
S-69	Y	Y	Y	Y	Y	Y	Y	P	Y	Y
S-70	Y	Y	Y	Y	Y	Y	Y	P	Y	P
S-71	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-72	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-73	P	N	P	N	Y	P	Y	Y	Y	N
S-74	Y	Y	Y	Y	Y	Y	Y	N	Y	Y
S-75	Y	Y	Y	Y	Y	Y	Y	Y	Y	P
S-76	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-77	P	Y	Y	Y	Y	Y	Y	Y	Y	Y
S-78	Y	Y	Y	Y	Y	P	Y	N	Y	Y
S-79	Y	Y	Y	N	Y	Y	Y	Y	N	Y
S-80	Y	Y	Y	Y	Y	Y	Y	P	Y	Y

- **Answering the research questions**

4.1. Modalities in DFL

DFL of WSNs commonly involves the use of one or more one mode to identify and locate objects and or people.

DFL techniques and classifications, in broad terms, have been summarized in Table 4 below against "Non-intrusiveness", "Privacy", "Low cost", and "Scalability".

Table 4. Device-free localization techniques and classifications

Technique	Description	Classification	Non-intrusive	Privacy	Low cost	Scalability
Radio tomographic imaging [14]	Measures the attenuation of RF signals passing through an environment to create an image of the scene	RF-based	No	Medium	Yes	Yes
Wi-Fi-based [9]	Utilizes the Received Signal Strength (RSS) of Wi-Fi signals to estimate the location of objects	RF-based	Yes	Medium	Yes	Yes
Bluetooth-based [84]	Relies on Bluetooth signals and RSSI measurements for localization purposes	RF-based	Yes	High	Yes	Yes
Ultrasonic-based [85]	Relies on ultrasonic signals and their properties for detecting and locating objects	Sound-based	Yes	High	Yes	Yes
Magnetic-based [86]	Utilizes magnetic field measurements to determine the location and movement of objects	Other (Magnetic field)	Yes	High	No	Yes
Ultra-Wide Band (UWB) [87]	Utilizes UWB signal for higher accuracy in localization and positioning	UWB signal	No	High	No	Yes
InfraRed (IR) [88]	Utilizes IR signals to locate and identify objects in the environment	IR signal	No	Medium	Yes	No

To summarize the table, it shows that specific entries on how intrusive or privacy-friendly the measurement method is as well as cost and scalability considerations all have their strengths & weaknesses. These factors influence which method is appropriate for a particular application, balancing far-reaching but detailed monitoring against the desire not to violate privacy or pay too much money for letting devices everywhere.

4.2. Statistical methods for device-free localization

DFL is a technique utilized for detecting and localizing objects or people without the need for them to carry any electronic device. DFL mainly applied statistical procedures to determine the position of the object or person that was detected based on the difference in the received signal strength across multiple sensors. Several common statistical methods employed in DFL are as follows:

- **Gaussian Process Regression (GPR).** This work demonstrated that GPR is a machine learning paradigm commonly employed in DFL. It entails creating a statistical model of the environment through the use of sensors, and this model is used to determine the location of the detected object or person [89].
- **Support Vector Regression (SVR).** The next machine learning method used in DFL is SVR or support vector regression. This involves developing an algorithm that finds the relationship between sensor data input and the output location of the object or the person being detected [90, 91].
- **Particle Filtering (PF).** Particle filtering is a statistical method used for estimating the state of unknown moving objects or people in random environments. This involves coming up with a population of particles that are in some way the possible location of the object or person being tracked. The distribution of these particles is then conditioned using sensor data [92].

Table 5. Statistical methods for device-free localization

Technique	Category	Merit	Demerit	Applications
Gaussian Process Regression (GPR) [93]	Probabilistic regression	Perform well on non-linear data	Computationally expensive	RSSI-based localization
Support Vector Regression (SVR) [94]	Machine learning regression	Perform well on small or medium datasets	Performance degraded on a large dataset	Passive Wi-Fi/ CSI localization
Particle Filtering (PF) [95]	Probabilistic filtering	robust for dynamic tracking	High computational cost	Real-time tracking for moving objects in a mesh network

Statistical methods play a pivotal role in enabling accurate and reliable localization in DFL, eliminating the need for individuals or objects to carry electronic devices. Table 5 in the literature provides a summary of these statistical methods.

4.3. Techniques based on compressive sensing methods

Compressive Sensing (CS) is a method employed to acquire and reconstruct signals at a lower sampling rate than what is typically required by the Nyquist-Shannon sampling theorem. Within the DFL realm, CS techniques can be applied to decrease the number of sensors needed for object or people detection and localization in each area while upholding localization accuracy. The following are some commonly utilized CS-based techniques in DFL:

- **Compressed Sensing for DFL (CS-DFL).** CS-DFL employs compressive sensing to generate a small number of sensors for detecting and localizing objects or people. Here, the environment is largely depicted as a sparse matrix, and the sensing matrix is designed to have low mutual coherence with the sparse matrix. An optimization algorithm is used to identify the location of the object or person that is detected [96].

• **Random Matrix Theory-based DFL (RMT-DFL).** RMT-DFL uses random matrix theory to estimate the environment's statistical characteristics. In the given model, the environment is represented as a random matrix. From this point of view, objects or people can be detected and localized from the analysis of the matrix properties.

• **Low-Rank Matrix Completion-based DFL (LRMC-DFL).** They apply low-rank matrix completion to estimate the missing entries in the sensor measurements in the case of LRMC-DFL. The sensor readings are depicted as a low-rank matrix, and an iterative algorithm is used to recover the lost information. The identified object or person is located using the completed matrix, facilitating easy tracking.

Finally, several benefits of these CS-based techniques have been summarized in DFL, such as low sensor cost, high energy efficiency, and scalability. As for all these systems, it is crucial to note that their practical applicability requires major design and optimization to attain the best localization results.

4.4. Radio tomographic imaging-based DFL techniques

DFL is a localization technique in which RTI is often employed for the detection and location of objects or people in a particular region. Here is a comparison of several standard RTI-based DFL techniques and the challenges associated with them:

• **Radio Tomography Imaging-based DFL (RTI-DFL).** The wireless sensors in RTI-DFL create a 2D or 3D map of the environment, which can be used for object or people localization. It also proposes the method of RTI-DFL, which can obtain high accuracy and is applicable to large-scale localization. However, it requires many sensors, which not only can be costly in implementation but also easily bog down [58].

• **Subspace-based RTI DFL (SUB-RTI-DFL).** In SUB-RTI-DFL, the subspace projection is used to decrease RTI data's dimensionality, leading to better localization performance. However, doing so requires a reliable RTI system and fine-tuning to produce reasonable outcomes.

• **Compressed RTI-based DFL (CRTI-DFL).** CRTI has also used compressive sensing principles to minimize the number of sensors needed for RTI, making the system cheaper and less complex. However, this may result in fewer sensors and, thus, lowered reliability; the design and implementation must be made to achieve the best performance [96].

• **Angle RTI-based DFL (ARTI-DFL).** To complement the angle of arrival for RTI, ARTI-DFL maximizes the utilization of fewer ports than the typical number used in conventional RTI, indirectly improving the localization precision.

The three techniques for DFL based on RTI have pros and cons, depending on the problem to solve; they encounter difficulties. The choice among these approaches depends on the localization system's specific needs, cost issues, and potential deployment scenarios.

4.5. Limitations of RTI-based DFL techniques

Unfortunately, radio tomography images have issues such as the inverse problem, which is very ill-posed when estimating the position in a targeted environment. Another issue with RTI is that prior information about RTI features is limited. Therefore, it is not possible to achieve better accuracy. Wu et al. [97] presented a model in which two CNN models with the same structure are used to reconstruct the RTIs for better accuracy. However, they have suggested that future time series fusion measurements be used to improve the RTI resolution and reconstruction.

Traditional RTI methods are still significant for passive localization, even with these issues. When there is a clear line of sight, RTI, based on shading, works well with both moving and still objects [64]. Conditions where there is NLOS are minimal. Variance-based RTI issues only happen with things that don't move. Sequential Monte Carlo (SMC) helps with some of these problems, but it needs a measurement step that doesn't happen online or in a blank environment [98]. This can be a problem in environments that are busy or changing quickly. However, once these problems are repaired, kernel-based RTI can make things more precise. This study's results demonstrate these flaws, which is why people seek improved passive localization systems.

Various difficulties arise with the RTI-based Device-Free Localization (DFL) techniques, although they have numerous benefits. These challenges include:

- **Multi-path Fading.** The effect of multi-path fading is realized through interference in the operational radio signals employed in the RTI process, which may lead to enhanced imprecision in product localization.
- **Signal Attenuation.** Another external factor that compromises the RTI-based DFL's precision is the weakness of radio signals.
- **Interference:** As noted earlier, interference from other wireless devices affects the accuracy of RTI-based DFL.
- **Computational Complexity.** The implementation of DFL using RTI-based methodology involves performing image reconstruction that requires a significant amount of computational capability, making real-time application questionable.

Though global RTI-based DFL techniques provide better accuracy and scalability, their achievement is not easy because of these challenges. It is essential to address these challenges to ensure the successful implementation of RTI-based DFL.

4.6. Deep learning with tomography approach

Passive localization should use cutting-edge technologies like deep learning instead of the old RTI methods because they are flawed. The study discovered that common methods are not accurate, especially when there is no line of sight, and the measurement needs to be done in a room with no other objects in it [99]. Because of these problems, passive localization is less accurate and useful, and deep learning is a hopeful answer because it can instantly gather and make sense of large amounts of data [100]. The study discovered that the complexity and depth of deep learning models can compensate for traditional RTI methods. Styla, Kiczek and Adamkiewicz [101] deep learning algorithms can learn from their mistakes and show specific trends in X-ray data, which makes the results more accurate and reliable.

As Fernandes [102] suggested, the position accuracy and performance of IPS can be improved by using an intelligent computer-based learning algorithm. Much research has also observed that automated feature extraction has many advantages over hand-crafted feature extraction. A Convolutional Neural Network (CNN) consists of multiple layers of networks, one of which is the input layer, some of which are convolutional layers used for feature extraction, and some of which are fully connected layers used as output. CNN can easily manipulate the organization of input images, and we can train and use the CNN model easily. However, Google has proposed a variation of the CNN Model called the depth-wise separable convolutional Model [103]. Unlike the standard model, the depth-wise separable CNN Model has depth-wise and pointwise convolutions for each depth-wise separable convolution. The purpose of depth-wise convolution is not to make any changes to the depth of the input image, and point-wise convolution applies a simple 1*1 convolution to the input image. The depth-wise separable variant of CNN is lightweight and has an advantage over the simple convolutional neural network.

Deep learning approaches seek the attention of researchers as features are not captured manually. This makes the localization system readily available and deployable in practice. Deep learning methods are considered an extension of machine learning methods that perform higher-level abstractions. The suggested techniques could require substantial computational resources for assessment and training, which could pose a challenge for professionals with restricted access to high-performance computing [104]. Deep learning techniques automatically capture the discriminative and more meaningful features from wireless sensors to classify activities in the targeted environment. The trained deep model can easily transfer to another task where only a few labeled data points are available due to the deep layered and complex architecture of deep learning models [105].

Passive indoor localization using Bluetooth technology and deep learning approaches made developing and training models for more accurate localization easy. Chenwei et al. proposed a passive localization system based on CNN. In this approach, first, CSI is used for constructing site images, and second, a deep CNN is used for building and training the model. Using CNN, the proposed approach only required the amplitude of the CSI images instead of manual feature extraction. In this approach, the passive localization problem is converted into a classification problem so that the deep learning approach makes a non-linear association between locations and CSI fingerprints. However, their proposed approach achieves 94.55% and 96.40% accuracy in office and empty corridor environments, respectively [106]. The problems that arise with the indoor positioning system are the complex structure of the system, and the second is the delay in localization. To cope with these problems, a depth-wise separable variant of the CNN model using WiFi CSI [103]. Their proposed approach used the fingerprinting technique for passive localization, which consists of two phases: the first is offline training, and the second is the online positioning phase. Offline, the targeted environment is divided into different reference points, and the CSI is used for each of the reference points. The differences in amplitude of CSI sub-carriers are extracted, and the CNN variant is trained accordingly. Online, the CSI image is collected at a reference point, then the model matches the test data with offline data, and the final position is estimated using a matching algorithm. The proposed model used a weighted mean-based probability for matching because the probability-based function is more accurate than classification. The proposed system achieved 97% accuracy, which is very high compared to previous approaches, and there was less delay in estimating the position. Table 6 provides a detailed chronological comparison of this approach's strengths and weaknesses.

Table 6. Comparison of Machine Learning (ML) based techniques

ML technique	Method	Accuracy	Multipath fading/ sensitivity	Merits	Demerits
ANN SVM, k-NN & DTs [107]	Range-based, Range-free	90%	Multipath Fading, Sensitivity	High accuracy, flexibility	Requires significant training data
CNN, LSTM [108]	Fingerprinting	98.3%	Multipath Fading	High accuracy, adaptable	Requires large training data
ANNs, SVMs, Random Forest [109]	Range-based	91%	Multipath Fading, Sensitivity	High accuracy, low-cost	Varies based on an algorithm
k-NN DT [110]	Range-based	92.6%	Multipath Fading, Sensitivity	High accuracy, low-cost	Requires calibration
SVMs [111]	Range-free	92.3%	None	High accuracy, low-cost	Limited to range-free
D/T Random Forest [112]	Range-based	85.1%	Multipath Fading	Low-cost, low-power	Limited range
NNs SVMs [3]	Fingerprinting	94.4%	Multipath Fading	High accuracy, adaptable	Limited to Wi-Fi signals
k-NN SVMs DTs [113]	Fingerprinting	95%	Multipath Fading, Sensitivity	High accuracy, low-cost	Requires calibration
k-NN DT [53]	Fingerprinting	95.5%	Multipath Fading	High accuracy, low-cost	Requires calibration

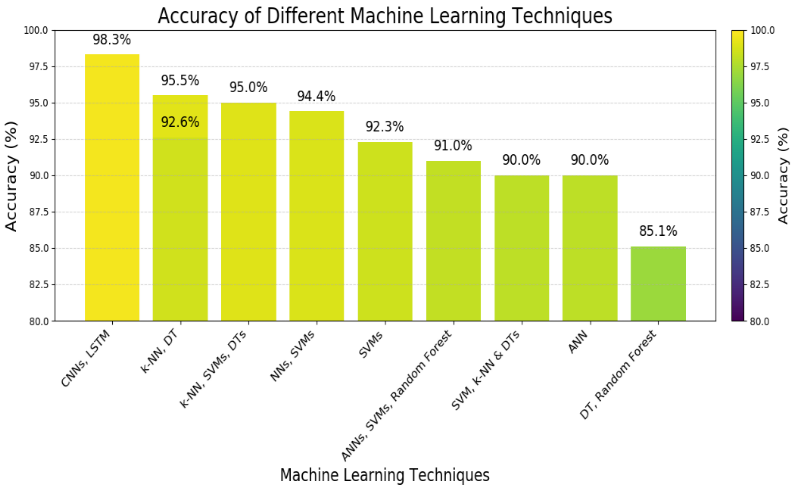

Fig 1. ML techniques analysis w.r.t. Accuracy

4.7. Comparative analysis and future directions

A very common issue in the field of localization is that there are not enough standardized benchmarking practices among studies. The results reported are usually measured under varying experimental conditions, e.g., different node density, deployment scenarios, frequency bands, or hardware platforms. For instance, a specific accuracy value measured in a controlled lab environment might be difficult to compare directly with values measured for large-scale real-world implementations. The other source of variability is from the data sets and training processes utilized. Some contributors employ publicly accessible data sets, while others utilize proprietary or locally gathered data, which are not made available to the community for use. Variations in training processes, parameter optimization, and performance measures (e.g., mean localization error versus accuracy under a certain threshold) make direct comparison even more challenging. Hence, numerical values across various publications must be viewed with skepticism.

Additionally, the heterogeneity of mathematical methods from probabilistic modeling and regression analysis to sophisticated deep learning architectures hinders the formulation of a shared baseline for equitable assessment. Every method has the potential to leverage certain assumptions or environmental properties, which are not necessarily the same across studies.

These considerations emphasize the need for creating standard datasets, shared evaluation criteria, and reproducible experimental protocols. Current efforts toward open-source sharing of datasets and benchmarking competitions are encouraging, but a standard remains to be universally adopted. Until such standards are in place, qualitative comparison is still useful in establishing general trends and mapping out areas of research need, with recognition of the inherent disadvantages of comparing cross-study performance.

Passive localization research has received increased attention in the last few years, and some methods for object or people detection and positioning that do not require special devices have been developed. However, there are still numerous avenues for future research and development in this field, including:

- **Multimodality approaches.** Improving passive localization systems and sensors such as Wi-Fi, Bluetooth, RFID, and magnetic field sensing for accuracy and reliability. Deep Learning Techniques: Using CNNs and RNNs to learn more discriminating features from sensor data for more effective passive localization of a target node.
- **Edge Computing.** Integrating edge computing approaches, such as distributed sensing and processing, to decrease the computations and energy intake of passive localization systems.
- **Privacy and security.** We can overcome the shrouds of privacy and local security by furthering passive localization methodologies, which are capable of safeguarding user identity while at the same time providing sound measures of protection. This is more important in areas like health care and smart homes.
- **Real-world deployment.** Further comprehensive real-life deployment and experimentation of passive localization systems in areas and conditions other than laboratory settings.

For the development of the passive localization technique, future work needs to be directed in these areas to enhance the estimation accuracy, overcome the limitations of privacy preservation, optimize the computational costs, and integrate techniques into practical applications. Current activity in passive localization research aims to optimize such systems' accuracy, robustness, confidentiality, and application using multimodal, deep learning, edge computing, and privacy and security challenges.

5. Conclusion

The review paper comprehensively analyses various indoor localization methods and available technologies, and compares systems on multiple parameters. The paper re-emphasizes the significance of the localization process, which actualizes the accurate placement of objects or devices in each environment, mainly involving the RF signals in wireless communication systems. It also brings insights into active and passive device localization strategies that may not be observed in other literature articles. Furthermore, the paper discusses methods for passive localization using tomography RSSI, a technique that calculates device position based on received signal strength indicators. Of the three techniques, passive localization is superior to active and free localization methods primarily because of its ability to consume less power. This research review paper presents an intricate analysis of the difficulties and restrictions, latest developments, implementations, possible uses, and direction of future research regarding tomography RSSI in passive localization. The findings of this review paper may be helpful for people who want to understand the strengths, weaknesses, and areas of utilizing indoor localization techniques and technologies in different fields.

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