A Systematic Review of Radio Wave Techniques for Indoor Positioning Systems

Emily Juliana Costa e Silva, Kaio Yukio Gonçalves Vieira Guedes, Pedro Augusto Araújo da Silva de Almeida Nava Alves, Paulo Rogério de Almeida Ribeiro, and Alex Oliveira Barradas Filho

***Abstract*—Indoor human positioning has become crucial for applications such as health monitoring, security surveillance, human pose identification and rescue operations. However, achieving reliable indoor human positioning is challenging due to numerous constraints.This paper aims to compare and analyze radio waves techniques and approaches for indoor positioning, providing a comprehensive review for human detection, positioning and activity recognition. A systematic review of the scientific literature and datasets was conducted. Four digital libraries, ACM Library Digital, IEEE Xplore, ScienceDirect and Springer Link were searched to identify results that met the selection criteria. A data extraction process was performed on the selected articles and datasets. The Parsifal platform was utilized to extract relevant information. After completing the systematic review, it was identified 26 eligible articles and extracted 11 methods for radio wave detection. The overview of indoor positioning system with radio waves was introduced. The most frequently mentioned tools in the articles for the capture stage were Radio Frequency Sensors, Antennas, WiFi, Radar Sensors and BLE Beacons. For the processing stage, Filtering and Transformation Methods, Deep Neural Networks Techniques, Specifc Algorithms followed by Fingerprint, Trilateration, and other machine learning algorithms formed the majority.**

Link to graphical and video abstracts, and to code: https://latamt.ieeer9.org/index.php/transactions/article/view/9219

***Index Terms*—Indoor positioning systems, Radio Waves, Radio Frequency Sensors, Antennas, Filtering, Fingerprint.**

I. INTRODUCTION

INDOOR Positioning Systems represent a relevant area for the development of methods capable of accurately monitoring the location of individuals indoors [1]–[3], especially in the context of human health monitoring [4], [5]. Precise location in real time can make it possible to track patients in hospitals or the elderly in homes [6], [7], making it easier to detect falls [8], [9] and abnormal behavior. This technology plays a crucial role in improving medical care, contributing to the safety and well-being of monitored individuals [10]–[13].

However, in human health monitoring, camera-based indoor positioning systems, although widely used due to their high accuracy [14]–[17], have limitations related to privacy [18], [19]. Constant surveillance by means of image-capturing devices raises ethical and operational concerns, given the potential for invasion of privacy in personal spaces [20], [21]. Radio frequency (RF) based systems are therefore emerging as a viable complementary technology, offering alternatives that do not rely on image capture to detect the presence and movements of individuals.

In this context, Radio Frequency (RF) techniques have gained prominence [22]–[24]. RF techniques encompass a set of methodologies, technologies, and devices applied in various domains, such as communication [25]–[27] and sensing [28]–[30]. In the realm of indoor positioning, RF techniques play a pivotal role in estimating human poses in environments with poor lighting and even through walls [31]–[33]. These methods are based on the interpretation of electromagnetic waves, which are effective for long-distance communication as they do not require a physical medium for propagation [34]–[36].

Wi-Fi and Bluetooth are widely recognized RF techniques used for indoor positioning [37]–[41]. These technologies estimate a target's position through the transmission and reception of RF signals between devices, such as smartphones and access points. By measuring signal strength, time of flight, and other relevant features, these systems can triangulate the target's position with relatively high accuracy [42].

Another approach involves deploying dedicated RF beacons or tags throughout the indoor environment [43]–[46]. These devices emit unique RF signals that can be detected and interpreted by strategically placed receivers or sensors. The target's position can be estimated using techniques such as trilateration or fingerprinting by analyzing the signal strength and arrival time of these beacon signals at different receiver nodes [47]–[50].

Moreover, Radio Frequency Identification (RFID) technology has facilitated the development of RFID-based indoor positioning systems [51]–[54]. These systems use RF tags or labels attached to objects or individuals, which emit signals detectable by RFID readers distributed throughout the environment. The position of tagged objects or individuals can be determined with precision by correlating readings from multiple RFID readers [55]–[58].

Indoor Positioning Systems (IPS) [59]–[61] are becoming increasingly vital for determining the locations of individuals and objects by leveraging resources such as smartphone sensors, embedded sources, localization mapping, and wireless communication networks [62], [63]. Among electromagnetic waves, radio waves stand out for their ability to transmit information wirelessly over long distances [64]. Radio waves

The associate editor coordinating the review of this manuscript and approving it for publication was Oscar Mauricio Caicedo (*Corresponding author: Emily Juliana Costa e Silva*).

Emily Juliana Costa e Silva, K. Y. G. V. Guedes, P. A. A. d. S. d. A. N. Alves, A. O. B. Filho, and P. R. d. A. Ribeiro are with Federal University of Maranhão, Brazil (e-mails: emily.costa@darti.ufma.br, yukio.kaio@discente.ufma.br, pedro.alves@darti.ufma.br, alex.barradas@ufma.br, and paulo.ribeiro@ecp.ufma.br).

are defined as the use of unguided propagating electromagnetic fields within the frequency range of 3 kHz to 300 GHz to convey information [65]. Their unique property of being able to travel through air, vacuum, or other materials with minimal attenuation allows for efficient communication across various environments [66]–[68]. Thus, understanding radio wave capture techniques, also referred to as RF techniques, is essential for developing effective indoor positioning systems.

A. Background

This section describes the studies that explore indoor localization with RF techniques reviewed by researchers proposed in the literature.

The paper [69] provides an overview of positioning systems, with an emphasis on indoor positioning systems (IPS). It highlights the growing use of radio frequency (RF) communication technologies, such as Wi-Fi, BLE, RFID and UWB. Among these technologies, the Received Signal Strength Indicator (RSSI) algorithm stands out for its effectiveness. In addition, the trilateration technique is recommended for its cost-effectiveness, ease of implementation and high accuracy.

The paper [70] provides a meta-analysis that carried out a comprehensive compilation of 62 review articles in the field of indoor positioning. Thus, the meta-analysis allows to quickly inspect the current state of IPS and serves as a guide to easily find more details about each technology used in IPS. The meta-analysis contributed insights into the abundance and academic importance of published GST proposals, using the criterion of the number of citations.

[71] examines radio wave signals for indoor environments, presenting the challenges faced by current algorithms and problem-solving strategies. The creation of radio maps and the use of crowdsourcing are considered promising strategies for improving regional accuracy in difficult environments. In addition, the combination of machine learning has been explored as a way to accurately and efficiently improve the indoor positioning at home.

Despite the significant advances documented in the academic literature, there is still a gap in the comprehensive analysis of radio wave capture techniques, including a detailed comparison of usability, advantages, limitations and accuracy in different usage scenarios. The papers reviewed provide an overview of the techniques available but there is still a need for in-depth analysis and systematic comparison.

B. Objectives

This systematic review aims to provide concepts about radio waves, while presenting a comprehensive study of the techniques used to capture these waves. Therefore, the objectives of this article are as follows: (1) to establish the definition of radio wave capture techniques; (2) to conduct a study that promotes discussions about the usability of each of these techniques; (3) to carry out a comparison between the techniques in order to obtain a more complete analysis of their implementations; and (4) to present the results obtained by each of the techniques mentioned in this article, highlighting their advantages, limitations and accuracy in different usage scenarios.

II. METHODOLOGY

This research followed the guidelines proposed by Kitchenham et al [72] for systematic literature reviews in software engineering for the planning and execution of the study proposed. The review was conducted in three main stages: planning, conducting research and analyzing the results. To assist in this process, we used the Parsifal.al tool [73], which offers an environment conducive to planning and carrying out systematic reviews. In this section, we will present in detail how this review was planned and performed.

A. Research Questions

In order to achieve the objectives of this systematic review, we established the following research questions:

- RQ1: What are the most widely used techniques for capturing radio waves?
- RQ2: What are the theoretical bases that underpin the development of these techniques?
- RQ3: What are the procedures used to carry out these techniques?
- RQ4: What tools are used to implement these techniques?
- RQ5: What processing techniques are used during signal capture?
- RQ6: What are the advantages and limitations of each technique?
- RQ7: Which technique has the best accuracy in capturing radio waves?

B. Search Strategy

The search aimed to identify studies that provided data relevant for this review. The following digital libraries were used: **ACM Library Digital, IEEE Xplore, ScienceDirect and Springer Link**. These libraries were selected due to the reliability of their studies in the field of technology. The search string was designed to look for sets of articles dealing with radio waves and the techniques used. This search was carefully developed based on the focus of the review and the established research questions. It was decided to use the boolean operator "OR" as a link between the alternative terms in order to obtain comprehensive results, and the boolean operator "AND" as a link between the sets of terms. In the end, the sets of duplicate articles were identified and removed using the Parsifal.al tool [73] tool. The terms used were:

("Radio Frequency" **OR** "Radio Wave") **AND** ("Approach" **OR** "Instrument" **OR** "Method" **OR** "Technique") **AND** ("Accuracy" **OR** "Assessment" **OR** "Efficiency" **OR** "Evaluation" **OR** "Measurement" **OR** "Testing")

C. Selection Criteria

A set of selection criteria was established to select the research articles. The selection process took place in two sequential stages: (1) filtering the studies by analyzing the metadata, such as title, abstract and keywords; (2) analyzing the full text of the articles selected in the first filtering stage.

TABLE I
DATA EXTRACTION

Information	Description
Title	Original title, preserving the original language
Authors	Include the names of all authors, regardless of quantity
Publication Venue	Database where the document is located
Year of Publication	Year of publication available in the journal and/or database
Publication Type	Indicate the type of publication, e.g., conference paper, academic journal article, etc.
Radio Wave Context	Discuss the context in which radio waves are embedded
Radio Wave Capture Techniques	Specify the techniques used or mentioned in the document
Methodology	Highlight the methodology employed by the publications
Accuracy	Present the obtained results

Inclusion Criteria
The paper describes the use of radio wave capture techniques. The paper makes a comparative study of radio wave capture techniques. The paper describes a process for developing a technique used to capture radio waves.

Exclusion Criteria
The paper deals with signals outside the scope of radio waves. The paper is duplicated, i.e. it was already selected from another digital library. The paper does not describe the use of radio wave capture techniques. The paper is not a scientific article, but a summary of a short course, introduction to a conference, etc. The paper was published before 2010.

D. Data Extraction

Throughout this stage, data were systematically gathered from the papers to address the research questions delineated in this review. A thoroughly designed form, elaborated in Table I, was employed for this purpose. The components within this form were thoughtfully devised to extract pertinent information from these studies, thereby enabling the acquisition of responses to the research inquiries and the discernment of research gaps and trends.

III. RESULTS

A. Study Selection

An overview of the review process is presented in the prism shown in Fig. 1 , in which 4 digital libraries (ACM, IEEE, ScienceDirect and Spring Link) were used to search for scientific articles that presented content relating to radio waves. A total of 54,499 articles were returned. After a meticulous analysis phase, a total of 54,473 articles were excluded based on predefined criteria. These criteria encompassed the following: The focus on signals outside the scope of radio waves; Duplication, where the article had already been selected from another digital library; A lack of description regarding the use of radio wave capture techniques; Classification as non-scientific publications, such as summaries of short courses or conference introductions; and publication dates prior to 2010. This process culminating in the final selection of 26 articles that met the requirements of interest.

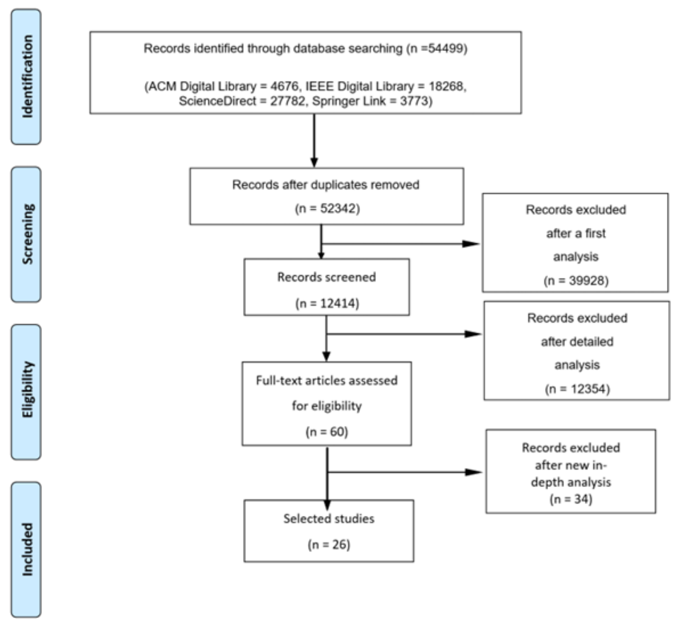

Fig. 1. Flowchart illustrating the Prism methodology applied in the systematic review process, detailing the stages of article selection, inclusion, and exclusion based on predefined criteria.

B. Techniques for Capturing Radio Waves

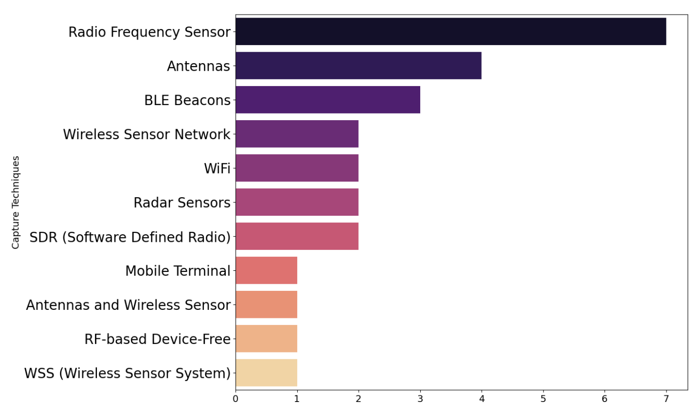

Fig. 2. Distribution of capture techniques in the reviewed studies, with radio frequency sensors being the most prevalent.

The analysis of capture techniques, as evidenced by the Fig. 2 illustrates the distribution of the most commonly used capture techniques in monitoring and localization systems. The techniques have been grouped and quantified in terms of usage frequency, providing an overview of how different approaches are applied in current technological environments. It reveals a greater utilization of RF-based techniques and antennas, which are widely applied to ensure accuracy in various fields such as healthcare, security, and indoor localization. In contrast, SDR, Radar, and Mobile Terminals are more commonly applied in specialized scenarios, with RF-based Device-Free showing a growing trend due to its non-intrusive application, although it still has a limited presence.

The most prevalent techniques are **Radio Frequency Sensors**, which are widely employed for monitoring and tracking objects due to their ability to measure signal intensity and characteristics [74]–[80]. This technique is particularly effective in industrial environments, where its robustness and resistance to interference make it an ideal choice for challenging settings.

Another essential component is **Antennas**, which are extensively used for transmitting and receiving radio waves [81]–[86]. They play a crucial role in signal detection and in determining the relative position of devices based on metrics such as signal strength and time of arrival. The capture process using Antennas can involve both directional versions, which offer greater precision for specific applications, and omnidirectional versions, which provide broader and more flexible coverage.

The use of **Wi-Fi** signals in indoor positioning systems is widely acknowledged for its ubiquity and easy integration with existing infrastructure [87], [88]. Wi-Fi signal capture involves measuring the signal strength received from multiple access points and applying triangulation techniques to estimate location, making it an effective approach, especially in locations with an established network infrastructure, minimizing the need for new installations

Radar sensors also hold significant importance, as indicated by the number of occurrences in the histogram, due to their ability to emit high-frequency radio waves and analyze the echoes to detect the position and movement of objects [89], [90]. The use of these sensors involves strategically installing devices to ensure the desired coverage of the environment, making them widely applied in security monitoring systems and scenarios that require high precision, particularly because they can operate efficiently in environments with obstacles such as thin walls.

BLE (Bluetooth Low Energy) beacons stand out as a capture technique due to their energy efficiency and ease of installation [42], [81], [91]. These devices transmit short signals at regular intervals and detect the proximity of mobile devices based on the received signal strength. The implementation process involves strategically placing the beacons within the environment and using processing algorithms to analyze the received signals and determine device location.

Wireless Sensor Systems (WSS) integrate multiple sensor technologies to create comprehensive monitoring networks [85], [92]–[94]. These systems are used for continuous and detailed tracking in complex environments, combining data from various types of sensors to provide a complete and accurate view of the monitored environment.

Software Defined Radio (SDR) emerges as a versatile capture technique due to its ability to perform signal processing through software rather than dedicated hardware [95], [96]. This flexibility allows SDR to dynamically adapt to different frequencies, modulation schemes and communication protocols, making it highly suitable for a variety of applications, including indoor positioning systems.

In research and development contexts, the use of **Universal Software Radio Peripheral (USRP)** is also relevant, although less frequently observed in the analysis. The USRP, as a hardware platform that supports SDR, facilitates advanced signal capture and processing testing, providing greater precision and control over experiments.

Finally, capture techniques based on **Mobile Terminals** [97], **Wireless Sensors**, and **RF-based Device-Free** [98] are less prevalent but remain relevant in specific niches, where mobility and integration with other monitoring systems are essential for accurate location and tracking data collection.

In summary, the analyzed capture techniques reveal a diversity of approaches that meet various needs and environments, ranging from security systems and industrial monitoring to applications in complex indoor environments, such as wireless sensor networks and radio signal-based positioning. The selection of the most suitable technique depends on the specificities of the environment and the requirements for precision and coverage, with careful consideration of the signal characteristics and the devices used.

C. Processing Techniques

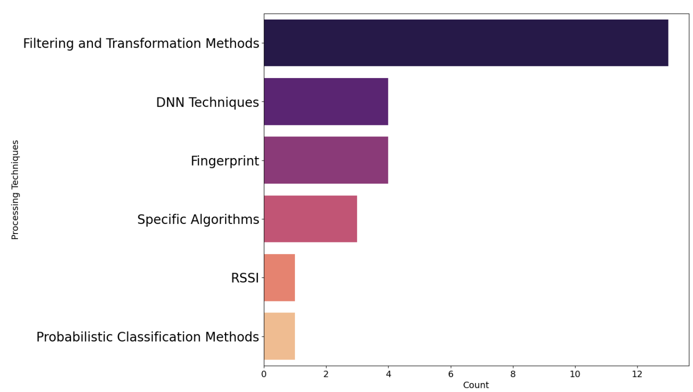

Fig. 3. Distribution of processing techniques in the reviewed studies, highlighting the dominance of filtering and transformation methods.

The Fig. 3 illustrates the distribution of processing techniques most commonly used in systems related to monitoring and localization. The techniques have been grouped and quantified based on their frequency of usage, providing an overview of how different approaches are applied in current technological environments. As shown in the histogram, Filtering and Transformation Methods are the most widely used processing techniques. These methods are crucial for data preprocessing, enhancing signal quality, and improving the accuracy of results, particularly in systems involving sensor data or signal processing.

In summary, the graph reveals that Filtering and Transformation Methods, alongside DNN Techniques, are the most common approaches in the field, with an increasing shift towards machine learning and deep learning techniques in modern processing systems. On the other hand, RSSI and

Probabilistic Classification Methods are applied in more specific contexts, where they provide precise solutions to particular challenges.

Filtering and transformation methods play a vital role in ensuring the quality of captured signals, especially in environments where noise and interference may affect the performance of positioning systems [74], [77], [82], [83], [85], [87]–[90], [93], [95], [96]. Techniques such as the Kalman filter, fast Fourier transform (FFT), and wavelets are utilized to filter out noise and extract relevant data, enabling more accurate location estimation. Efficient filtering helps maintain system accuracy by removing inconsistencies and unwanted interferences, even in challenging conditions.

Following closely are the **DNN Techniques (Deep Neural Networks)**. DNN techniques have gained prominence due to their ability to handle complex sensor data, such as Wi-Fi and Bluetooth signals, and identify intricate patterns to improve location estimation [75], [78], [80], [84], [85], [98]. Inspired by the neural structures of the human brain, these models learn from large datasets and are particularly effective in environments where high precision is required.

Specific Algorithms also feature prominently in the histogram. They are designed to address specific positioning challenges through optimization, error correction, and adaptive approaches [81], [83], [86], [87], [91], [94]. These algorithms are customized to work with various signal types, such as Wi-Fi, BLE, and RFID, and are adapted to the unique characteristics of indoor environments. This category includes classical methods like trilateration and probabilistic techniques, as well as innovative combinations that improve the accuracy of position calculations.

Trilateration is a classical geometric processing technique used to calculate the position of an object by measuring the distance from three or more known reference points [47]. This method is common in radio signal systems that rely on signal strength or time of arrival (TOA) data to estimate distances [87]. While robust and well-established, trilateration can be affected by signal reflections and interference, necessitating additional corrections in more complex scenarios.

Probabilistic classification methods are employed to process positioning data by estimating the probability of an object being located within a set of possible positions [79]. These methods are particularly effective for managing uncertainties and variations in data, using models such as Bayesian analysis and Monte Carlo techniques to predict the most likely location. This approach provides reliable positioning estimates even under conditions of high variability and noise.

Fingerprinting is another essential method used for processing radio wave data. This approach involves creating prerecorded signal maps that can be compared with captured signals to determine a device's location [42], [75], [91]. Fingerprinting provesvhighly effective in environments where other methods, such as trilateration, may struggle due to signal variability. Its application is widespread in complex indoor environments, like shopping centers and airports, where detailed signal maps enhance positioning precision

Fingerprint Matching and SVM (Support Vector Machines) appear in the histogram, reflecting their use in matching fingerprint data to known templates and applying machine learning techniques, such as SVM [97], for classification tasks, commonly in security and authentication systems. Additionally, **Fingerprinting and DNN Techniques** and **Filtering and Transformation Methods and DNN Techniques** are presented as combined approaches, highlighting the integration of traditional fingerprinting or filtering methods with deep learning techniques to enhance processing accuracy and predictive power.

RSSI (Received Signal Strength Indicator) is another technique used for positioning, which involves measuring the strength of the received signal to estimate the distance between the device and the source [92]. While not as prevalent as some other techniques, RSSI remains an important method in wireless positioning systems.

These varied processing techniques, each with distinct methodologies and applications, emphasize the significant advancements in radio wave signal processing. Their implementation holds considerable potential across fields such as healthcare, security, and wireless connectivity, driving improvements in accuracy and reliability within indoor positioning systems. The continuous development and refinement of these methods are expanding the possibilities for more precise, adaptable, and robust location-based solutions.

D. Accuracy

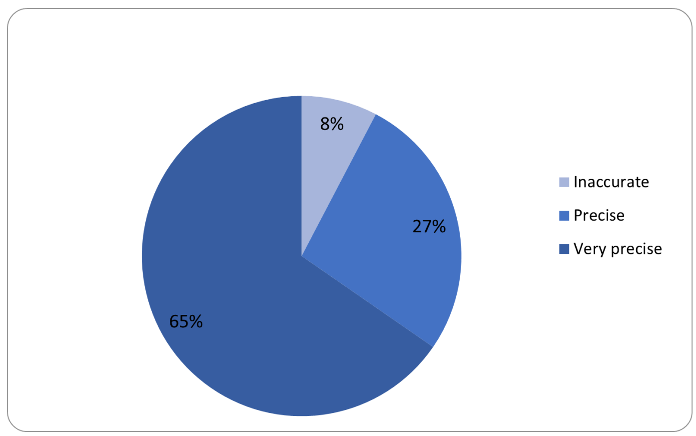

Fig. 4. Accuracy evaluation of methods for indoor positioning and human activity recognition using RF signals.

This section focuses on assessing the accuracy of the methods discussed in the previous sections. Accuracy is a crucial element in assessing the quality and reliability of methods used to locate and recognize human activity based on radio frequency (RF) signals indoors.

Furthermore, accuracy is indispensable in safeguarding the security and privacy of users, as well as meeting the demands and expectations inherent in the possible applications of these methods. In order to summarize the levels of accuracy of the studies examined, a Fig. 4 was drawn up classifying them into categories of low, moderate and high accuracy.

Inaccurate: Accuracy is less than 80% or average error is greater than 1 m.

Precise: Accuracy is between 80% and 95% or the average error is between 0.5 m and 1 m.

Very precise: Accuracy is greater than 95% or the average error is less than 0.5 m.

This metric is based on typical values found in the literature [99], [100] and can vary depending on the context and application of the methods. This metric was chosen to make it simpler and more intuitive to compare the articles and highlight the most accurate ones.

The accuracy of the localization and detection systems discussed in this review is a critical factor for applications in areas such as health monitoring, security surveillance, human pose identification, and rescue operations. Accuracy is measured in different ways depending on the technology used and the application scenario, and the results indicate significant advancements in the precision of these systems, especially in complex and dynamic environments.

In **health monitoring** [89], systems based on radar and depth sensors showed highly accurate results, with radar sensors achieving an average error of less than 0.04 m/s for walking speeds between 0.5 m/s and 0.8 m/s. These sensors maintained a standard deviation of less than 0.08 m/s, demonstrating great capability for monitoring movement in healthcare environments such as hospitals and clinics, with precise tracking of patients' mobility. In parallel, depth sensors showed an average error of less than 0.03 m/s, with standard deviation below 0.08 m/s, further reinforcing the reliability of these systems for continuous monitoring of patient movement.

For **security surveillance**, the RF-Capture system [76], used to identify and track body parts in controlled environments, achieved 99.13% accuracy in detecting body parts at a distance of 3 meters, with a hand tracking error of only 2.19 cm (median). These results highlight the high precision of the system, which is essential for real-time surveillance in high-density areas and in non-line-of-sight (NLOS) conditions, common in urban or indoor environments with obstacles. The high performance of RF-Capture makes it a valuable tool for security systems in real-time, enabling precise detection of people and objects in critical areas.

In the field of **human pose identification** [85], the WiPose system, which uses Wi-Fi signals to reconstruct 3D poses, achieved an average error of 2.83 cm in locating human skeleton joints, representing a 35% improvement in accuracy compared to previous radar-based systems. The high accuracy of WiPose is crucial for applications that require detailed tracking of human movements, such as in augmented reality environments or rehabilitation systems, as well as in rescue operations, where accurate pose reconstruction can be used to identify people at risk in disaster situations.

In **rescue operations**, where the ability to detect and locate individuals in real-time is vital, systems like RF-Net [98] and RFlow [77] demonstrated superior accuracy. RF-Net, used for human activity recognition, achieved 95% accuracy with only one example per class (one-shot learning), making it ideal for dynamic environments like rescue scenarios, where rapid identification of human activities is needed. RFlow, used for gesture tracking, achieved an average error of less than 5 cm, equivalent to an accuracy greater than 95%. This high accuracy is crucial for gesture detection in complex environments with obstacles, such as in rescue operations in areas with limited visibility or access.

For **indoor localization**, such as in hospitals or industrial environments, the RFMap system [84] proved highly effective, with the ability to generate well-defined maps without the need for extensive movement of the setup. This demonstrates the effectiveness of the method for mobile device navigation in closed environments, with qualitatively high accuracy, although no exact error values were provided in the article.

These results demonstrate that the monitoring and detection systems have achieved very high accuracy across various applications, with most systems exhibiting average errors below 1 meter. This precision is essential for ensuring the effectiveness of these systems in health monitoring, security surveillance, human pose identification, and rescue operations, where high accuracy not only enhances operational efficiency but also contributes to the safety and well-being of individuals in critical situations. The continuous advancement in RF and machine learning-based technologies has allowed these systems to reach high levels of precision, showing their potential to improve security and effectiveness in challenging and dynamic environments.

E. Advantages and Limitations

Technological advances in the area of positioning and detection based on Radio Frequency (RF), Wi-Fi and Bluetooth Low Energy (BLE) signals have enabled a wide range of applications, from precise indoor location to the detection of objects and people through obstacles. This section analyzes the main advantages and limitations found, as can be seen bellow.

Table II summarizes the principal characteristics of diverse positioning and detection methods and systems utilizing RF, Wi-Fi, and BLE signals. It is evident that these approaches provide several noteworthy advantages; however, they also entail significant limitations. Analyzing the main ones:

High Accuracy and Low Latency: Numerous articles, exemplified by [42] and [97], underscore the capability to deliver high accuracy and low latency. This aspect holds particular significance for time-sensitive applications like indoor navigation and asset tracking.

Need for Specialized Infrastructure: Conversely, articles like [74] and [83] require necessitate specialized infrastructure, such as deploying multiple sensors or antennas, thereby potentially elevating implementation costs and complexity.

Consideration of Signal Variation: Certain articles, exemplified by [93], leverage pre-existing infrastructure but may encounter signal variations stemming from network congestion or interference, thereby impacting accuracy.

Use of Machine Learning and Signal Processing: Articles integrating machine learning and signal processing methodologies, such as [98] and [85], showcase promising outcomes; however, they frequently demand significant computational complexity and extensive training datasets.

Detection through obstacles: The capability to detect through barriers, as demonstrated in [95] and [87] is noteworthy. However, limitations in resolution and false alarm rates may arise.

TABLE II
ADVANTAGES AND RESTRICTIONS OF CAPTURE AND PROCESSING TECHNIQUES

Article	Capture Technique	Processing Technique	Advantages	Restrictions
[42]	BLE Beacons	Fingerprint	High accuracy and low latency	Requires a large number of BLE beacons; increased cost and complexity
[92]	Wireless Sensor Network	RSSI	Does not require prior knowledge; handles dynamic changes	RSSI fluctuations affect accuracy and robustness
[95]	SDR	Filtering and Transformation Methods	Uses existing Wi-Fi devices; detection through walls	Low resolution and high false alarm rate
[81]	Beacons and Mobile Node Operate and Antennas	Specific Algorithms	Theoretical analysis and experimental validation	Ideal scenarios; does not reflect realistic conditions
[74]	Radio Frequency Sensor	Filtering and Transformation Methods	Accurate detection and tracking	High complexity and calibration; affected by noise
[97]	Mobile Terminal	Fingerprint Matching and SVM (Support Vector Machine)	High accuracy and low complexity	Requires a large amount of training data
[75]	Radio Frequency Sensor	Fingerprinting and DNN Techniques	High accuracy and adaptability	High computational complexity
[93]	Wireless Sensor	Filtering and Transformation Methods	Existing LTE-A infrastructure; wide coverage	Low accuracy and high latency due to RSSI variations
[82]	Antennas	Filtering and Transformation Methods	Low power consumption; fast response	Low accuracy and robustness due to interference
[83]	Antennas	Filtering and Transformation Methods and Specific Algorithms	High accuracy and resolution	High hardware cost and complexity
[84]	Antennas	DNN Techniques	High-quality indoor maps	High computational complexity and memory requirements
[85]	Antennas and Wireless Sensor	Filtering and Transformation Methods and DNN Techniques	Detailed information; combines signal processing and machine learning	Low accuracy and stability due to noise
[76]	Radio Frequency Sensor	Filtering and Transformation Methods	Robust information	Low resolution and detail
[77]	Radio Frequency Sensor	Filtering and Transformation Methods	Natural user interaction	Low accuracy and responsiveness due to latency
[98]	RF-based Device-Free	DNN Techniques	High accuracy and adaptability	High computational complexity and memory requirements
[87]	WiFi	Filtering and Transformation Methods and Specific Algorithms	NLOS detection using common Wi-Fi devices	Low accuracy and reliability due to interference
[78]	Radio Frequency Sensor	DNN Techniques	High security and robustness	High computational complexity and energy consumption
[88]	WiFi	Filtering and Transformation Methods	Improves positioning accuracy and robustness	High complexity and calibration requirements
[79]	Radio Frequency Sensor	Probabilistic Classification Methods	Improves DFPL performance and scalability	Low accuracy and stability due to uncertainty
[91]	Beacons BLE	Fingerprinting and Specific Algorithms	Accuracy, Dynamic Management, Cost Reduction	Prior knowledge, Interference, Complexity
[89]	Radar Sensors	Filtering and Transformation Methods	Robust Estimation, Noisy Data, Multi-Sensors	Parameter Selection, Bias, Non-Linearity
[86]	Antennas	Specific Algorithms	Wave Patterns, Efficient Mining, Propagation Modeling	Loss of Rare Patterns, Redundant Sequences, High Cost
[96]	SDR (Software Defined Radio)	Filtering and Transformation Methods	Filter Design, Resource Reduction, Field Implementation	Balance, Output Errors, Design Limitations
[94]	WSS (Wireless Sensor System)	Specific Algorithms	High Resolution, Sampling Reduction, MLE	Sparsity, Reconstruction Errors, Complexity
[90]	Radar Sensors	Filtering and Transformation Methods	High Resolution, Chip Integration, Signal Generation	Design Challenges, Phase Noise Degradation, Antenna Design
[80]	Radio Frequency Sensor	DNN Techniques	Identification, Fast Training, Temporal Features	Labeled Data, Domain Adaptation, Overfitting / Underfitting

Energy Consumption: [82] emphasizes low energy consumption. Nevertheless, accuracy may be compromised by interference.

Security and Intrusion: [78] addresses security issues, albeit at the expense of increased computational complexity and energy consumption.

Calibration and Training Data: Numerous articles, such as [88] and [79], require necessitate calibration procedures and extensive training datasets, thereby amplifying the implementation workload.

The selection of the most suitable method hinges on the specific requirements of an application. While certain methods boast high accuracy and diminished latency, others prioritize ease of implementation and scalability. A comprehensive understanding of these advantages and limitations is imperative to steer the selection and development of positioning and detection solutions. As research progresses in this domain, it is plausible that novel innovations will emerge to alleviate some of the identified limitations, ushering in a new era of increasingly precise and resilient applications.

IV. Final Considerations

After completing the systematic review, It was identified 26 eligible articles and extracted 11 methods for radio wave detection . The overview of indoor positioning system with radio waves was introduced. The most frequently mentioned tools in the articles for the capture stage were Radar Sensors, Wireless Sensor, and Antennas. For the processing stage, DNN Techniques, Processing Algorithms followed by Filtering, Fingerprint, Trilateration, and other machine learning algorithms formed the majority.

Of the analyzed works, 65% showed accuracy with the "very precise" metric, indicating that the methods are effective and robust for indoor positioning. Conversely, 27% returned "precise" results, while only 8% were found to be inaccurate, suggesting that there are still challenges and limitations to overcome, such as high implementation costs and high computational complexity.

The implications of this study encompass the theoretical realm of radio wave investigation, fostering a more profound comprehension of the hurdles encountered in utilizing radio waves indoors. Drawing from the gaps unearthed in this systematic review of radio wave acquisition, numerous promising avenues for prospective research emerge.

Acknowledgments

The authors thank the Foundation for the Support of Research and Scientific and Technological Development of Maranhão (FAPEMA - Processo UNIVERSAL - 07003/22) for the financial support for the development of this work.

References

[1] F. Firmansyah, F. Rahma, K. D. Irianto, and A. M. Shiddiqi, "Indoor positioning system: A brief review of its technologies and signal-filtering techniques," in *2024 International Symposium on Machine Learning and Applications (SIML)*, pp. 1–7, 2024. https://ieeexplore.ieee.org/document/10578093.

[2] S. Subedi and J.-Y. Pyun, "A survey of smartphone-based indoor positioning system using rf-based wireless technologies," *Sensors*, vol. 20, no. 24, p. 7230, 2020. https://doi.org/10.3390/s20247230.

[3] L. Bai, F. Ciravegna, R. Bond, and M. Mulvenna, "A low cost indoor positioning system using bluetooth low energy," *IEEE Access*, vol. 8, pp. 136858–136871, 2020. https://doi.org/10.1109/ACCESS.2020.3012342.

[4] L. Sevrin, N. Noury, N. Abouchi, F. Jumel, B. Massot, and J. Saraydaryan, "Characterization of a multi-user indoor positioning system based on low cost depth vision (kinect) for monitoring human activity in a smart home," in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 5003–5007, 2015. https://doi.org/10.1109/EMBC.2015.7319515.

[5] A. Sonny, A. Kumar, and L. R. Cenkeramaddi, "A survey of application of machine learning in wireless indoor positioning systems," *arXiv preprint arXiv:2403.04333*, 2024. https://doi.org/10.48550/arXiv.2403.04333.

[6] R. Montoliu, E. Sansano, A. Gascó, O. Belmonte, and A. Caballer, "Indoor positioning for monitoring older adults at home: Wi-fi and ble technologies in real scenarios," *Electronics*, vol. 9, no. 5, p. 728, 2020. https://doi.org/10.3390/electronics9050728.

[7] M.-Y. Chen, "Establishing a cybersecurity home monitoring system for the elderly," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 7, pp. 4838–4845, 2022. https://doi.org/10.1109/TII.2021.3114296.

[8] P. Gharti, "A study of fall detection monitoring system for elderly people through iot and mobile based application devices in indoor environment," in *2020 5th International Conference on Innovative Technologies in Intelligent Systems and Industrial Applications (CITISIA)*, pp. 1–9, 2020. https://doi.org/10.1109/CITISIA50690.2020.9371773.

[9] L. di Biase, P. M. Pecoraro, G. Pecoraro, M. L. Caminiti, and V. Di Lazzaro, "Markerless radio frequency indoor monitoring for telemedicine: Gait analysis, indoor positioning, fall detection, tremor analysis, vital signs and sleep monitoring," *Sensors*, vol. 22, no. 21, p. 8486, 2022. https://doi.org/10.3390/s22218486.

[10] J. Wichmann, "Indoor positioning systems in hospitals: A scoping review," *Digital Health*, vol. 8, p. ID: 20552076221081696, 2022. https://doi.org/10.1177/20552076221081696.

[11] P. Li, W. Wu, Z. Zhao, and G. Q. Huang, "Indoor positioning systems in industry 4.0 applications: Current status, opportunities, and future trends," *Digital Engineering*, vol. 3, p. 100020, December 2024. https://www.sciencedirect.com/science/article/pii/S2950550X24000207.

[12] F. Che, Q. Z. Ahmed, P. I. Lazaridis, P. Sureephong, and T. Alade, "Indoor positioning system (ips) using ultra-wide bandwidth (uwb)—for industrial internet of things (iiot)," *Sensors*, vol. 23, no. 12, p. 5710, 2023. https://doi.org/10.3390/s23125710.

[13] S. R. Misal, S. R. Prajwal, H. M. Niveditha, H. M. Vinayaka, and S. Veena, "Indoor positioning system (ips) using esp32, mqtt and bluetooth," in *2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC)*, pp. 79–82, 2020. https://doi.org/10.1109/ICCMC48092.2020.ICCMC-00015.

[14] C.-Z. Dong and F. N. Catbas, "A review of computer vision–based structural health monitoring at local and global levels," *Structural Health Monitoring*, vol. 20, no. 2, pp. 692–743, 2021. https://doi.org/10.1177/1475921720935585.

[15] C.-Z. Dong and F. N. Catbas, "A review of computer vision–based structural health monitoring at local and global levels," *Structural Health Monitoring*, vol. 20, no. 2, pp. 692–743, 2021. https://doi.org/10.1177/1475921720935585.

[16] U. Eswaran and A. Khang, "Artificial intelligence (ai)-aided computer vision (cv) in healthcare system," in *Computer Vision and AI-Integrated IoT Technologies in the Medical Ecosystem*, pp. 125–137, CRC Press, 2024. ISBN: 9781003429609.

[17] S. Rishabh, P. Mayank, G. Swapnil, *et al.*, "Smart home automation using computer vision and segmented image processing," in *2019 International Conference on Communication and Signal Processing (ICCSP)*, pp. 0429–0433, IEEE, 2019. https://doi.org/10.1109/iccsp.2019.8697997.

[18] X. Liu, L. Xie, Y. Wang, J. Zou, J. Xiong, Z. Ying, and A. V. Vasilakos, "Privacy and security issues in deep learning: A survey," *IEEE Access*, vol. 9, pp. 4566–4593, 2020. https://doi.org/10.1109/access.2020.3045078.

[19] S. Sahoo and B. Choudhury, "Exploring the use of computer vision in assistive technologies for individuals with disabilities: A review," *Journal of Future Sustainability*, vol. 4, no. 3, pp. 133–148, 2024. https://doi.org/10.5267/j.jfs.2024.7.002.

[20] R. A. Waelen, "The ethics of computer vision: an overview in terms of power," *AI and Ethics*, vol. 4, no. 2, pp. 353–362, 2024. https://doi.org/10.1007/s43681-023-00272-x.

[21] A. K. Mishra, S. Tiwari, A. K. Tyagi, and M. O. Arowolo, "Security, privacy, trust, and provenance issues in internet of things–based edge environment," in *IoT Edge Intelligence*, pp. 233–263, Springer, 2024.

[22] T. Kim Geok, K. Zar Aung, M. Sandar Aung, M. Thu Soe, A. Abdaziz, C. Pao Liew, F. Hossain, C. P. Tso, and W. H. Yong, "Review of indoor positioning: Radio wave technology," *Applied Sciences*, vol. 11, no. 1, p. 279, 2020. https://doi.org/10.3390/app11010279.

[23] N. Soltanieh, Y. Norouzi, Y. Yang, and N. C. Karmakar, "A review of radio frequency fingerprinting techniques," *IEEE Journal of Radio Frequency Identification*, vol. 4, no. 3, pp. 222–233, 2020. https://doi.org/10.1109/jrfid.2020.2968369.

[24] S. Subedi and J.-Y. Pyun, "A survey of smartphone-based indoor positioning system using rf-based wireless technologies," *Sensors*, vol. 20, no. 24, p. 7230, 2020. https://doi.org/10.3390/s20247230.

[25] K.-L. Du and M. N. Swamy, *Wireless communication systems: from RF subsystems to 4G enabling technologies*. Cambridge University Press, 2010. https://doi.org/10.1017/cbo9780511841453.

[26] L. Cui, Z. Zhang, N. Gao, Z. Meng, and Z. Li, "Radio frequency identification and sensing techniques and their applications—a review of the state-of-the-art," *Sensors*, vol. 19, no. 18, p. 4012, 2019. https://doi.org/10.3390/s19184012.

[27] A. Jagannath, J. Jagannath, and P. S. P. V. Kumar, "A comprehensive survey on radio frequency (rf) fingerprinting: Traditional approaches, deep learning, and open challenges," *Computer Networks*, vol. 219, p. 109455, 2022. https://doi.org/10.1016/j.comnet.2022.109455.

[28] S. A. Shah and F. Fioranelli, "Rf sensing technologies for assisted daily living in healthcare: A comprehensive review," *IEEE Aerospace*

and Electronic Systems Magazine, vol. 34, no. 11, pp. 26–44, 2019. https://doi.org/10.1109/maes.2019.2933971.

[29] L. Cui, Z. Zhang, N. Gao, Z. Meng, and Z. Li, “Radio frequency identification and sensing techniques and their applications—a review of the state-of-the-art,” *Sensors*, vol. 19, no. 18, p. 4012, 2019. https://doi.org/10.3390/s19184012.

[30] M. H. Alsharif, S. Kim, and N. Kuruoğlu, “Energy harvesting techniques for wireless sensor networks/radio-frequency identification: A review,” *Symmetry*, vol. 11, no. 7, p. 865, 2019. https://doi.org/10.3390/sym11070865.

[31] T. Pfister, J. Charles, and A. Zisserman, “Flowing convnets for human pose estimation in videos,” in *Proceedings of the IEEE international conference on computer vision*, pp. 1913–1921, 2015. https://doi.org/10.1109/iccv.2015.222.

[32] M. Zhao, T. Li, M. Abu Alsheikh, Y. Tian, H. Zhao, A. Torralba, and D. Katabi, “Through-wall human pose estimation using radio signals,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 7356–7365, 2018. https://doi.org/10.1109/cvpr.2018.00768.

[33] F. Adib, C.-Y. Hsu, H. Mao, D. Katabi, and F. Durand, “Capturing the human figure through a wall,” *ACM Transactions on Graphics (TOG)*, vol. 34, no. 6, pp. 1–13, 2015. https://doi.org/10.1145/2816795.2818072.

[34] X. Zhou, T. Jin, Y. Dai, Y. Song, and Z. Qiu, “Md-pose: Human pose estimation for single-channel uwb radar,” *IEEE Transactions on Biometrics, Behavior, and Identity Science*, vol. 5, no. 4, pp. 449–463, 2023. https://doi.org/10.1109/tbiom.2023.3265206.

[35] Y. Song, T. Jin, Y. Dai, and X. Zhou, “Efficient through-wall human pose reconstruction using uwb mimo radar,” *IEEE Antennas and Wireless Propagation Letters*, vol. 21, no. 3, pp. 571–575, 2021. https://doi.org/10.1109/lawp.2021.3138512.

[36] Y. Song, T. Jin, Y. Dai, Y. Song, and X. Zhou, “Through-wall human pose reconstruction via uwb mimo radar and 3d cnn,” *Remote Sensing*, vol. 13, no. 2, p. 241, 2021. https://doi.org/10.3390/rs13020241.

[37] S. S. Rahman, M. A. Kamaruzaman, R. A. Rashid, J. E. Calveen, E. T. Tashbib, M. Imran, and M. A. Sarijari, “A survey of internet of things based indoor positioning systems based on bluetooth low energy beacon,” *ELEKTRIKA-Journal of Electrical Engineering*, vol. 23, no. 1, pp. 43–50, 2024. https://doi.org/10.11113/elektrika.v23n1.449.

[38] M. S. Hossain and R. J. Wandell, “Indoor positioning system for smart spaces,” in *2024 6th International Conference on Electrical Engineering and Information & Communication Technology (ICEEICT)*, pp. 1112–1117, IEEE, 2024. https://doi.org/10.1109/iceeict62016.2024.10534435.

[39] M. Niang, M. Ndong, P. Canalda, F. Spies, I. Dioum, I. Diop, and M. Abdel El Ghany, “A comparative study of machine-learning algorithms for indoor localization based on the wi-fi fingerprint according to user postures,” in *International Congress on Information and Communication Technology*, pp. 227–237, Springer, 2024. https://doi.org/10.1007/978-981-97-3305-7_18.

[40] F. Firmansyah, F. Rahma, K. D. Irianto, and A. M. Shiddiqi, “Indoor positioning system: A brief review of its technologies and signal-filtering techniques,” in *2024 International Conference on Smart Computing, IoT and Machine Learning (SIML)*, pp. 1–7, IEEE, 2024. https://doi.org/10.1109/siml61815.2024.10578093.

[41] V.-C. Ta, T.-K. Dao, D. Vaufreydaz, and E. Castelli, “Smartphone-based user positioning in a multiple-user context with wi-fi and bluetooth,” in *2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, pp. 206–212, 2018. https://doi.org/10.1109/ipin.2018.8533809.

[42] V. Vladislav and B. Marina, “Implementation of indoor positioning methods: virtual hospital case,” *Procedia Computer Science*, vol. 193, pp. 183–189, 2021. https://doi.org/10.1016/j.procs.2021.10.018.

[43] T.-M. T. Dinh, N.-S. Duong, and Q.-T. Nguyen, “Developing a novel real-time indoor positioning system based on ble beacons and smartphone sensors,” *IEEE Sensors Journal*, vol. 21, no. 20, pp. 23055–23068, 2021. https://doi.org/10.1109/jsen.2021.3106019.

[44] L. Bai, F. Ciravegna, R. Bond, and M. Mulvenna, “A low cost indoor positioning system using bluetooth low energy,” *Ieee Access*, vol. 8, pp. 136858–136871, 2020. https://doi.org/10.1109/access.2020.3012342.

[45] B. P. Guamán and J. Cordero, “Indoor positioning system using beacon technology,” in *2020 15th Iberian Conference on Information Systems and Technologies (CISTI)*, pp. 1–4, IEEE, 2020. https://doi.org/10.23919/cisti49556.2020.9141009.

[46] L. Bouse, S. A. King, and T. Chu, “Simplified indoor localization using bluetooth beacons and received signal strength fingerprinting with smartwatch,” *Sensors*, vol. 24, no. 7, p. 2088, 2024. https://doi.org/10.3390/s24072088.

[47] J. Cecílio, K. Duarte, P. Martins, and P. Furtado, “Robustpathfinder: handling uncertainty in indoor positioning techniques,” *Procedia computer science*, vol. 130, pp. 408–415, 2018. https://doi.org/10.1016/j.procs.2018.04.061.

[48] B. Andò, S. Baglio, R. Crispino, and V. Marletta, “An introduction to indoor localization techniques. case of study: A multi-trilateration-based localization system with user–environment interaction feature,” *Applied Sciences*, vol. 11, no. 16, p. 7392, 2021. https://doi.org/10.3390/app11167392.

[49] T. W. Moleski and J. P. Wilhelm, “Trilateration positioning using hybrid camera–lidar system with spherical landmark surface fitting,” *Journal of Guidance, Control, and Dynamics*, vol. 45, no. 7, pp. 1213–1228, 2022. https://doi.org/10.2514/1.g006248.

[50] A. El-Naggar, A. Wassal, and K. Sharaf, “Indoor positioning using wifi rssi trilateration and ins sensor fusion system simulation,” in *Proceedings of the 2019 2nd International Conference on Sensors, Signal and Image Processing*, pp. 21–26, 2019. https://doi.org/10.1145/3365245.3365261.

[51] Z. Xiong, Z. Y. Song, A. Scalera, F. Sottile, R. Tomasi, and M. A. Spirito, “Enhancing wsn-based indoor positioning and tracking through rfid technology,” in *2012 Fourth International EURASIP Workshop on RFID Technology*, pp. 107–114, 2012. https://doi.org/10.1109/rfid.2012.26.

[52] M. Merenda, L. Catarinucci, R. Colella, D. Iero, F. G. Della Corte, and R. Carotenuto, “Rfid-based indoor positioning using edge machine learning,” *IEEE Journal of Radio Frequency Identification*, vol. 6, pp. 573–582, 2022. https://doi.org/10.1109/jrfid.2022.3182819.

[53] A. Vena, I. Illanes, L. Alidieres, B. Sorli, and F. Perea, “Rfid based indoor localization system to analyze visitor behavior in a museum,” in *2021 IEEE International Conference on RFID Technology and Applications (RFID-TA)*, pp. 183–186, IEEE, 2021. https://doi.org/10.1109/rfid-ta53372.2021.9617265.

[54] A. A. N. Shirehjini and S. Shirmohammadi, “Improving accuracy and robustness in hf-rfid-based indoor positioning with kalman filtering and tukey smoothing,” *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 11, pp. 9190–9202, 2020. https://doi.org/10.1109/tim.2020.2995281.

[55] Z. Wei, J. Chen, H. Tang, and H. Zhang, “Rssi-based location fingerprint method for rfid indoor positioning: a review,” *Nondestructive Testing and Evaluation*, pp. 1–29, 2023.

[56] E. Matrosova and A. Tikhomirova, “Intelligent data processing received from radio frequency identification system,” *Procedia computer science*, vol. 145, pp. 332–336, 2018. https://doi.org/10.1016/j.procs.2018.11.080.

[57] G. Xu, P. Sharma, X. Hui, and E. C. Kan, “3-d indoor device-free object detection by passive radio frequency identification,” *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–13, 2021. https://doi.org/10.1109/tim.2021.3059309.

[58] Y. Ma, W. Ning, B. Wang, and X. Liang, “A data augmentation-based method for robust device-free localization in changing environments of passive radio frequency identification system,” *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–13, 2021. https://doi.org/10.1109/tim.2021.3065426.

[59] F. Alkhawaja, M. Jaradat, and L. Romdhane, “Techniques of indoor positioning systems (ips): A survey,” in *2019 Advances in Science and Engineering Technology International Conferences (ASET)*, pp. 1–8, IEEE, 2019. https://doi.org/10.1109/icaset.2019.8714291.

[60] J. Singh, N. Tyagi, S. Singh, F. Ali, and D. Kwak, “A systematic review of contemporary indoor positioning systems: Taxonomy, techniques, and algorithms,” *IEEE Internet of Things Journal*, 2024. https://doi.org/10.1109/jiot.2024.3416255.

[61] O. Casha, “A comparative analysis and review of indoor positioning systems and technologies,” 2024. https://doi.org/10.5772/intechopen.1005185.

[62] T. Kim Geok, K. Zar Aung, M. Sandar Aung, M. Thu Soe, A. Abdaziz, C. Pao Liew, F. Hossain, C. P. Tso, and W. H. Yong, “Review of indoor positioning: Radio wave technology,” *Applied Sciences*, vol. 11, no. 1, p. 279, 2020. https://doi.org/10.3390/app11010279.

[63] M. Li, X. Qiu, S. Zhu, Z. Sheng, Y. Liu, Y. Zhao, X. Zhao, R. You, S. Wang, and D. Bi, “Intelligent robotic arm for human pose recognition based on teleoperation system,” in *Journal of Physics: Conference Series*, vol. 2741, p. 012015, IOP Publishing, 2024. https://doi.org/10.1088/1742-6596/2741/1/012015.

[64] H. Hertz, *Electric waves: being researches on the propagation of electric action with finite velocity through space*. Dover Publications, 1893. https://doi.org/10.4324/9780429198960-14.

[65] W. Gosling, *Radio Antennas and Propagation: Radio Engineering Fundamentals*. Newnes, 1998. https://doi.org/10.1016/b978-075063741-1/50002-0.

[66] C. Bai, H.-P. Ren, W.-Y. Zheng, and C. Grebogi, “Radio-wave communication with chaos,” *IEEE Access*, vol. 8, pp. 167019–167026, 2020. https://doi.org/10.1109/access.2020.3022632.

[67] A. V. Gurevich and E. E. Tsedilina, *Long distance propagation of HF radio waves*. Springer, 1985. https://doi.org/10.1007/978-3-642-70249-5.

[68] T. S. Rappaport and S. Sandhu, “Radio wave propagation for emerging wireless personal communication systems,” *Wireless Personal Communications: Research Developments*, pp. 1–27, 1995. https://doi.org/10.1007/978-1-4757-2368-7_1.

[69] N. H. A. Wahab, N. Sunar, S. H. Ariffin, K. Y. Wong, Y. Aun, *et al.*, “Indoor positioning system: A review,” *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 6, 2022. https://doi.org/10.14569/ijacsa.2022.0130659.

[70] G. M. Mendoza-Silva, J. Torres-Sospedra, and J. Huerta, “A meta-review of indoor positioning systems,” *Sensors*, vol. 19, no. 20, p. 4507, 2019. https://doi.org/10.3390/s19204507.

[71] T. Kim Geok, K. Zar Aung, M. Sandar Aung, M. Thu Soe, A. Abdaziz, C. Pao Liew, F. Hossain, C. P. Tso, and W. H. Yong, “Review of indoor positioning: Radio wave technology,” *Applied Sciences*, vol. 11, no. 1, p. 279, 2020. https://doi.org/10.3390/app11010279.

[72] B. A. Kitchenham, P. Brereton, M. Turner, M. K. Niazi, S. Linkman, R. Pretorius, and D. Budgen, “Refining the systematic literature review process—two participant-observer case studies,” *Empirical Software Engineering*, vol. 15, pp. 618–653, 2010. https://doi.org/10.1007/s10664-010-9134-8.

[73] “Parsif.al.” Available at http://parsif.al.

[74] A. Buonanno, M. D’Urso, G. Prisco, M. Felaco, L. Angrisani, M. Ascione, R. S. L. Moriello, and N. Pasquino, “A new measurement method for through-the-wall detection and tracking of moving targets,” *Measurement*, vol. 46, no. 6, pp. 1834–1848, 2013. https://doi.org/10.1016/j.measurement.2012.12.021.

[75] M. Liu, J. Wang, N. Zhao, Y. Chen, H. Song, and F. R. Yu, “Radio frequency fingerprint collaborative intelligent identification using incremental learning,” *IEEE Transactions on Network Science and Engineering*, vol. 9, no. 5, pp. 3222–3233, 2021. https://doi.org/10.1109/tnse.2021.3103805.

[76] F. Adib, C.-Y. Hsu, H. Mao, D. Katabi, and F. Durand, “Capturing the human figure through a wall,” *ACM Transactions on Graphics (TOG)*, vol. 34, no. 6, pp. 1–13, 2015. https://doi.org/10.1145/2816795.2818072.

[77] H. Bedri, O. Gupta, A. Temme, M. Feigin, G. Charvat, and R. Raskar, “Rflow: User interaction beyond walls,” in *Adjunct Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology*, pp. 45–46, 2015. https://doi.org/10.1145/2815585.2817801.

[78] P.-F. Gimenez, J. Roux, E. Alata, G. Auriol, M. Kaâniche, and V. Nicomette, “Rids: Radio intrusion detection and diagnosis system for wireless communications in smart environment,” *ACM Transactions on Cyber-Physical Systems*, vol. 5, no. 3, pp. 1–1, 2021. https://doi.org/10.1145/3441458.

[79] C. Xu, B. Firner, Y. Zhang, R. Howard, J. Li, and X. Lin, “Improving rf-based device-free passive localization in cluttered indoor environments through probabilistic classification methods,” in *Proceedings of the 11th international conference on Information Processing in Sensor Networks*, pp. 209–220, 2012. https://doi.org/10.1145/2185677.2185734.

[80] X. Wang, Y. Zhang, H. Zhang, Y. Li, and X. Wei, “Radio frequency signal identification using transfer learning based on lstm,” *Circuits, Systems, and Signal Processing*, vol. 39, pp. 5514–5528, 2020. https://doi.org/10.1007/s00034-020-01417-7.

[81] V. Pasku, M. L. Fravolini, and A. Moschitta, “Effects of antenna directivity on rf ranging when using space diversity techniques,” *Measurement*, vol. 98, pp. 429–438, 2017. https://doi.org/10.1016/j.measurement.2015.11.030.

[82] T. Ni, Y. Chen, K. Song, and W. Xu, “A simple and fast human activity recognition system using radio frequency energy harvesting,” in *Adjunct Proceedings of the 2021 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2021 ACM International Symposium on Wearable Computers*, pp. 666–671, 2021. https://doi.org/10.1145/3460418.3480399.

[83] S. Yue, H. He, P. Cao, K. Zha, M. Koizumi, and D. Katabi, “Cornerradar: Rf-based indoor localization around corners,” *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 6, no. 1, pp. 1–24, 2022. https://doi.org/10.1145/3517226.

[84] U. M. Khan, R. H. Venkatnarayan, and M. Shahzad, “Using rf signals to generate indoor maps,” *ACM Transactions on Sensor Networks*, vol. 19, no. 1, pp. 1–30, 2023. https://doi.org/10.1145/3534121.

[85] W. Jiang, H. Xue, C. Miao, S. Wang, S. Lin, C. Tian, S. Murali, H. Hu, Z. Sun, and L. Su, “Towards 3d human pose construction using wifi,” in *Proceedings of the 26th Annual International Conference on Mobile Computing and Networking*, pp. 1–14, 2020. https://doi.org/10.1145/3372224.3380900.

[86] N. Suzuki and H. Matsuno, “Radio wave environment analysis at different locations based on frequent pattern mining,” *Procedia computer science*, vol. 112, pp. 1396–1403, 2017. https://doi.org/10.1016/j.procs.2017.08.061.

[87] S. Fang, R. Alterovitz, and S. Nirjon, “Non-line-of-sight around the corner human presence detection using commodity wifi devices,” in *Proceedings of the 1st ACM International Workshop on Device-Free Human Sensing*, pp. 22–26, 2019. https://doi.org/10.1145/3360773.3360879.

[88] S. Harada, M. Mochizuki, K. Murao, and N. Nishio, “A wi-fi positioning method considering radio attenuation of human body,” in *Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers*, pp. 1472–1478, 2018. https://doi.org/10.1145/3267305.3267513.

[89] J. Wagner, P. Mazurek, A. Miękina, and R. Z. Morawski, “Regularised differentiation of measurement data in systems for monitoring of human movements,” *Biomedical Signal Processing and Control*, vol. 43, pp. 265–277, 2018. https://doi.org/10.1016/j.bspc.2018.02.010.

[90] T. Ma, Z. Chen, J. Wu, W. Zheng, S. Wang, N. Qi, M. Lin, and B. Chi, “A 77 ghz fmcw mimo radar system based on 65nm cmos cascadable 2t3r transceiver,” *Science China. Information Sciences*, vol. 64, no. 1, p. 114301, 2021. https://doi.org/10.1007/s11432-019-1511-5.

[91] J. Cecílio, K. Duarte, P. Martins, and P. Furtado, “Robustpathfinder: handling uncertainty in indoor positioning techniques,” *Procedia computer science*, vol. 130, pp. 408–415, 2018. https://doi.org/10.1016/j.procs.2018.04.061.

[92] K. Oguchi, S. Maruta, and D. Hanawa, “Human positioning estimation method using received signal strength indicator (rssi) in a wireless sensor network,” *Procedia Computer Science*, vol. 34, pp. 126–132, 2014. https://doi.org/10.1016/j.procs.2014.07.066.

[93] A. Al-Habashna and G. Wainer, “Rssi-based indoor localization with lte-a ultra-dense networks,” in *2020 International Symposium on Performance Evaluation of Computer and Telecommunication Systems (SPECTS)*, pp. 1–7, IEEE, 2020.

[94] E. Balestrieri, L. De Vito, F. Picariello, and I. Tudosa, “A method exploiting compressive sampling for localization of radio frequency emitters,” *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 5, pp. 2325–2334, 2019. https://doi.org/10.1109/tim.2019.2954759.

[95] I. Cushman, D. B. Rawat, A. Bhimraj, and M. Fraser, “Experimental approach for seeing through walls using wi-fi enabled software defined radio technology,” *Digital Communications and Networks*, vol. 2, no. 4, pp. 245–255, 2016. https://doi.org/10.1016/j.dcan.2016.09.001.

[96] A. Hugeat, J. Bernard, G. Goavec-Mérou, P.-Y. Bourgeois, and J.-M. Friedt, “Filter optimization for real-time digital processing of radio frequency signals: Application to oscillator metrology,” *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 67, no. 2, pp. 440–449, 2019. https://doi.org/10.1109/tuffc.2019.2945013.

[97] J. Lu, “A new indoor location algorithm based on radio frequency fingerprint matching,” *IEEE Access*, vol. 8, pp. 83290–83297, 2020. https://doi.org/10.1109/access.2020.2989137.

[98] S. Ding, Z. Chen, T. Zheng, and J. Luo, “Rf-net: A unified meta-learning framework for rf-enabled one-shot human activity recognition,” in *Proceedings of the 18th Conference on Embedded Networked Sensor Systems*, pp. 517–530, 2020. https://doi.org/10.1145/3384419.3430735.

[99] F. Abuhoureyah, Y. C. Wong, A. S. B. M. Isira, and M. N. Al-Andoli, “Csi-based location independent human activity recognition using deep learning,” *Human-Centric Intelligent Systems*, vol. 3, no. 4, pp. 537–557, 2023. https://doi.org/10.1007/s44230-023-00047-x.

[100] G. A. S. Surek, L. O. Seman, S. F. Stefenon, V. C. Mariani, and L. d. S. Coelho, “Video-based human activity recognition using deep learning approaches,” *Sensors*, vol. 23, no. 14, p. 6384, 2023. https://doi.org/10.3390/s23146384.

Emily Juliana Costa e Silva Master's Student in Aerospace Engineering at the Federal University of Maranhão. Bachelor's Degree in Computer Science from the Federal University of Maranhão - UFMA. She is currently researcher at the Data Analytics & Artificial Intelligence Laboratory (DARTi Lab). Interested in recommender systems, data analysis, computer vision and machine learning applications .

Kaio Yukio Gonçalves Vieira Guedes Undergraduate student in Computer Science at the Federal University of Maranhão (UFMA).He is a researcher at the DARTi Lab (Laboratory of Data Analysis and Artificial Intelligence). Conducting research in the fields of Artificial Intelligence and Signal Processing.

Pedro Augusto Araújo da Silva de Almeida Nava Alves Phd student in Computer Science at Universidade de São Paulo (USP) on the field of Artificial Intelligence, Optimization and Neural Architecture Search. Interests includes: Artificial Intelligence, Neural Networks, Neural Architecture Search, Signal Processing, Artificial Intelligence applied to Signal Processing and Electroencephalogram Analysis.

Paulo Rogério de Almeida Ribeiro He received the Ph.D. degree in Neuroscience from the University of Tübingen (Germany) in 2015, Master degree in Mechatronics Engineering from the University of Minho (Portugal) in 2012, and the Bachelor degree in Computer Science from the Federal University of Maranhão (Brazil) in 2009. He is an Assistant Professor (tenured position), since 2016, within the Department of Computer Engineering at the Federal University of Maranhão (UFMA) in Brazil. His research interests include Robotics, Autonomous Mobile Robot, Control and Automation Systems, Data Science, Artificial intelligence, Neuroscience and Brain-Computer Interface.

Alex Oliveira Barradas Filho He has a degree in Information Systems (2006) from the Centro Universitário do Maranhão, a master's degree (2009) and a PhD (2015) in Electrical Engineering, with an emphasis on computer science, from the Federal University of Maranhão. He did a post-doctoral internship at the Federal University of Maranhão (2015). He has professional experience (in industry and academia) as a systems analyst, manager, consultant, teacher and researcher. He is currently Adjunct Professor III at the Federal University of Maranhão and a permanent member of the Postgraduate Program in Aerospace Engineering (PPGAERO/UFMA), coordinator of the Specialization Course in Data Analysis and Artificial Intelligence (DTED/UFMA) and vice-coordinator of PPGAERO/UFMA. He is part of the Bioeconomy, Environment, Innovation, Intelligence, Technologies, Education and Health Center (BAITES/UFMA) as an AI Manager and Senior Researcher. He leads the Data Analysis and Artificial Intelligence Laboratory (DARTiLab) and its teams (Stellaris, Sinapse and Game Analysis). He works in the field of data analysis and artificial intelligence, with applications in biofuels, education, aerospace technologies (satellites and predictive models of ionospheric scintillation) and health.