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High-precision indoor localization in multi-level buildings

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***Abstract*—Accurate localization in multi-floor indoor environments is essential for applications such as large-scale inventory management, healthcare, and security systems. However, achieving high-precision tracking with passive Radio Frequency Identification (RFID) tags in these complex settings presents significant challenges, including managing vertical spatial data, reducing signal interference between floors, and maintaining computational efficiency. This paper presents a novel approach that leverages holographic algorithms to enhance the localization accuracy of passive RFID tags in multi-floor buildings. By deploying multiple RFID readers across floors and constructing 3D holographic representations from signal phase data, our approach effectively distinguishes vertical positions, allowing for precise floor-specific tracking. The proposed method achieves an average localization error of approximately 5 cm, even in multi-floor environments, through optimized reader placement and computational overhead reduction. This advancement has broad applications in sectors requiring highly accurate object tracking across large, multi-level indoor spaces, positioning holographic localization as a promising solution for modern multi-floor localization needs.**

***Keywords*—RFID,multi-floor indoor localization, Holographic Algorithm, location-based services, indoor tracking**

I. Introduction

IN today's rapidly evolving technological landscape, the need for precise localization of objects within indoor spaces has become critical for numerous applications, such as inventory management, healthcare, and security. Multi-floor environments, common in office buildings, hospitals, and warehouses, introduce added complexity to localization, particularly when using passive Radio Frequency Identification (RFID) systems. Unlike single-floor settings, multi-floor environments demand accurate tracking not only horizontally but also vertically to differentiate floor levels effectively. However, achieving high-precision indoor localization in these complex settings is challenging due to increased signal interference, multipath effects, and the need for vertical accuracy. Conventional indoor localization methods often struggle to maintain accuracy in multi-floor contexts, where signal attenuation and floor-crossing interference can lead to incorrect positioning. Traditional approaches, such as Received Signal Strength Indication (RSSI) and trilateration, face limitations in vertical positioning and are further complicated by varying structural and environmental factors across floors. These methods often require extensive calibration, additional hardware, and synchronization, which are impractical in large-scale, multi-floor applications. Recent studies highlight the inadequacies of these traditional methods in dynamic environments; for instance, a study demonstrated that integrating pedestrian dead reckoning with landmark recognition significantly improved localization accuracy in multi-floor settings by reducing positioning errors [33] . This paper presents a holographic algorithm-based approach for multi-floor indoor localization using passive RFID technology. By leveraging holographic techniques, this method overcomes the limitations of conventional methods, offering precise 3D spatial mapping that effectively distinguishes objects' vertical positions across floors. Our approach involves the deployment of multiple RFID readers across floors, each dynamically capturing phase-based signal data, enabling the construction of a holographic representation that identifies the location of tagged objects with high accuracy. Through optimized reader placements and reductions in computational overhead, the proposed solution achieves a localization error of approximately 5 cm within a multi-floor environment. In the following sections, we discuss the limitations of existing multi-floor localization approaches, detail our holographic methodology tailored for complex indoor spaces, and present simulation results demonstrating our approach's accuracy and computational efficiency. This work contributes a scalable, precise localization method that meets the demands of modern multi-floor facilities, supporting applications that require seamless tracking and management of assets across multiple levels. Notably, recent advancements in RFID technology have shown promising results in enhancing positioning accuracy through innovative algorithms and system designs [34], [35].

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II. Related works

Indoor localization has been an area of extensive research due to its critical role in applications such as emergency response, healthcare, and security. Extending localization methods to multi-floor environments introduces unique challenges, particularly for achieving high accuracy in vertical positioning, managing signal interference between floors, and maintaining computational efficiency across large spaces. A range of techniques has been developed to address these issues, focusing on multi-dimensional spatial mapping and various signal-based strategies. One primary challenge in multi-floor localization is precise floor detection, a crucial feature in applications where users must be located quickly and accurately in vertical structures. Traditional methods, such as WiFi-based Received Signal Strength Indicator (RSSI) and fingerprinting, have been widely used to estimate 2D and 3D locations. However, these approaches struggle with accuracy in multi-floor environments due to signal attenuation and multipath interference. For instance, Mostafa et al. (2022) provide a comprehensive survey of multi-floor localization systems, underscoring the limitations of conventional RSSI-based approaches and emphasizing the need for robust 3D spatial mapping to overcome signal interference in multi-floor scenarios [36]

Several recent innovations attempt to improve floor estimation accuracy using a fusion of technologies. For example, Nguyen-Huu and Lee (2021) introduce a hybrid system that combines pedestrian dead reckoning (PDR) with WiFi fingerprinting and barometric pressure readings to enhance floor-level identification [37]. Their method utilizes landmarks and activity-based map matching to reduce error accumulation, demonstrating that hybrid systems can effectively calibrate positioning in multi-floor settings. This combination of PDR with WiFi and barometer data provides a promising baseline for floor estimation in multi-story environments, though it requires extensive infrastructure and calibration to maintain accuracy. Another approach incorporates advanced filtering techniques with various signal sources. The Kalman and particle filters have been integrated with multi-source data, such as WiFi, Bluetooth, and inertial sensors, to improve robustness in floor detection. Such systems employ multiple landmarks (e.g., stairs or turning points) and integrate neural network-based methods to refine accuracy further [38]. Although these methods improve performance, they can require significant computational resources and may still encounter challenges with interference across floors, especially in environments with complex architectural layouts. Holographic localization methods present a compelling alternative by leveraging phase-based signal processing to create detailed 3D spatial mappings. These techniques, used extensively in passive RFID localization, can offer centimeter-level accuracy by constructing voxel-based holograms that reduce errors common in multi-floor environments. Unlike traditional signal-strength-based methods, holographic algorithms can mitigate the effects of interference by focusing on phase information, making them especially suitable for applications requiring high precision across multiple floors. By deploying RFID readers at strategic locations and generating 3D holograms that account for floor-specific spatial differences, these systems can achieve superior positioning accuracy with minimal additional infrastructure. This work builds on prior methodologies by incorporating holographic algorithms with passive RFID technology to address the specific demands of multi-floor environments. Through a multi-reader approach and optimized reader placements, this paper proposes an efficient, scalable solution that achieves high localization accuracy in complex, vertically structured spaces.

III. METHODOLOGY

The methodology utilized in this study expands upon our earlier exploration of RFID localization in a two-dimensional region [39]. The holographic localization method initiates by subdividing the area into 3D grids with consistent dimensions. Each point within these 3D grids is defined as a voxel, representing a potential Tag location. This approach transforms the localization area into a finite set of potential Tag positions confined within these voxels. Subsequently, the holographic localization method produces a hologram based on the phase of the signal received by the reader from the tag and the discrete set of voxels. In fact, the phase of the signal reflected by the Tag in a suggested voxel θ_r is theoretically given by equation (1) below [39]:

$$\theta_r = 2\pi * \frac{2d}{\lambda} mod 2\pi \tag{1}$$

where λ is the wavelength of the carrier frequency and d is the distance betwin the suggested voxel and the reader.

At this juncture, the Reader captures the phase value of the received signal, represented as (θ_t), and then contrasts it with the theoretically calculated value (θ_r). This theoretical calculation takes into account the Reader's current position and the anticipated phase alteration attributable to the presence of the Tag. This comparative analysis enables the Reader to ascertain whether the suggested Tag position aligns with the actual position.

If $(\theta_t = \theta_r)$, the Reader infers that the Tag is positioned in the currently computed voxel. However, when $((\theta_t \neq \theta_r))$, the Reader computes the phase disparity between the received and anticipated values, denoted as $\Delta\theta = |\theta_t - \theta_r|$. This phase difference is directly related to the distance between the computed position and the actual Tag location. We define then the voxel value of each position (x_i, y_j, z_k) as described in equation (2) with J is an imaginary number, $e^{J\theta}$ represents a signal of amplitude 1:

$$V(x_i, y_j, z_k) = e^{J\Delta\theta} = e^{J(\theta_t - \theta_r)} \tag{2}$$

Utilizing the voxel values of all the grids of the localization area, a 3D-Matrix called hologram can be generated.For an altitude z_k, the representation of the constructed hologram H_k is as described in the equation (3)below :

$$H_k = \begin{pmatrix} V(x_1, y_b, z_k) & \dots & V(x_a, y_b, z_k) \\ \dots & \dots & \dots \\ V(x_1, y_1, z_k) & \dots & V(x_a, y_1, z_k) \end{pmatrix} \tag{3}$$

However, a single hologram alone cannot precisely determine the Tag's position due to the periodic nature of phase values. Consequently, multiple grids exhibit identical voxel values, making it challenging to pinpoint the Tag's location accurately. To address this challenge, a solution involves the superimposition of multiple holograms. This superimposition is accomplished by establishing a virtual antenna network wherein a Reader is systematically relocated to different positions along the diagonal of one side of the 3D localization area. At each position of the reader, the voxel values for all grids are computed, leading to the creation of a 3D hologram as formulated in the equation (3)

Given that the Reader's antenna is repositioned N times, N holograms are generated and subsequently overlaid or superimposed to refine the localization accuracy. This results in a combined 3D hologram generated by a single Reader in diferent positions. After superimposing the corresponding voxel values at all Reader positions, the final voxel value of the grid is calculated as described in the equation (4) below:

$$\sum_{\ell=1}^{N} V(x_i, y_j, z_k) = M \tag{4}$$

As a result, the Voxel value M of a grid is a number between 0 and N, representing the likelihood of the Tag's location in that position. The grid with the highest voxel value corresponds to the position of the Tag.

To enhance the method's performance even further, we suggest employing five Readers, each navigating along the diagonal of one side of the localization area, as visualized in figure 1 . Specifically, Readers R1 and R3 move in opposing directions, proceeding step by step, on the diagonals of repectively the left and right side faces of the 3D localization area.

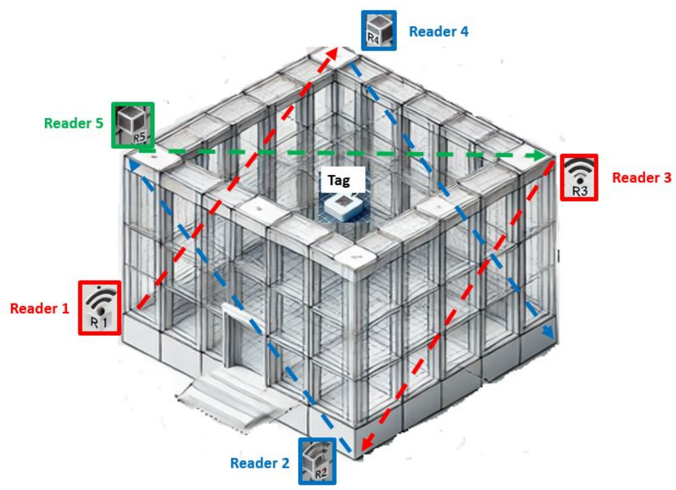

Fig. 1. Localization in multi-floor building

while a similar motion pattern is applied to Readers R2 and R4, finally, Reader R5 is moving along the diagonal of the top side of the localization area. This strategic arrangement allows us to superimpose five holograms, one for each reader. After superimposing the corresponding Voxel values obtained by the five readers at all positions, the Voxel value of a position (x_i, y_j, z_k) is calculated as shown in equation (5) and is varying between 0 and $5 \times N$:

$$\sum_{\alpha=1}^{5} \sum_{\ell=1}^{N} V(x_i, y_j, z_k) = M \tag{5}$$

by regrouping the voxel values of all grids in the localization area in a 3D matrix, we obtain a hologram H'.For an altitude z_k, the two-dimensional representation of the final 3D hologram H' is given by the following 2D hologram H'_k:

$$H'_k = \begin{pmatrix} \sum\limits_{\alpha=1}^{5} \sum\limits_{\ell=1}^{N} |V(x_1, y_b, z_k)| & \dots & \sum\limits_{\alpha=1}^{5} \sum\limits_{\ell=1}^{N} |V(x_a, y_b, z_k)| \\ \dots & \dots & \dots \\ \sum\limits_{\alpha=1}^{5} \sum\limits_{\ell=1}^{N} |V(x_1, y_1, z_k)| & \dots & \sum\limits_{\alpha=1}^{5} \sum\limits_{\ell=1}^{N} |V(x_a, y_1, z_k)| \end{pmatrix} \tag{6}$$

When the coordinates (x_i, y_j, z_k) perfectly align with the actual position of the Tag, the Voxel value in the corresponding grid reaches its maximum. By extracting this maximum value from the 3D hologram H', which is formed by combining 2D matrices H'_k as described in equation (6), we can precisely determine the grid associated with the estimated Tag location.

To make this Tag localization method suitable for practical use, we've devised an algorithm that efficiently oversees the entire localization process within indoor environments. This algorithm has been meticulously crafted and put into operation to ensure the effective implementation of the proposed 3D Holographic Multi-Reader (3DHMR) method for Tag localization.

Algorithm 1, tailored for 3D holographic localization, is a novel approach for simulating the localization of multiple tags within a three-dimensional space. It operates through a series of key steps: initialization of parameters such as reader movements, voxel dimensions, and the dimensions of the localization area; generation of random tag positions; initialization of a holographic representation; and movement of five readers in a predetermined pattern. During reader movement, the algorithm calculates holographic contributions from each reader and updates a global hologram. After all reader movements are completed, the algorithm estimates the tag positions by evaluating the maximum voxel value in the hologram and calculates the location error for each tag. This iterative process continues until all tags have been localized. This algorithm holds promise for applications in real-world localization scenarios, such as tracking objects within confined spaces, and offers valuable insights into the development of multi-reader holographic systems for localization purposes.

IV. Simulation Results and discussion

In this section, we present the outcomes of our simulations that revolve around indoor holographic localization using a system comprising five RFID readers. We conducted these simulations utilizing the Python programming language on a

Algorithm 1 Multi-Reader Holographic Localization Algorithm

$R_{\text{mvt}} \leftarrow 4$ (▷) $R_{\text{mvt}} : Readersmovementsnumber$
$V_d \leftarrow 10\,\text{cm}$ (▷) $V_d : Voxeldimension$
$A_{\text{dim}} \leftarrow 900\,\text{cm}$ (▷) $A_{\text{dim}} : Horizontaldimensions$
$H \leftarrow 300\,\text{cm}$ (▷) $H : HeightoflocalizationArea$
$K \leftarrow 100$ (▷) $NumberofTagstoLocalize$

while $K \neq 0$ **do**
  $(X_{\text{tag}}, Y_{\text{tag}}, Z_{\text{tag}}) \leftarrow \text{Randint}(A_{\text{dim}}, A_{\text{dim}}, H)$
  (▷) Generate a tag position randomly
  $H_g \leftarrow \text{zeros}\left(\frac{A_{\text{dim}}}{V_d}, \frac{A_{\text{dim}}}{V_d}, \frac{H}{V_d}\right)$
  (▷) $H_g : InitialHologram$
  $R1_{\text{pos}} \leftarrow (0, 0, 0)$ (▷) $InitialpositionforReader1$
  $R2_{\text{pos}} \leftarrow (A_{\text{dim}}, 0, 0)$ (▷) $InitialpositionforReader2$
  $R3_{\text{pos}} \leftarrow (A_{\text{dim}}, A_{\text{dim}}, H)$ (▷) $InitialpositionforReader3$
  $R4_{\text{pos}} \leftarrow (0, A_{\text{dim}}, H)$ (▷) $InitialpositionforReader4$
  $R5_{\text{pos}} \leftarrow (0, A_{\text{dim}}, H)$ (▷) $InitialpositionforReader5$
  while $R_{\text{mvt}} \neq 0$ **do**
    $Hol \leftarrow H_1 + H_2 + H_3 + H_4 + H_5$
    $H_g \leftarrow H_g + Hol$
  (▷) $MovereaderswithonestepasdescribedinFigure(1)$
    $R1_{\text{pos}} \leftarrow R1_{\text{pos}} + (0, \frac{A_{\text{dim}}}{R_{\text{mvt}}}, \frac{H}{R_{\text{mvt}}})$
    $R2_{\text{pos}} \leftarrow R2_{\text{pos}} + (-\frac{A_{\text{dim}}}{R_{\text{mvt}}}, 0, \frac{H}{R_{\text{mvt}}})$
    $R3_{\text{pos}} \leftarrow R3_{\text{pos}} + (0, -\frac{A_{\text{dim}}}{R_{\text{mvt}}}, -\frac{H}{R_{\text{mvt}}})$
    $R4_{\text{pos}} \leftarrow R4_{\text{pos}} + (\frac{A_{\text{dim}}}{R_{\text{mvt}}}, 0, -\frac{H}{R_{\text{mvt}}})$
    $R5_{\text{pos}} \leftarrow R5_{\text{pos}} + (\frac{A_{\text{dim}}}{R_{\text{mvt}}}, \frac{A_{\text{dim}}}{R_{\text{mvt}}}, 0)$
    $R_{\text{mvt}} \leftarrow R_{\text{mvt}} - 1$
  end while
  /* Check for the maximum voxel value of the Hologram H_g which corresponds to the estimated location of the Tag $(\tilde{X}_{\text{tag}}, \tilde{Y}_{\text{tag}}, \tilde{Z}_{\text{tag}})$ */
  $LE \leftarrow \sqrt{(X_{\text{tag}} - \tilde{X}_{\text{tag}})^2 + (Y_{\text{tag}} - \tilde{Y}_{\text{tag}})^2 + (Z_{\text{tag}} - \tilde{Z}_{\text{tag}})^2}$
  (▷) $LE : LocationError$
  $K \leftarrow K - 1$
end while

standard personal computer equipped with an Intel i7-7500U processor operating at 2.7 GHz and boasting 8 GB of RAM. Our evaluation of localization performance hinged on two pivotal metrics: accuracy and computational efficiency.

Our primary objective during this evaluation was to validate the effectiveness of our proposed 3D holographic localization method while gaining insights into how various parameters influence both accuracy and the time required for localization. These two aspects, accuracy and time, hold utmost importance as they exert a substantial impact on the reliability and quality of applications reliant on localization results. The significance of achieving high accuracy cannot be overstated, as it directly translates into precise localization, thus enabling applications to provide enhanced services and elevate user experiences. For instance, in a retail setting, having precise knowledge of a customer's exact location can facilitate personalized shopping experiences. Similarly, in healthcare, the accurate tracking of medical equipment and personnel locations proves indispensable for ensuring the smooth operation of healthcare facilities. On the flip side, imprecise localization results carry the risk of introducing errors and misinterpretations, consequently undermining the overall effectiveness and efficiency of an application. Hence, professionals and researchers in the indoor localization domain persistently strive to innovate and refine methods for achieving greater accuracy, thereby bolstering the dependability and user-friendliness of indoor localization applications.

Within this research, we delve into a comprehensive assessment of our localization method's performance, addressing four key factors. Initially, we delve into an investigation of the number of reader movements and their profound influence on both localization time and accuracy. Subsequently, we turn our attention to the voxel dimensions aiming to unravel the impact of grid size variations, which play a crucial role in the localization process, on the obtained results. Lastly, we embark on an exploration of "Localization Area Dimensions" with the objective of dissecting how adjustments to the horizontal and vertical dimensions of the localization area contribute to the overall effectiveness and efficiency of our holographic localization approach.

A. Localization Results

In the initial phase, the selection of the number of reader movements necessitates careful consideration due to its direct impact on both the precision of localization and the time required for localization. To clarify, a higher number of reader movements promotes a more efficient convergence of the hologram to the actual tag position, albeit at the cost of increased algorithmic processing time. The figures 2 and 3 vividly demonstrate how the average localization error and localization duration can exhibit variations across three case scenarios: when employing three reader movements, localization time is minimized, albeit at the expense of compromised accuracy. Conversely, with four reader movements, although the localization time experiences a slight increase, the accuracy of localization significantly improves. That's why we have chosen to keep the number of reader movements at 4 for the remainder of the work.

Following that, a research investigation was initiated to delve into the consequences of varying voxel dimension values

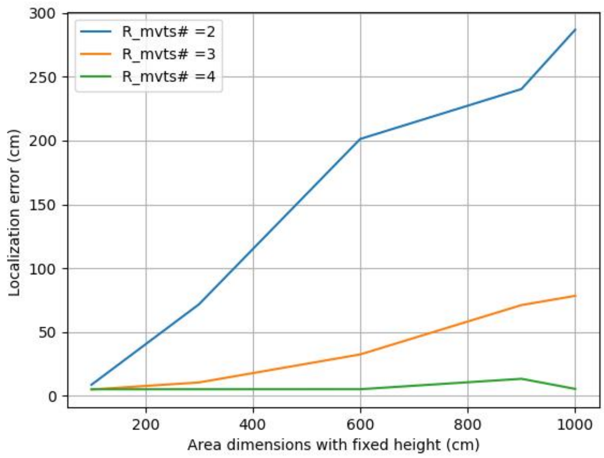

Fig. 2. localization error (cm) by horizental dimensions, Height = 300 cm, Voxel dimensions=10 cm

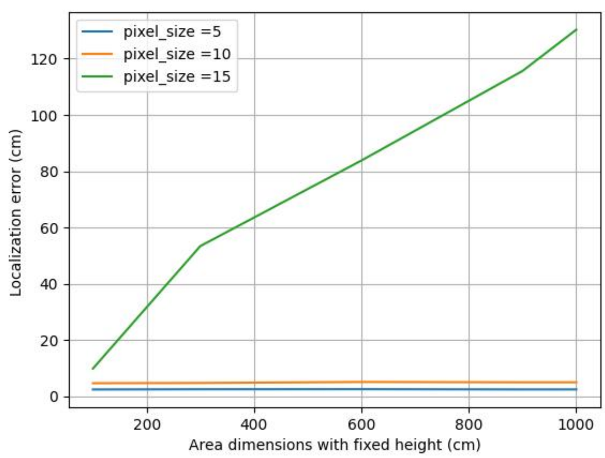

Fig. 4. localization error (cm) by horizental dimensions, Height = 300 cm

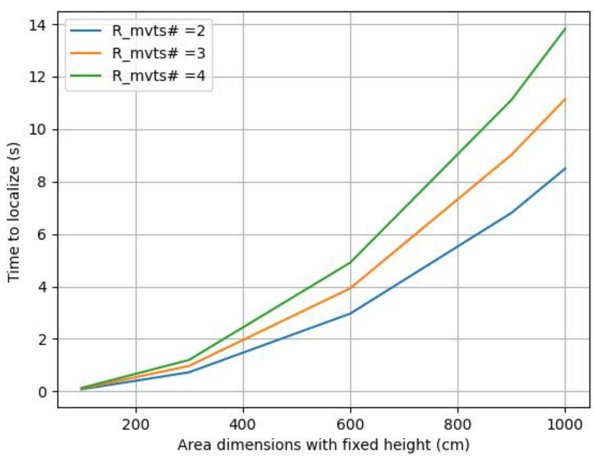

Fig. 3. localization time (s) by horizental dimensions, Height = 300 cm, Voxel dimensions=10 cm

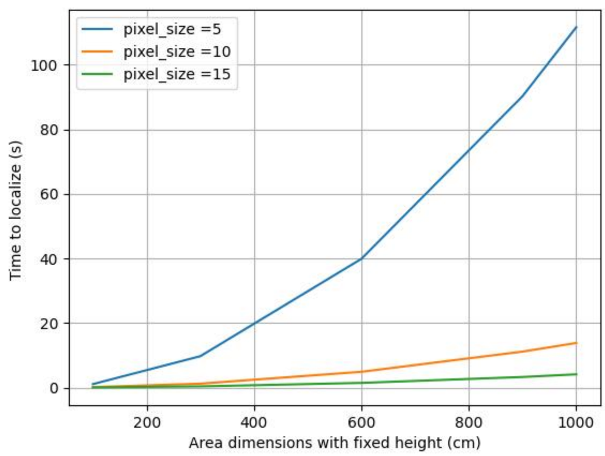

Fig. 5. localization time (s) by horizental dimensions, Height = 300 cm

on the effectiveness of the proposed algorithm. As described in figures 4 and 5, opting for a 5cm voxel dimension yields remarkably precise localization, albeit with a significant increase in calculation time. Conversely, when employing a 10cm voxel dimension, we can attain a reasonable level of accuracy while keeping the localization time within acceptable bounds.That's why we have decided to use the 10 cm voxel dimensions for the remainder of the work.

For a number of reader movement steps set to 4 and a voxel dimension of 10cm, the proposed algorithm is simulated for different localization area dimensions and for three fixed heights. As shown in the figure 6 and figure 7, for a localization area with a height of 3 meters, the average localization error ranges from 5 cm to 10 cm, but the localization time increases with the horizontal dimensions of the area. For instance, in the case of an area measuring $10 \times 10 \times 3$ m^3 , the algorithm can determine the tag's location with an average error of just 5 cm, exemplifying its exceptional precision. Nonetheless, it is important to acknowledge that achieving this level of accuracy in a 3D space necessitates a computation time of 12 seconds.

These findings underscore the practical significance of the algorithm's outcomes, showcasing its potential in real-world applications where both precision and computational efficiency are paramount. Such applications include healthcare, manufacturing, warehousing, logistics, and supply chain management

B. Performances indicators

To verify the accessibility and dependability of our solution, as delineated in Table 1, we conducted a comprehensive comparative analysis with various existing methodologies, including IWOA [23] method for Tag localization., RFID-UWB [24], 3DinSAR [30], 3DRLA [28], Lobain [29], PhaseRelock

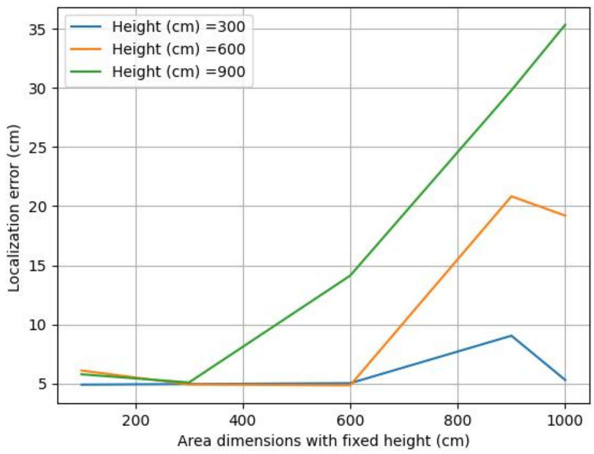

Fig. 6. localization error (cm) by horizental dimensions, voxel dimensions =10 cm, readers steps =4

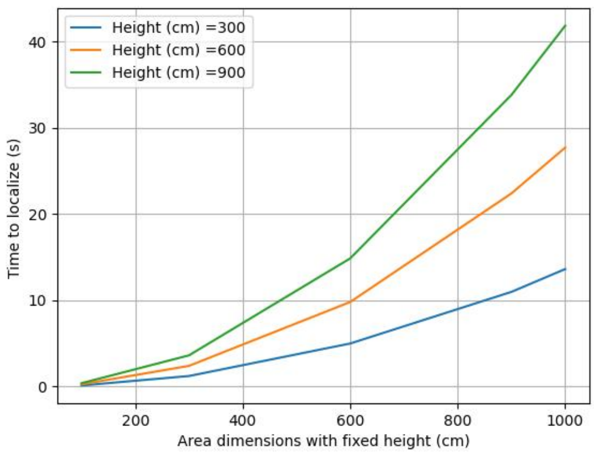

Fig. 7. localization time (s) by horizental dimensions, voxel dimensions =10 cm, readers steps =4

[25], Wifi Time of Flight (ToF) [31] , and RFID polarization phase [27].

Within these methodologies, the 3DinSAR approach [30], introduced by Lanxin Qiu and colleagues in 2016, employs interferometric synthetic aperture radar (InSAR) principles to simulate a multiantenna array by moving antennas in the plane for positioning. Nevertheless, in contrast to our methodology, 3DinSAR exhibits notable errors and deployment challenges.

Another approach proposed by Anastasios Tzitzis and colleagues in 2019, the Phase Relock method [25], integrates a single antenna onto a robot, simulating an antenna array through the robot's movement. Despite its lower computational complexity and higher real-time performance compared to the 3DinSAR algorithm, it suffers from increased errors, making it an unsuitable option for positioning.

TABLE I
PERFORMANCE COMPARISON

Method	Area dimension	Localization error
3DinSAR [30]	$1.5 \times 1.5 \times 1.5\,\mathrm{m}^3$	24 cm
Phase ReLock [25]	$4 \times 4 \times 4\,\mathrm{m}^3$	54.86 cm
3DLRA [28]	—	10.2 cm
Lobain [29]	$3 \times 3 \times 2.7\,\mathrm{m}^3$	6.7cm
SAR [26]	$5 \times 2.5 \times 2\,\mathrm{m}^3$	58.5 cm
Polarization phase [27]	$2 \times 2 \times 2\,\mathrm{m}^3$	9 cm
RFID-UWB [24]	$6 \times 6 \times 6\,\mathrm{m}^3$	115 cm
IWOA [23]	$5 \times 5 \times 6\,\mathrm{m}^3$	7.85 cm
Wi-Fi Time of Flight [31]	—	17 cm
3D Multialteration [32]	$6 \times 4 \times 1.5\,\mathrm{m}^3$	13 cm
3D-HMR (ours)	$\mathbf{10 \times 10 \times 3m^3}$	**5 cm**

In 2020, Shuyan Cheng and colleagues introduced the 3DLRA method [28], utilizing deep learning with phase, received signal strength, and time stamp as features input into a convolutional neural network (CNN) for positioning. While it achieves high accuracy, deep learning-based methods often require extensive training time and are heavily dependent on the environment, lacking portability.

In 2022, Hassan Bardareh and Osama Moselhi proposed a combined RFID and UWB method for indoor localization of materials in construction [24]. However, with an average positioning error of about 115 cm in a 3D environment with dimensions of $6x6x6m^3$, this level of accuracy proves unsuitable for applications requiring high precision in indoor localization.

Also in 2022, Xianmeng Meng and colleagues introduced a 3D indoor VLP system based on an improved whale optimization algorithm (IWOA) [23]to mitigate errors caused by photodiode (PD) rotation. The average error in 3D positioning for this method was 7.85 cm in a localization area with dimensions of $5x5x6m^3$.

In the most recent work, Doan Perdana and colleagues (2023) proposed a High-Accuracy Indoor-Positioning System based on combining Wi-Fi Time of Flight (ToF) and a deep learning approach [31]. The localization error for this method was approximately 17 cm.

In comparison to these methods, the proposed 3D holographic multi-reader (3DHMR) method in this paper is significantly more effective in achieving accurate indoor localization than the methods reported in previous studies. Table 1 highlights that the proposed method has achieved the best location estimation accuracy, outperforming all other methods with an exceptional localization error of only 5 cm in a $10 \times 10 \times 3$ m^3 indoor environment.

C. Discussion

The proposed passive RFID-based localization system, enhanced by holographic algorithms, proved effective for multi-floor indoor localization. The integration of phase-based localization and voxel-based mapping addressed common multi-floor challenges, such as vertical differentiation and interference from floor-crossing signals. Compared to conventional methods relying on RSSI or fingerprinting, the holographic approach demonstrated superior resilience to signal instability and multipath interference, contributing to high accuracy even in challenging conditions. In practical applications, this method could be particularly useful for asset tracking, navigation, and emergency response within multi-floor buildings, where vertical positioning accuracy is essential. However, some limitations were identified, such as the dependency on initial calibration data for structural and environmental variations across floors. Future work could explore adaptive calibration models to further enhance robustness and reduce the need for extensive initial setup. Overall, these results highlight the effectiveness and scalability of the holographic localization approach, positioning it as a strong candidate for precise multi-floor indoor localization using passive RFID technology.

V. Conclusion

This paper introduced a high-precision indoor localization system tailored for multi-level buildings, leveraging the capabilities of passive RFID technology enhanced by holographic algorithms. The strategic deployment of multiple RFID readers and the generation of 3D holographic representations have demonstrated a localization accuracy of 5 cm, even in complex multi-floor environments. This method effectively addresses key challenges such as vertical positioning, signal interference, and computational efficiency, positioning it as a robust solution for diverse applications, including asset tracking, healthcare, security, and logistics in multi-level facilities.

The results underscore the scalability and practicality of the proposed system, offering a transformative improvement over conventional localization methods. By optimizing reader placement and employing a voxel-based mapping approach, the system achieves unparalleled accuracy while maintaining computational feasibility. Future research will focus on further refining the calibration process and adapting the system to dynamically changing environments, ensuring even broader applicability and reliability.

References

[1] Tripicchio, P., D'Avella, S. Unetti, M. Efficient localization in warehouse logistics: a comparison of LMS approaches for 3D multilateration of passive UHF RFID tags. Int J Adv Manuf Technol 120, 4977–4988 (2022). https://doi.org/10.1007/s00170-022-09018-1

[2] T. Sanpechuda and L. Kovavisaruch, "A review of RFID localization: Applications and techniques," 2008 5th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology, Krabi, Thailand, 2008, pp. 769-772, https://doi.org/10.1109/ECTICON.2008.4600544

[3] Moutaz Haddara, Anna Staaby,RFID Applications and Adoptions in Healthcare: A Review on Patient Safety,Procedia Computer Science, Volume 138,2018,Pages 80-88,ISSN 1877-0509, https://doi.org/10.1016/j.procs.2018.10.012

[4] K. Vidyasagar and Ssit and Sathupally and G. Naveen Balaji and Karthikeyan Reddy,RFID-GSM imparted School children Security System,Foundation of Computer Science FCS, New York, USA Volume 2 – No.2, June 2015, https://doi.org/10.5120/cae-1673

[5] Rácz-Szabó A, Ruppert T, Bántay L, Löcklin A, Jakab L, Abonyi J. Real-Time Locating System in Production Management. Sensors (Basel). 2020 Nov 26;20(23):6766. https://doi.org/10.3390/s20236766. PMID: 33256090; PMCID: PMC7730894.

[6] Rostamian, Majed ,Wang, Jing , Bolic, Miodrag. (2017). An Accurate Passive RFID Indoor Localization System Based on Sense-a-Tag and Zoning Algorithm. https://doi.org/10.1007/978-3-319-51204-422

[7] S. Subedi, E. Pauls and Y. D. Zhang, "Accurate Localization and Tracking of a Passive RFID Reader Based on RSSI Measurements," in IEEE Journal of Radio Frequency Identification, vol. 1, no. 2, pp. 144-154, June 2017, https://doi.org/10.1109/JRFID.2017.2765618.

[8] Shi W, Du J, Cao X, Yu Y, Cao Y, Yan S, Ni C. IKULDAS: An Improved kNN-Based UHF RFID Indoor Localization Algorithm for Directional Radiation Scenario. Sensors (Basel). 2019 Feb 25;19(4):968. https://doi.org/10.3390/s19040968. PMID: 30823553; PMCID: PMC6413016.

[9] D. A. Savochkin, "Simple approach for passive RFID-based trilateration without offline training stage," 2014 IEEE RFID Technology and Applications Conference (RFID-TA), Tampere, Finland, 2014, pp. 159-164, doi: 10.1109/RFID-TA.2014.6934220.

[10] Liu F, Zhong D, Luo S. A three-dimensional localization algorithm for passive radio-frequency identification device tag. International Journal of Distributed Sensor Networks. 2017;13(10). https://doi.org/10.1177/1550147717736176

[11] Mondal S, Kumar D, Chahal P. Recent Advances and Applications of Passive Harmonic RFID Systems: A Review. Micromachines (Basel). 2021 Apr 12;12(4):420. https://doi.org/10.3390/mi12040420. PMID: 33921474; PMCID: PMC8069358.

[12] Liu X, Cen J, Zhan Y, Tang C. An efficient crowdsourcing-based approach for fingerprint database updating. International Journal of Distributed Sensor Networks. 2019;15(6). https://doi.org/10.1177/1550147719858512

[13] Khandker, S.; Torres-Sospedra, J.; Ristaniemi, T. Analysis of Received Signal Strength Quantization in Fingerprinting Localization. Sensors 2020, 20, 3203. https://doi.org/10.3390/s20113203

[14] Tian Sun, Lingxiang Zheng, Ao Peng, Biyu Tang, Gang Ou,Building information aided Wi-Fi fingerprinting positioning system, Computers and Electrical Engineering,Volume 71,2018,Pages 558-568,ISSN 0045-7906, https://doi.org/10.1016/j.compeleceng.2018.08.008

[15] Wen, Yutian and Tian, Xiaohua and Wang, Xinbing and Lu, Songwu. (2015). Fundamental limits of RSS fingerprinting based indoor localization. 2479-2487. https://doi.org/10.1109/INFOCOM.2015.7218637

[16] Yoo J. Multiple Fingerprinting Localization by an Artificial Neural Network. Sensors (Basel). 2022 Oct 3;22(19):7505. https://doi.org/10.3390/s22197505 PMID: 36236604; PMCID: PMC9573177.

[17] Paige Wenbin Tien, Shuangyu Wei, Jo Darkwa, Christopher Wood, John Kaiser Calautit, Machine Learning and Deep Learning Methods for Enhancing Building Energy Efficiency and Indoor Environmental Quality – A Review, Energy and AI,Volume 10,2022,100198,ISSN 2666-5468, https://doi.org/10.1016/j.egyai.2022.100198

[18] Bohr A, Memarzadeh K. The rise of artificial intelligence in healthcare applications. Artificial Intelligence in Healthcare. 2020:25–60. https://doi.org/10.1016/B978-0-12-818438-7.00002-2 Epub 2020 Jun 26. PMCID: PMC7325854.

[19] Linardatos P, Papastefanopoulos V, Kotsiantis S. Explainable AI: A Review of Machine Learning Interpretability Methods. Entropy (Basel). 2020 Dec 25;23(1):18. https://doi.org/10.3390/e23010018 PMID: 33375658; PMCID: PMC7824368.

[20] Cuomo, S., Di Cola, V.S., Giampaolo, F. et al. Scientific Machine Learning Through Physics–Informed Neural Networks: Where we are and What's Next. J Sci Comput 92, 88 (2022). https://doi.org/10.1007/s10915-022-01939-z

[21] Taye, M.M. Understanding of Machine Learning with Deep Learning: Architectures, Workflow, Applications and Future Directions. Computers 2023, 12, 91. https://doi.org/10.3390/computers12050091

[22] Ajroud, C., Hattay, J. and Machhout, M. A novel holographic technique for RFID localization in indoor environments. Multimed Tools Appl (2023). https://doi.org/10.1007/s11042-023-16539-8

[23] Meng, X.; Jia, C.; Cai, C.; He, F.; Wang, Q. Indoor High-Precision 3D Positioning System Based on Visible-Light Communication Using Improved Whale Optimization Algorithm. Photonics 2022, 9, 93. https://doi.org/10.3390/photonics902009

[24] Bardareh H, Moselhi O (2022). An integrated RFID–UWB method for indoor localization of materials in construction, ITcon Vol. 27, pg. 642-661, https://doi.org/10.36680/j.itcon.2022.032

[25] A. Tzitzis, S. Megalou, S. Siachalou, E. Tsardoulias, T. Yioultsis and A. G. Dimitriou, "3D Localization of RFID Tags with a Single Antenna by a Moving Robot and "Phase ReLock"," 2019 IEEE International Conference on RFID Technology and Applications (RFID-TA), Pisa, Italy, 2019, pp. 273-278, https://doi.org/10.1109/RFID-TA.2019.8892256

[26] A. Motroni et al., "SAR-Based Indoor Localization of UHF-RFID Tags via Mobile Robot," 2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN), Nantes, France, 2018, pp. 1-8, https://doi.org/10.1109/IPIN.2018.8533847

[27] Shi, W., Chen, Z., Zhao, K. et al. 3D target location based on RFID polarization phase model. J Wireless Com Network 2022, 17 (2022). https://doi.org/10.1186/s13638-022-02102-w
[28] Cheng, S.; Wang, S.; Guan, W.; Xu, H.; Li, P. 3DLRA: An RFID 3D Indoor Localization Method Based on Deep Learning. Sensors 2020, 20, 2731. https://doi.org/10.3390/s20092731
[29] M. Liu, H. Wang, Y. Yang, Y. Zhang, L. Ma and N. Wang, "RFID 3-D Indoor Localization for Tag and Tag-Free Target Based on Interference," in IEEE Transactions on Instrumentation and Measurement, vol. 68, no. 10, pp. 3718-3732, Oct. 2019, https://doi.org/10.1109/TIM.2018.2879678
[30] L. Qiu, Z. Huang, N. Wirström and T. Voigt, "3DinSAR: Object 3D localization for indoor RFID applications," 2016 IEEE International Conference on RFID (RFID), Orlando, FL, USA, 2016, pp. 1-8, https://doi.org/10.1109/RFID.2016.7488026
[31] Doan Perdana, I Made Arya Indra Tanaya, Abdul Aziz Marwan, Fityanul Akhyar, "Evaluation of a High-Accuracy Indoor-Positioning System with Wi-Fi Time of Flight (ToF) and Deep Learning", Journal of Computer Networks and Communications, vol. 2023, Article ID 6777759, 14 pages, 2023. https://doi.org/10.1155/2023/6777759
[32] P. Tripicchio, S. D'Avella, M. Unetti, Efficient localization in warehouse logistics: a comparison of LMS approaches for 3D multilateration of passive UHF RFID tags. Int J Adv Manuf Technol 120, 4977–4988 (2022). https://doi.org/10.1007/s00170-022-09018-1
[33] Nguyen-Huu Khanh, Lee Seon-Woo, A Multi-Floor Indoor Pedestrian Localization Method Using Landmarks Detection for Different Holding Styles, Mobile Information Systems, 2021, 6617417, 15 pages, 2021. https://doi.org/10.1155/2021/6617417
[34] P Tan, T.H. Tsinakwadi, Z. Xu, H. Xu, Sing-Ant: RFID Indoor Positioning System Using Single Antenna with Multiple Beams Based on LANDMARC Algorithm. Appl. Sci. 2022, 12, 6751. https://doi.org/10.3390/app12136751
[35] Ali Montaser, Osama Moselhi,RFID indoor location identification for construction projects, Automation in Construction,Volume 39,2014,Pages 167-179,ISSN 0926-5805, https://doi.org/10.1016/j.autcon.2013.06.012
[36] Mostafa Sherif, Harras Khaled, Youssef Moustafa. (2022). A Survey of Indoor Localization Systems in Multi-Floor Environments. https://doi.org/10.36227/techrxiv.20439648.v1
[37] Nguyen-Huu Khanh, Lee Kyungho, Lee Seon-Woo. (2017). An indoor positioning system using pedestrian dead reckoning with WiFi and map-matching aided. 1-8. https://doi.org/10.1109/IPIN.2017.8115898
[38] P. Tan, T.H. Tsinakwadi, Z. Xu, H. Xu, Sing-Ant: RFID Indoor Positioning System Using Single Antenna with Multiple Beams Based on LANDMARC Algorithm. Appl. Sci. 2022, 12, 6751. https://doi.org/10.3390/app12136751
[39] C. Ajroud, J. Hattay, and M. Machhout, A novel holographic technique for RFID localization in indoor environments. Multimed Tools Appl (2023). https://doi.org/10.1007/s11042-023-16539-8