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RESEARCH ARTICLE

A UHF Passive RFID Tag Position Estimation Approach Exploiting Mobile Robots: Phase-Only 3D Multilateration Particle Filters With No Unwrapping

PAOLO TRIPICCHIO [1], (Senior Member, IEEE), SALVATORE D'AVELLA [1], (Member, IEEE), MATTEO UNETTI [1], ANDREA MOTRONI [2], (Member, IEEE), AND PAOLO NEPA [2], (Senior Member, IEEE)

[1]Mechanical Intelligence Institute, Department of Excellence in Robotics and AI, Scuola Superiore Sant'Anna, 56127 Pisa, Italy
[2]Department of Information Engineering, University of Pisa, 56126 Pisa, Italy

Corresponding author: Paolo Tripicchio (paolo.tripicchio@santannapisa.it)

ABSTRACT Radio-frequency identification is one of the Internet of Things' most promising technologies and has been recently used in combination with mobile robots for logistics in business and retail applications. This manuscript deals with the localization of passive UHF RFID tags within industrial environments employing receiving antennas mounted on a mobile robot by using multilateration techniques that exploit narrowband phase-delay measurements. Two distinct Particle Filter approaches are presented to solve the 3D multilateration problem online and take advantage of a synthetic aperture created by the motion of the robot in the environment. One of the methods can operate in the presence of acquisition jumps since it does not rely on an unwrapping technique. Experimental results show promising performance concerning the recent literature. Moreover, the presented approach enables robust estimations concerning signal loss due to communication disturbances in noisy environments, typical of the industrial setting.

INDEX TERMS Radio frequency identification (RFID), industry 4.0, mobile robot, phase unwrapping, warehouse, logistics, particle filter.

I. INTRODUCTION

In the last years, Industry 4.0 aims to advance the current industrial environment by exploiting emerging pillar technologies to automate some human jobs like bin picking [1] or quality inspection [2] throughout autonomous and intelligent systems [3] and computer vision endowed with artificial intelligence techniques [4], even though many companies view such technologies as "black boxes" [5]. Furthermore, the Internet of Things (IoT) [6] has brought widespread benefits to machine-machine communication, self-monitoring, reliability in robot localization [7], and visual control technologies for enabling remote operations [8].

Wi-Fi and Bluetooth signal strength indicators [9], [10], as well as time of flight metrics common to optical [11], ultrasonic [12], and Ultra Wide Band (UWB) communications [13], [14], have recently been used to stimulate the adoption of successful IoT solutions in industrial environments. Due to its low cost, radio-frequency identification (RFID) is one of the Internet of Things' most promising technologies and it is frequently used in business and retail services. Furthermore, it has the advantage of associating a unique identifier to each tag and it is not impacted by lighting conditions like machine vision techniques, allowing it to be

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used even in dark surroundings. It is worth mentioning the possibility of robot tracking algorithms development based on passive RFID landmarks as in [15].

This work addresses the challenge of RFID tag localization, namely the 2π phase-cyclicity [16] and the presence of phase offsets [17], by employing multilateration algorithms that use narrowband phase-delay measurements exploiting RFID signals to estimate the location of passive RFID tags. A synthetic aperture is obtained by moving the receiving antenna in the environment through a mobile robot platform. The system gets the RFID tag phase readings and develops a distance model. In 3D space, the solution of a multilateration problem is comparable to the computation of the intersection of two-sheeted hyperboloids. The hyperboloid surface can be obtained by knowing the robot pose at two separate time instants and the phase difference between the two measurements. With further measurements, additional hyperboloid surfaces can be generated and, computing intersections between them, the positions of the tags can be reconstructed with an increasing degree of accuracy.

In formulating the multilateration problem through a Taylor series expansion, particle filtering methods are applied for localization estimation. One of the presented methods exploits direct phase measurements thus overcoming consistency issues that are typical of phase-unwrapping based methods. Experimental tests employing synthetic and real measurements have been conducted to evaluate the performance of the proposed methods. Virtual measurements have been generated analytically in a simple scenario simulated in Matlab and in a complex warehouse simulation through the use of the Gazebo simulator. On such datasets, Monte Carlo simulations have been run with varying noise conditions comprising effects related to signal reflections, multipath routing, thermal, and electrical noises. Real acquisitions have been conducted in a laboratory environment to validate further the methods concerning real noise conditions on a specific setup.

Recent literature on radiofrequency identification in localization and tracking applications is discussed in section II. Section III will introduce the proposed four different particle filter methods, and it will be followed by a discussion on the performed tests and experimental results in section IV. Conclusions and final remarks are drawn in the closing section V.

II. STATE OF THE ART

Due to their low cost and the possibility of being employed in massive quantities, passive RFID tags are favored options since they require minimal electronic components and no power supply. RFID tags produce a backscatter signal with a specific strength (RSS - Received Signal Strength) in dBm when interrogated. Additionally, the propagation of their signal in free space may be predicted using a conventional radio frequency propagation model [18]. This indicator could be used to estimate the tag's approximate distance from the reading antenna. Since omnidirectional antennas present homogeneous radiation patterns, the signal attenuation can be formulated as a function of the distance. This signal is commonly affected by destructive or constructive interference phenomena, absorption, and reflection. Unfortunately, the antennae of tags and readers are directional, adding yet another source of error that, when combined with multipath effects, may render the distance estimation unreliable. Hence, due to the requirement to accurately characterize several parameters like reader and tag antenna radiation patterns and alignments, RSS measurements are often combined with other approaches in recent literature [19].

RFID phase-based distance estimations rely on quick, repeated measurements of the RFID signal phase. The time of arrival (TOA) and Time difference of arrival (TDOA) are not applicable with commercial RFID devices due to a lack of signal bandwidth and synchronization between the reader and tags. The phase difference of arrival (PDOA) [20] can be used to estimate distances (although with ambiguity). PDOA permits measurements that can be collected using equipment already used in industries for logging items and that are relatively insensitive to reflections and multipath effects. The angle of arrival (AOA) approach [21] helps to determine the direction in which tags are traveling and requires specialized setups to achieve acceptable accuracy. However, their use in industrial applications is constrained by the need for particular setups and an understanding of the antenna properties.

Concerning PDOA, an important aspect to take into consideration is that the computed phase difference will surpass 2π if the robot motion is greater than a quarter of wavelength between two subsequent measurements, generating ambiguity with the same received value at different distances. In situations where the reader value exhibits jumps, the phase angle signal should be conveniently unwrapped to become continuous to employ the phase difference measurement effectively. Unwrapping is a technique that has been used in RFID localization to remove phase cycle ambiguity and achieve promising results [22].

Alternatively, strategies that utilize a single moving antenna to simulate a synthetic aperture radar (SAR), have been suggested in recent years to minimize the necessity for numerous antenna systems and to improve the accuracy of localization [23] while solving the phase-measurements ambiguity. SAR techniques were originally intended for offline reconstruction due to the grid-based nature of such algorithms [24]. Recently, online estimation results have been obtained using optimization algorithms like Particle Swarm Optimization (PSO) [25], which, however, do not guarantee convergence of the result due to the non-convexity of the objective function investigated to find the position of the tag. A mobile robot can move the antenna around the environment, making it possible to sort RFID tags in libraries, production lines, or offices [26] and even localize itself [27]. In any case, the RFID tag localization problem exceeds that of sorting in complexity and requires more effort from an algorithmic and computational burden point of view.

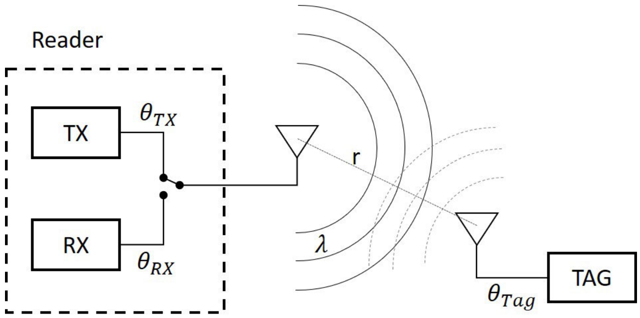

FIGURE 1. Simplified scheme of the elements involved in an RFID communication scheme. r is the range between the reader and tags antennas. θ_{TX}, θ_{RX}, and θ_{Tag} are characteristics that depend upon the electronic circuits and are contained in the phase offset ϕ_0. TX represents the transmitting electronics and RX the receiving electronics components.

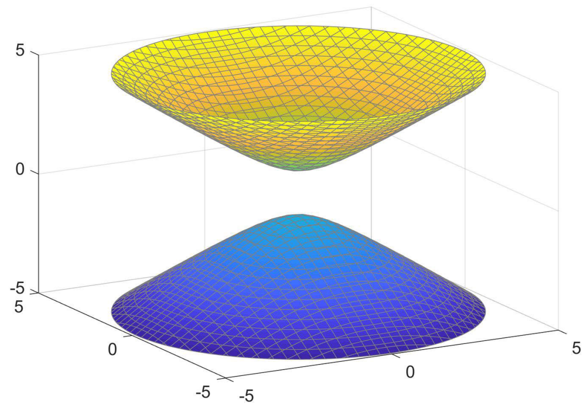

FIGURE 2. Two sheeted hyperboloid in canonical form.

A different PDOA approach offering limited issues caused by phase ambiguity consists of exploiting geometrical relations for the localization of RFID tags and results in computing or estimating the intersections between multiple hyperbolae [28]. A hyperbola is mathematically defined as a set of points that have a specific geometrical relation with other two points in the space, called foci since the difference of their distance with each of them is constant. By this definition, if two antennas are exactly located on the foci, then the tag belongs to the associated hyperbolic curve and accurate position estimation can be obtained by the intersection of multiple conics. Compared to the SAR approaches, these techniques typically exhibit lower elaboration time.

A large number of RFID approaches deal with tag localization in two dimensions since application environments like warehouses store goods and products in scaffolds, shelves, or boxes and thus 2D solutions can efficiently localize them. However, recent approaches to 3D localization can be found in the literature. For instance, in [29] and [30] the authors use backscattered signal phase and synthetic apertures to estimate the 3D position of passive RFID tags using two RFID reader antennas on a mobile robot. Neither large phased array antennas nor reference tags are needed. However, the method proposed in [29] requires a large elaboration time for large spaces due to the exhaustive grid-search approach for pinpointing tag location. Reference [30] relies on phase unwrapping to get faster results with an iterative algorithm exploring a convex function, but it is subject to unwrapping failures.

In [31], the authors have put forth a novel technique for localizing 3D RFID tags that involves driving the motion of an antenna coupled to a mobile robot along non-straight paths. Results show a 35 cm mean error in a case where tags are positioned on several vertical planes. The work in [32] has reported an improved Interferometric SAR-based 3D localization that enables quick estimations with a mean accuracy of 18.4 cm on a moving single antenna system. A recent approach exploited synthetic apertures and phase unwrapping together with least square methods to solve the multilateration problem [33], obtaining an accuracy of around 12 cm, further improving localization accuracy with respect to previous works.

Following this trend, this work will introduce particle filter methods for the 3D localization of goods in warehouse and retail scenarios [34]. Opposed to previous results, the presented approach proposes a solution to address situations when a correct unwrap of the phase signal is not possible. Moreover, the usage of Particle Filtering leads to a reliable method capable of operating within more complex environments. Compared to other optimization algorithms that can be employed for tags' position estimation, such as PSO, the particle filter is a Monte Carlo estimator that aims to reconstruct a probability density function (pdf), which allows for greater control over the output of the algorithm and in the validation of performance.

III. METHODS

By considering a reader antenna on a moving robot, and considering a given RFID tag, the relative distance r between the antenna and the tag changes. The moving reader antenna can interrogate the tag numerous times to acquire a phase observation sequence, and the signal phase variation can be used to determine the relative phase history of the signal. The mathematical relation between the effective distance r_i and the measured phase signal ϕ_i at time instant i is given by:

$$\phi_i = \left(\frac{2\pi}{\lambda} 2r_i + \phi_0\right) \bmod 2\pi, \tag{1}$$

where λ is the free space wavelength and ϕ_0 is the phase offset (see Figure 1). To eliminate the dependence on the phase offset ϕ_0, differential measurements can be employed

$$\Delta(\phi_i) = \left(\frac{2\pi}{\lambda} 2\Delta(r_i)\right) \bmod 2\pi \tag{2}$$

where the operator $\Delta(\cdot)$ is defined as the difference between successive timesteps values, i.e., i and $i-1$.

The multilateration problem can be solved by computing the intersection of two-sheeted hyperboloids (quadric surfaces) in three dimensions. The location of the tag on

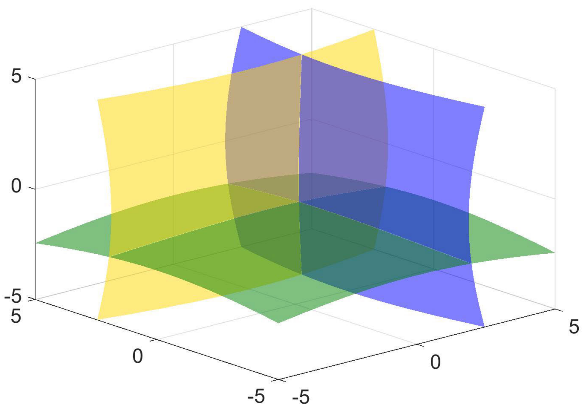

FIGURE 3. A tag position can be estimated as the intersection among three hyperboloids.

the hyperboloid surface can be determined by exploiting two successive robot poses and the corresponding measured phase difference. Figure 2 shows the solution space of possible tag positions generated by moving the antenna from one position to another, which corresponds to a two-sheeted hyperboloid. Exploiting additional measurements, a more accurate approximation of the tag's location can be obtained by intersecting multiple hyperboloids generated by the antenna and robot motion. Figure 3 illustrates this concept graphically for the minimal case of three hyperbolae.

The distance range between the tag coordinates $P = [x, y, z]^T$ and the i-th position of the moving antenna $P_i = [x_i, y_i, z_i]^T$ can be computed as:

$$r_i = \|P_i - P\| = \sqrt{(x_i - x)^2 + (y_i - y)^2 + (z_i - z)^2} \quad (3)$$

It is usually convenient to work with the pseudo-ranges m_i representing the time difference of a traveling wavefront touching each antenna position, and that can be defined starting from the first reading r_1 as:

$$m_i = r_i - r_1 \ , \qquad i = (2, 3, 4, \dots, n) \quad (4)$$

Concerning phase measurements, it is usually important to employ an unwrapping procedure to address the uncertainty caused by the phase cycle. When the absolute jumps between successive phase samples are more than or equal to the jump tolerance π, the phase angles are adjusted by adding additional cycles. Naming the unwrapped phase ϕ^u, the procedure is equivalent to:

$$\phi_1^u = \phi_1 \quad (5)$$

$$\phi_i^u = \phi_i - 2\pi * \left\lfloor \frac{\phi_i - \phi_{i-1}^u}{2\pi} + \frac{1}{2} \right\rfloor \quad (6)$$

However, it is important to notice that to successfully use an unwrapping procedure the tag readings acquired from the antennas should be continuous and not present large holes, i.e., the spatial sampling must be below $\lambda/4$. This is a limitation of many existing methods that rely on such a technique and thus require highly reliable antenna readings.

The following paragraphs will introduce particle filter (PF) methods for the estimation of tag positions either relying on an unwrapped phase signal or exploiting a direct phase signal, thus allowing the tag position estimation even in the presence of signal loss or occlusions of tags during the acquisition. These filters exploit a Taylor series expansion formulation of the pseudo-ranges system of equations as presented in the following.

A. TAYLOR SERIES EXPANSION

Defining the function $h(P) = h_i(x, y, z) = m_i + \epsilon_i$ with $i = 2, 3, \dots, n$ where m_i are the pseudo ranges in (4) and ϵ_i are the estimation errors of range difference with covariance matrix Q. Given the tag position P and an initial estimation of it $P_v = [x_v, y_v, z_v]^T$, affected by an estimation error $\Xi = [\xi_x, \xi_y, \xi_z]^T$, this could be obtained by expanding the function h_i as

$$h_i(P) \approx h_i(P_v) + a_{i,1}\xi_x + a_{i,2}\xi_y + a_{i,3}\xi_z = m_i + \epsilon_i \quad (7)$$

where

$$a_{i,1} = \frac{\partial h_i}{\partial x}\Big|_{P_v} = \frac{x_1 - x_v}{r_1} - \frac{x_i - x_v}{r_i}, \quad (8)$$

$$a_{i,2} = \frac{\partial h_i}{\partial y}\Big|_{P_v} = \frac{y_1 - y_v}{r_1} - \frac{y_i - y_v}{r_i}, \quad (9)$$

$$a_{i,3} = \frac{\partial h_i}{\partial z}\Big|_{P_v} = \frac{z_1 - z_v}{r_1} - \frac{z_i - z_v}{r_i}. \quad (10)$$

The equations can be combined in matrix form as

$$A\,\Xi = D + E\,, \quad E = \begin{bmatrix} \epsilon_2 \\ \epsilon_3 \\ \dots \\ \epsilon_n \end{bmatrix} \quad (11)$$

$$A = \begin{bmatrix} a_{2,1} & a_{2,2} & a_{2,3} \\ a_{3,1} & a_{3,2} & a_{3,3} \\ \dots & & \\ a_{n,1} & a_{n,2} & a_{n,3} \end{bmatrix}, D = \begin{bmatrix} m_2 - h_2(P_v) \\ m_3 - h_3(P_v) \\ \dots \\ m_n - h_n(P_v) \end{bmatrix} \quad (12)$$

and an estimation of the Ξ vector can be found as

$$\Xi = (A^T Q^{-1} A)^{-1} A^T Q^{-1} D \quad (13)$$

This allows finding a new estimation, and by iterating the procedure, the estimation error can be reduced below a desired threshold, which should be lower than the noise measurement reading.

B. PARTICLE FILTERS

Starting from the solution found with the Taylor expansion, a PF can be designed considering typical process and observation models defined as:

$$x_i = f(x_{i-1}, u_i, w_i) \quad (14)$$

$$z_i = h(x_i, v_i) \quad (15)$$

where x_i is the state at time instant i, u_i is the input at time i, z_i is related to the measured phase signal at time i, w_i and v_i are white noises independent of each other.

f is a function representing the evolution of the state of the process and h is an observation function as defined in the previous paragraph. The process model is used to compute the state that is expected at a certain instant in time, given all measurements up to such an instant. Measurements are used in the observation model to refine the expected state estimate using Bayes' theorem and obtain a posterior distribution.

A PF represents the posterior probability $bel(x_i)$ of the system state x_i at time instant i with a distribution of samples called particles. Such distribution is an approximation of the real posterior and can assume any shape and be multi-hypothesis. Each particle x_i^k is a hypothesis of x_i. In our approach, in order to reduce the computational cost of the particle filter, each particle represents the state vector composed only by the position of the RFID tag $[x, y, z]^T$.

A typical PF is composed of three steps. In the first step, each particle estimation is updated by sampling a new value from the state transition distribution probability function $p(x_i|u_i, x_{i-1})$. In our methods, this first step is omitted since the positions of the RFID tags are considered fixed in time and do not require any update during the antenna motion ($x_i = x_{i-1}$).

The second step of the filter concerns the computation of the importance factor w_i^k for each particle k. This factor is used to embed the measurement z_i in the set of particles and is defined as $w_i^k = p(z_i|x_i^k)$.

The third step of a PF is the resampling phase, in which particles are sampled from the original set based on their importance factor to obtain a new set of particles with the same dimension as the original one but with a probability distribution that better resembles $bel(x_i)$. The aim is to prevent the degeneracy of the propagated particles and improve the exploration of the state space.

It has to be considered that by skipping the first step of the PF no randomness is introduced in the particle position. Thus, randomness is introduced during the resampling phase. A random indetermination is added to the position of the particles that should replace existing ones while winning particles remain unchanged.

Since the process model is stationary ($p(x_i|x_{i-1}) = 1$), it is possible to formulate the problem by recursion as a sequential estimate of the distribution states at time $i - 1$ as:

$$p(x_i|z_{1:i}) \propto p(z_i|x_i) \int p(x_{i-1}|z_{1:i-1})dx_{i-1} \tag{16}$$

The following paragraphs will present two different PFs based on the presented formulation.

The first filter employs the phase unwrapping technique, and it needs to control its consistency. The other PF has been designed to run without unwrapping and it only requires the first phase measurement and the first antenna position to compute future PDOA. The advantage of such a method is that there is no need to verify the antenna positions to check the unwrapping consistency.

C. PF WITH KALMAN FILTERING AND PHASE UNWRAP (PF-KU)

Since there is no a-priori knowledge of the correct initial hypothesis, the proposed PF starts creating a random distribution of N tag position hypothesis (particles) in the 3 dimensions. In this filter, the particle state contains the position of the tag $[x, y, z]^T$.

An independent Extended Kalman Filter (EKF) is associated with each particle. As previously introduced, since there is no control input, the predicted state will be equal to the previous one plus a certain process Gaussian noise.

At each reading, the antenna position and phase are stored and a new position of each particle is generated.

The update of the particle positions is realized with a Kalman filter that uses as input the unwrapped distance that corresponds to the $r_i - r_1$ difference and the following expected measure:

$$\bar{z}_i = h_i(x, y, z) = m_i \cdot \eta + \hat{v}_i \tag{17}$$

with $\hat{v}_i$ the measurement noise, and the constant η that converts the expected distance in the expected phase and it is equal to:

$$\eta = \frac{4\pi}{\lambda} \tag{18}$$

Computing the Taylor expansion of the h function at the actual point P_i it is possible to write:

$$\bar{z}_i = h_i(P_i) + H_i(P - P_i) \tag{19}$$

with H_i the matrix of partial derivatives of h_i.

The effective measure results equal to the difference between the first unwrapped phase (ϕ_1^u) and the actual unwrapped phase (ϕ_i^u) readings:

$$z_i = \phi_i^u - \phi_1^u \tag{20}$$

The H matrix has been computed by converting the phases into lengths. Hence, it is possible to write:

$$\Delta P_i = K_i(z_i(t) - \bar{z}_i(t))/\eta \tag{21}$$

$$\hat{P}_i = P_i + \Delta P_i \tag{22}$$

where K_i is the Kalman gain

$$K_i = C_i H_i^T (H_i C_i H_i^T + R_i)^{-1} \tag{23}$$

with R_i the measurement noise covariance matrix and C_i the prior estimate uncertainty predicted at the previous step.

In this way, the particle position is corrected by the EKF filter that tries to set to zero the innovation. The importance factor is given by the measurement probability:

$$w_i^k = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}\frac{\Delta z_i^2}{\sigma^2}} \tag{24}$$

where the standard deviation σ^2 represents the phase measurement indetermination.

Finally, the weight factor w_i is filtered with a low-pass filter to reduce the sensitivity to localization errors or spurious readings.

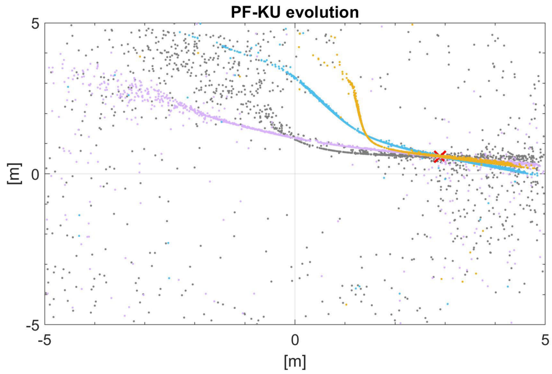

FIGURE 4. Evolution of the PF-KU method in estimating a tag position in the plane employing 1600 particles. The exact tag location is shown as a red X marker. Color mapping has been chosen to distinguish between different iterations (4) of the PF algorithm. In all iterations, the particles are arranged along the last hyperbola hypothesis that depends upon the current position of the antenna. All the hypotheses have a common intersection in the actual solution.

Due to the efficacy of the Kalman filter, there is no need for a resampling procedure. Only the particles that move out of the workspace are re-sampled randomly.

With this method, the particles tend to arrange along the actual hyperbola as shown in Figure 4.

D. PF WITH KALMAN FILTERING WITHOUT UNWRAP (PF-KW)

The main idea of this filter builds upon the EKF concept of innovation, which is the difference between the sensor measurement and the expected measurement model output. When the estimate of the tag position is correct, the innovation value will be close to zero. Hence, it is possible to consider phase differences (appropriately converted to lengths) as input for the innovation. Removing the dependency on the unwrapped phase allows for using measurements that are not continuous in time and improving the estimations even in the presence of few sensor readings. In this way, we can consider the expected measure as:

$$\bar{z}_i = h_i(x, y, z) = (m_i \cdot \eta)\mathrm{mod}2\pi + \hat{v}_i \tag{25}$$

and the measure as:

$$z_i = \phi_i - \phi_1 \tag{26}$$

As in the previous filter, each particle corrects its position in the update phase towards a direction computed starting from the measurement z_t.

It is important to notice that since the phase is not unwrapped, the probability measurement is periodic with period π. Moreover, the PF is sensible to symmetry in the solutions. For this reason, the direction in which the antenna is facing is used to solve the ambiguity introduced by the symmetry.

IV. METHOD VALIDATION

The performances of the suggested approaches have been examined by using three different datasets. Two datasets include artificial data that was produced with different simulation techniques. A third dataset was obtained from an indoor testing environment. All of the datasets offer locations of two moving antennas attached to a mobile robot and of the corresponding phase signals that were recorded by the antennas detecting a set of tags fixed to the surroundings.

Multiple Monte Carlo simulations over various noise circumstances, taking into account signal reflections, multipath, electrical, and thermal disturbances, were run thanks to synthetic datasets. The actual dataset demonstrates how closely the estimated performance matches the information. The 3D error metric employed to assess the accuracy of the proposed methods on the conducted tests is:

$$E_{3D} = \sqrt{(x-\hat{x})^2 + (y-\hat{y})^2 + (z-\hat{z})^2} \tag{27}$$

where the tag actual location has coordinates $P = [x, y, z]^T$ while the tag estimated position is referred as $\hat{P} = [\hat{x}, \hat{y}, \hat{z}]^T$.

A. MATLAB SYNTHETIC DATASET

A simulation has been created with Matlab by generating motion trajectories for two antennas and phase signals pattern considering a free workspace and a passive RFID tag with coordinates $P = [1, -0.5, 1.5]^T$ m. The motion of the antennas is coupled since they are considered attached to the body of a mobile robot that moves in the environment. The antennas' coordinates in the simulation present an offset from the ground (z-axis) of 0.95 m for the lower antenna and 1.2 m for the upper one. The top antenna motion starts at $P_1 = [0.5, -2.0, 1.2]^T$ m moving on a straight line to the coordinates $P_{66} = [3.75, -2.0, 1.2]^T$ m generating new coordinates every 5 cm. The motion continues with a change of orientation (on the y-axis), reaching the position $P_{133} = [3.75, 1.35, 1.2]^T$ m with the same stride of 5 cm and moves again on the x-axis toward the tag reaching the final position $P_{200} = [0.4, 1.35, 1.2]^T$ m with 67 additional steps. An equivalent path is generated for the lower antenna. The motion of the antennas and the tag coordinates are shown in Figure 5. A 1 mm random noise has been added to the z-coordinates of the antennas to improve the numerical stability of the algorithms.

The simulation considers an empty environment with straight signal path propagation, and to globally account for environmental disturbances, a zero-mean Gaussian noise with 0.1 rad standard deviation is added to the generated phase. Repeated simulations have been conducted in 100 runs to statistically validate the robustness of the presented methods under varying noise conditions considering not modeled phenomena like thermal fluctuations.

Analyzing the localization error, the results demonstrate accurate predictions using both approaches, with values in the centimeter range. The boxplot of the resulting errors is shown in Figure 6.

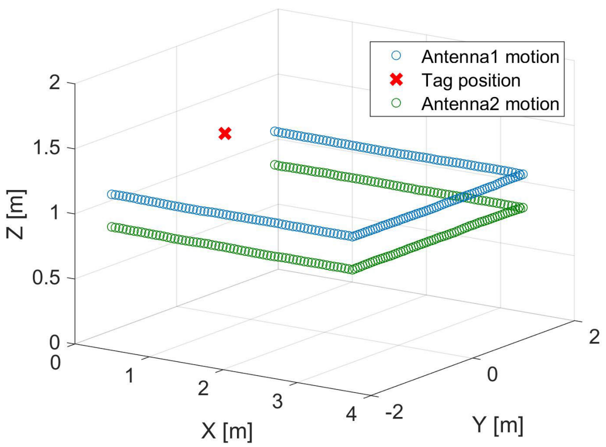

FIGURE 5. Trajectories of the two antennas and the tag position in the Matlab synthetic dataset.

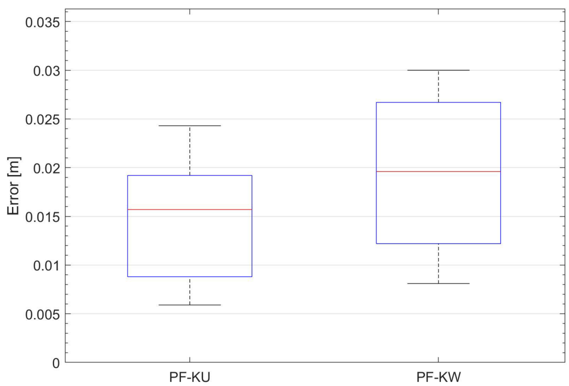

FIGURE 6. Boxplot of the E_{3D} error of the methods in the Matlab synthetic dataset.

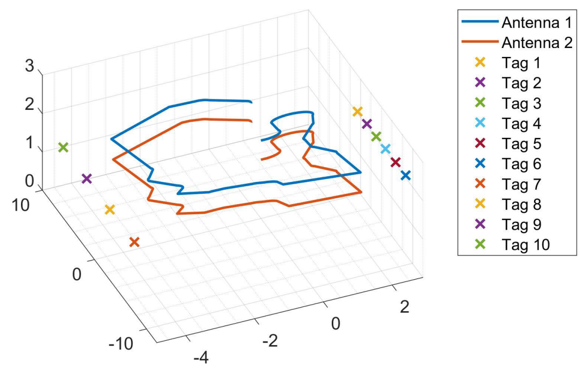

FIGURE 7. Example trajectories performed by the two virtual antennas of the Gazebo synthetic dataset. The plot illustrates the position of 10 tags deployed in the simulated environment.

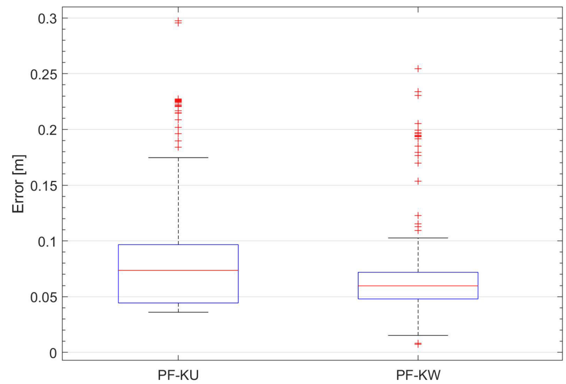

FIGURE 8. Boxplot of the E_{3D} error obtained from the presented methods on the Gazebo synthetic dataset.

B. GAZEBO SYNTHETIC DATASET

A second testing campaign has been run on a dataset generated in Gazebo under ROS thanks to an RFID plugin [35] that allows placing tags and antennas freely inside any simulation. The RFID phase model equation used in the simulator is consistent with eq. (2). Two antennas have been attached on top of a mobile robot that has been moved inside a warehouse environment to generate synthetic apertures and estimate the position of 10 tags placed at different heights within the environment. Six tags are attached to a scaffold at a height of 2.05 m, with the remaining tags on a second scaffold at a lower height of 1.85 m.

To collect statistical information on the localization methods' performance, a Monte Carlo simulation has been performed on the same warehouse environment without altering the location of the tags but generating 100 different paths for the motion of the mobile robot. The simulator allows specifying model noise properties to account for possible disturbance sources and phenomena and a Gaussian Noise with zero mean and 0.1 rad standard deviation has been selected for the generation of the data. Figure 7 shows one example trajectory motion of the simulated robot and the 10 tags placed in the synthetic environment, while Figure 8 depicts the E_{3D} errors obtained by the proposed methods as a bar plot. With respect to the prior dataset, the estimation error variability is higher for all presented methods. This could be due to the variety of the robot's motion trajectories generated, which differ in the produced synthetic apertures, and by the various positions of the tags in the surrounding environment. In fact, depending on how close the antenna was to each tag during the robot's motion, a trajectory might be good for estimating one tag but bad for predicting another.

For both approaches, the median error values were below 8 cm, making them competitive in light of recent academic research in the area.

It has to be noticed that if there is a jump in the reading of a certain tag due to excessive distance from the powering antenna or due to occlusions, the PF-KU method could fail, and the error estimation reported in the boxplot statistics refers to optimal conditions where tags are read continuously by the antennas. If this is not the case, the error could easily shift above 3 meters. Figures 9 and 10 show what happens to the tag position estimation when the measurements are not continuous in the case of employing the PF-KU and the PF-KW respectively.

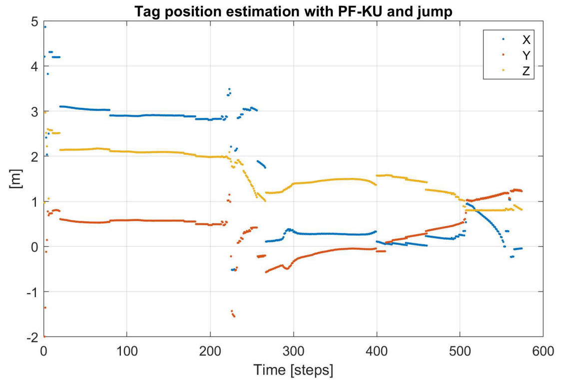

FIGURE 9. Estimation values of a tag position using the PF-KU method. The estimation error is small until step 220 when there is a first jump in the reading. Due to this discontinuity, the successive estimations are not correct anymore.

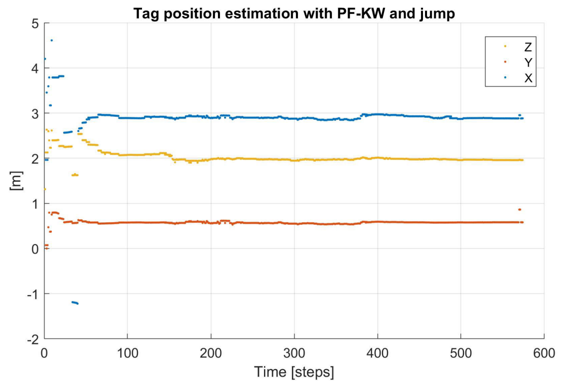

FIGURE 10. Estimation values of a tag position using the PF-KW method. In this case, even in the presence of multiple jumps starting at step 220, the estimation error remains bounded.

C. EXPERIMENTAL DATASET

An indoor environment has been used to carry out an experimental campaign using a mobile robot manufactured by the MobileRobots firm, the Pioneer 3-AT UGV. The robot has been equipped with an antenna system composed of two circularly polarized UHF-RFID antennas (WANTENNAX019) manufactured by C.A.E.N. RFID and a reader platform by Impinj (Speedway Revolution R420). Figure 11 shows the setup of the antennas mounted on the mobile robot at a 125 cm and 71 cm height from the ground.

The robot has a zero-radius rotation capability and skid-steers on four wheels. It has a computer linked to a microcontroller and 16 sonars distributed across its four sides. The microcontroller on the robot employs sonar sensing to detect obstacles, is responsible for the position update from the wheels' encoders, and it interfaces with the motors for the actuation commands. An additional input source for the robot localization is provided by a laser range finder device, the Hokuyo UTM-30LX. The tags employed for the measurement campaign are Impinj Monza R6 chips with a -22.1 dBm sensitivity. The acquisition has been performed

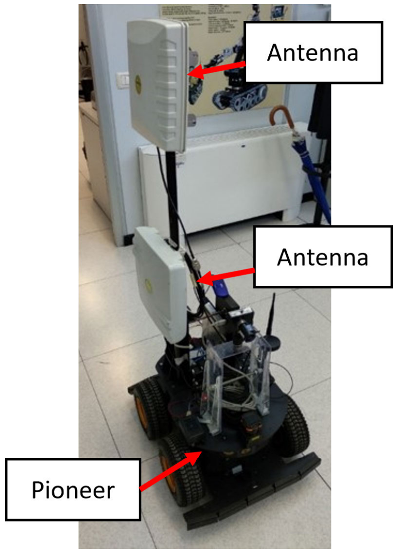

FIGURE 11. Hardware equipment employed for the experimental dataset. The mobile robot is a Pioneer3-AT with two RFID antennas on top.

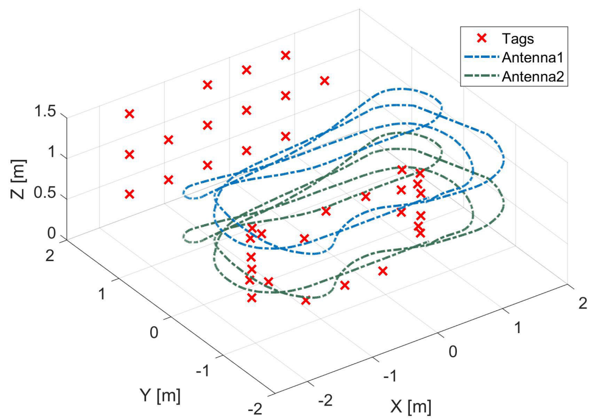

FIGURE 12. Trajectories performed by the two antennas of the mobile robot during the experimental session. 38 RFID tags were displaced on the walls and attached to carton supports in the middle of the scenario.

at a frequency of 865.7 MHz (ETSI Channel 4) and with a transmission power of 27 dBm.

A Simultaneous Localization and Mapping (SLAM) method [36] predicted the antennas' pathways with centimeter order accuracy as the robot was maneuvered around the indoor environment using a joystick interface. Robot motion followed curved paths inside an office scenario moving around some tags displaced at the center of the environments and facing several tags mounted on the office walls. Figure 12 shows the acquired motions of the antennas and the tags' positions.

The trials were carried out in an office with metallic elements such as structural beams, computers, electronic gadgets that might induce electrical interference, reflective surfaces such as walls, and office desks that produced multipath phenomena.

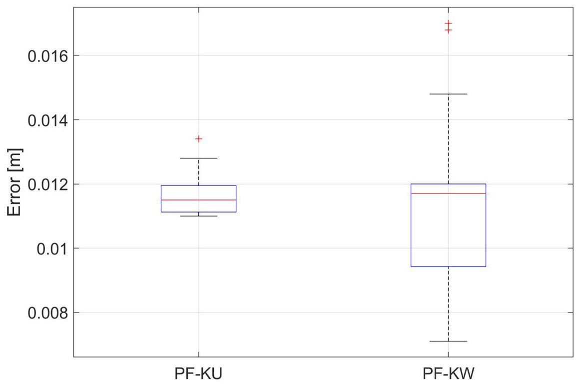

FIGURE 13. Localization errors obtained in the experimental tests with the proposed methods.

TABLE 1. A comparison with state-of-the-art methods concerning 3D location error.

Method	3D Localization error: median (std)
Work in [31]	34.8 cm (28.2 cm)
Work in [32]	20.27 cm (26.0 cm)
Work in [33]	13.0 cm (6.3 cm)
PF-KU	1.15 cm (0.1 cm)
PF-KW	1.17 cm (0.3 cm)

Figure 13 depicts the localization error obtained in the experimental dataset 3. The obtained accuracy is competitive concerning the most recent literature. The presented methods obtained a median accuracy lower than 2 cm. Approaches based on the Kalman filter exhibit good repeatability of the estimation in comparison to earlier results achieved using synthetic datasets. This might be because Gaussian noise was injected into the synthetic data for each Monte Carlo run, while for the 10 experiments, the noise conditions were presumably similar.

Table 1 presents a comparison with SOTA algorithms concerning 3D localization accuracy summarizing the obtained results on similar setups.

D. IMPORTANT REMARKS

Analyzing the results and the methods' behavior in the performed tests, some interesting points could be drawn. The synthetic aperture strategy is used by all methods, and the final obtained estimation accuracy depends on the antenna's trajectory. Particularly, the particle predictions are more accurate close to where the actual tags are located. Therefore, a thorough exploration of the environment will be an effective procedure. Another important matter is the aperture size in the z-coordinate. In fact, even though the proposed algorithms may be used with either a single antenna or multiple antenna configurations interchangeably, the performance of single antenna setups is worse than double antenna ones due to the larger set of solutions that satisfy the phase equation (a big portion of an ellipsoid). Finally, compared to previous approaches in the literature, the algorithms can operate without the need for a phase unwrapping procedure because the observed phase signal is sufficient to calculate the likelihood of the created particles thus resulting as suitable even when the measured phase signal is discontinuous due to the missing reception of a tag information.

V. CONCLUSION

One of the most critical tasks in Industry 4.0 for logistics is the automatic management of inventory. Accurate localization, mapping, and environmental awareness are necessary for effective robot motion and planning, and goods position estimation. The overall efficiency mainly relies on sophisticated sensing technologies to track the robot's mobility and measure items' placements. This article introduces particle filter techniques that use phase measurements and synthetic apertures to estimate the 3D positions of tags by solving a multilateration problem formulated through a Taylor series expansion. Experimental tests have been run on synthetic and real datasets showing state-of-the-art results. It is worth noticing that since the approaches utilize synthetic apertures, the performance of the methods depends both on the trajectory of the reading antenna and the distribution of particles in the surrounding environment. In light of these considerations, forthcoming efforts will focus on enhancing the motion dynamics of the mobile platform, aiming to minimize the ambiguity in tag location estimation. Additionally, there will be an exploration of innovative tactics for particle sampling within the environment aimed at circumventing local minima and directing predictions toward areas of high probability.

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PAOLO TRIPICCHIO (Senior Member, IEEE) received the master's degree in automation engineering from the University of Pisa, and the Ph.D. degree (cum laude) in perceptual robotics from Sant'Anna School of Superior Studies, in 2012. He was an Invited Lecturer with Orizaba Institute of Technology, Mexico, during 2012, teaching classes on virtual reality and its applications. In 2016, he taught computer vision for autonomous drones with the Autonomous University of Toluca (UNAM), Mexico. Since January 2013, he has been the Scientific Program Manager of Gustavo Stefanini Advanced Robotics Research Center, La Spezia, Italy, dedicated to the advancements in mobile and field robotics. He is currently an Assistant Professor with the Department of Excellence in Robotics and AI, Mechanical Intelligence Institute (IIM), Scuola Superiore Sant'Anna, Pisa, Italy. His research interests include different technological topics, such as studies on robotic perception, applications and theories of computer vision, AI systems and their applications, and human–machine interaction, with a particular focus on haptics, the fast-growing industrial robotics sector, field robotics applications, and the use of virtual and augmented reality for visualization, interaction, and simulation. He was a recipient of the Best Paper Award at the International Conference on Systems, Analysis and Automatic Control (SAC) of the 11th International Multi-Conference on Systems, Signals and Devices (IEEE SSD 2014), the Best Paper Award Finalist at the 2019 IEEE International Conference on Real-Time Computing and Robotics (IEEE RCAR 2019), the One Star Innovation Award at MBDA Innovation Awards 2020, and the 2020 Researcher Prize in Artificial Intelligence from the Department of Excellence in Robotics and AI, Scuola Superiore Sant'Anna.

SALVATORE D'AVELLA (Member, IEEE) received the bachelor's degree (Hons.) in computer engineering from the University of Pisa, the master's degree (Hons.) in embedded computer systems from Sant'Anna School of Advanced Studies, and the Ph.D. degree (Hons.) in perceptual robotics from the Department of Excellence in Robotics and AI, Sant'Anna School of Advanced Studies. He was a Visiting Ph.D. Student with the Institute of Robotics and Mechatronics (DLR), Munich, Germany. He is currently an Assistant Professor with the Department of Excellence in Robotics and AI, Institute of Mechanical Intelligence, Scuola Superiore Sant'Anna. His research interests include computer vision, artificial intelligence, and robotics, applied to industry 4.0, and logistics. He has been the session chair and the co-chair of many international conferences and an Associate Editor (AE) of the 16th IEEE/SICE International Symposium on System Integration (SII) and the 2024 IEEE International Conference on Robotics and Automation (ICRA) conferences. He is also an AE of the IEEE ROBOTICS AND AUTOMATION LETTERS.

MATTEO UNETTI received the M.Sc. degree in automation engineering from the University of Pisa, in 2003. He is currently a Research Fellow with Gustavo Stefanini Advanced Robotics Research Center, a joint research center between Scuola Superiore Sant'Anna (SSSA) and Leonardo Company (formerly Finmeccanica) on mobile robots. His research interests include robotics, sensor fusion, localization, computer vision, and control systems.

ANDREA MOTRONI (Member, IEEE) received the M.E. degree (Hons.) in telecommunication engineering and the Ph.D. degree (Hons.) in information engineering from the University of Pisa, Pisa, Italy, in 2017 and 2021, respectively. In 2019, he was the President of the IEEE Student Branch University of Pisa. In 2020, he was a Visiting Ph.D. Student with Graz University of Technology, Graz, Austria. He is currently an Assistant Professor with the University of Pisa. His current research interests include indoor radiolocalization systems, with a specific focus on UHF-RFID and UWB technology for robot and vehicle localization, the integration of robotic systems with RFID toward new systems for industry and logistics, UHF-RFID smart gates and other RFID-based applications for the Internet of Things, industry 4.0, and people safety in both indoor and outdoor environments. He is an Executive Member of the IEEE CRFID's Technical Committee on Motion Capture and Localization. He was the Finalist at the IEEE CRFID Educational Mega Challenge and a recipient of the Best Paper Award, the Best Student Paper Award at IEEE RFID-TA 2019, and the Young Scientist Award from the International Union of Radio Science, Commission B, in 2018, 2019, and 2021. In 2022, he was awarded the IEEE/ABB Italy Section Award for Ph.D. Thesis, the "2021 Best Ph.D. Dissertation" in the field of information and industrial engineering from the University of Pisa, in 2022, and the "Best Poster Award" at IEEE M&N 2022. In 2023, he was again recognized with the Young Scientist Award from the International Union of Radio Science, Commission B, and the "Best Poster Award" at IEEE RFID 2023. He has joined the Organizing Committee and has been the session chair of several IEEE international conferences. He serves as an Associate Editor for the IEEE JOURNAL OF RADIO FREQUENCY IDENTIFICATION.

PAOLO NEPA (Senior Member, IEEE) received the Laurea degree (summa cum laude) in electronics engineering from the University of Pisa, Pisa, Italy, in 1990. Since 1990, he has been with the Department of Information Engineering, University of Pisa, where he is currently a Full Professor. In 1998, he was a Visiting Scholar with the Electro Science Laboratory (ESL), The Ohio State University (OSU), Columbus, OH, USA, where he was involved in efficient hybrid techniques for the analysis of large antenna arrays. He has coauthored more than 300 international journal articles and conference contributions. His current research interests include the design of wideband and multiband antennas, and antennas optimized for near-field coupling and focusing. In the context of UHF-RFID systems, he is working on techniques for radiolocalization of either tagged objects or readers. He is a member of the Technical Advisory Board of URSI Commission B-Fields and Waves. He was a recipient of the Young Scientist Award from the International Union of Radio Science, Commission B, in 1998. He served as the General Chair for the IEEE RFID-TA 2019 International Conference. Since 2016, he has been serving as an Associate Editor for the IEEE ANTENNAS AND WIRELESS PROPAGATION LETTERS.

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