Pinpoint Achilles’ Heel in RFID Localization: Phase Calibration of RFID Antenna based on Linear Localization Model

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Abstract—In the context of Industrial Internet of Things (IIoT), RFID technologies have been widely applied to locate or track tagged objects for achieving item-level intelligence. However, prior localization work encounters two main issues. First, the phase measurement usually contains physical deviation. Existing localization work generally takes the physical center of an RFID antenna as its phase center, which is a key factor in improving localization accuracy but actually different from the physical center in practice. Second, the non-linear localization model is likely to be too complex to run on edge nodes with limited computing resources. In this paper, we present a Linear localization solution, called LION, to perform the phase calibration for antennas with no need for the complex computation nor strong limitations. Specifically, we provide a novel lightweight model to pinpoint the actual antenna position quickly and accurately. Compared to previous localization methods, we reduce the intersection of circles or hyperbolas into radical lines, which greatly reduces the computation cost while guaranteeing the high accuracy. Further, to adapt to the complex environment with various ambient noise and multi-path effect, we leverage the weighted least square method to determine the optimal position. Moreover, we propose an adaptive parameter selection scheme to automatically choose optimal parameters for localization. In this way, LION is able to perform the accurate localization robustly. We implement LION using commercial RFID devices, and evaluate its performance extensively. Experimental results show the necessity of phase calibration as well as the high time efficiency of LION, e.g., the average accuracy improves by 6× and 2.1× for 2D and 3D localization, and the average time consuming is 0.02s and 1.8s for 2D and 3D cases.

Index Terms—RFID, Phase Calibration, Localization

I. INTRODUCTION

Benefiting from advantages like low-cost and battery-less, RFID technologies have been widely applied for locating or tracking tagged items. With the development of Industrial IoT, localization algorithms for industrial applications need to satisfy the following requirements: 1) High Accuracy: To realize fine-grained tasks like grasping small items, the algorithm is expected to achieve millimeter-level accuracy for localization. 2) Complex Environment: There can be prevalent ambient noise and serious multi-path effect in practical scenarios, the algorithm should have the ability to adapt to the real complex environment robustly and flexibly. 3) High Time Efficiency: The algorithm is expected to run in a real-time manner at the edge node with limited computing resources, so the localization model should be as simple as possible.

In recent years, phase-based RFID localization has attracted increasing attention due to its high resolution, but it is still difficult to achieve these goals. The Achilles’ heel in traditional RFID localization exists two aspects. On one hand, phase measurements generally contain unknown physical deviation, including the center inconsistency and additional offset. Existing work takes the physical center of antenna as the phase center, i.e., the point transmitting and receiving signals. However, they are usually not the same position due to intrinsic hardware characteristics [1], as shown in Fig. 1. This approximation will give rise to some small measurement errors, which cannot meet the specific applications that require fine-grained localization in millimeter level. Moreover, the reported phase measurements also contain additional phase offset, i.e., the difference between the phase caused by distance and the collected phase. The phase offset may be various for different hardware, which could degrade the accuracy when using their relative phase measurements. Thus, it is essential to calibrate antennas for obtaining the phase center and the phase offset. On the other hand, an intuitive solution of phase calibration is to locate the antenna with tags using existing localization methods, but they usually have their own limitations. The hologram-based methods [2–5] locate the target by building holograms to calculate the likelihood that each position in the monitoring area is the target position. However, their fine-grained accuracy requires the high computation overhead of building the hologram, e.g., tens of seconds for 1–2m² with grid size of 1mm. Thus they usually cannot satisfy the requirement of high time efficiency. The model-based methods leverage models like parabola, hyperbola, angle and angle-of-
arrival to reduce the computation overhead. But the hyperbola-based solution still takes seconds to get the optimal solution to lots of quadratic equations, while other solutions may limit the shape of scanning trajectory to linear [6] or circular [7], or limit the spatial dimension [8].

In this paper, we present a Linear localization solution, called LION, which performs the phase calibration for antennas, with no need for the complex computation nor strong limitations. Specifically, the phase calibration includes the phase center calibration and the phase offset calibration. The phase center calibration means pinpointing the actual antenna position instead of the manual measured physical center of antenna. The phase offset calibration means determining the additional phase rotation except the distance-related part, benefiting the scenario based on the phase difference among antennas. The basic idea of LION is to locate the antenna with a tag moving along the known trajectory, and then leverage the estimated antenna position to calculate the center displacement and phase offset for each antenna.

LION has two competitive advantages besides precision: light-weight and robustness. 1) Light-weight refers to determining the accurate target position in a real-time manner with limited computing resources. To reduce the computation overhead, LION reduces the traditional non-linear problem to a linear model. We observe that the target can be viewed as locating at the intersection of radical lines, other than circles, parabolas or hyperbolas. Thus, we exploit pairs of phase measurements collected at different positions to extract radical lines and generate the coefficient matrix. By solving the linear equations, we can take the optimal solution as the target position. 2) Robustness refers to adapting to the complex environment with various ambient noise and multi-path effect while guaranteeing the accuracy. To achieve the robustness, LION leverages the weighted least square method to derive the optimal solution to the linear model. In the real environment, phase measurements collected at different positions may be distorted to different extent. Through adding weights to phase measurements according to their residuals, we can enhance the impact of radical lines determined by cleaner phase measurements, so as to reduce the interference of ambient noise and multi-path effect efficiently. Moreover, we notice that the parameters of algorithm also play an important role in the performance of localization. We further propose an adaptive parameter selection scheme to automatically choose optimal parameters for the localization model. In this way, LION is able to adapt to complex scenarios with high flexibility.

In summary, we make three key contributions in this paper.

- First, we figure out that the antenna calibration of phase center and offset is essential for improving the localization accuracy, especially in a multi-antenna case.
- Second, we propose a novel linear model that locates the antenna in a fine-grained, light-weight, and robust way, regardless of the trajectory shape and spatial dimension.
- Third, we implement LION using commercial RFID devices. Experimental results show the necessity of phase calibration as well as the high time efficiency of LION, e.g., the average accuracy improves by 6× and 2.1× for 2D and 3D localization, and the average time consuming is 0.02s and 1.8s for 2D and 3D cases.

In the following, we conduct empirical studies in Sec. II. Sec. III elaborates the linear localization model. Sec. IV explains the system design of LION. Sec. V presents the implementation and evaluates the performance. Sec. VI overviews the related work. Finally, we conclude our work in Sec. VII.

II. PRELIMINARY

In this section, we show the necessity of phase calibration, including the phase center and offset. Then, we discuss the experience and limitations of typical localization methods.

A. Phase Center

Traditionally, we take the physical center of RFID antenna as phase center, that is, signals are viewed as being transmitted and received from the physical center. However, the actual phase center is usually not identical to the physical center. To verify such difference, as shown in Fig. 2, denote the physical center as the origin, we put a tag in front of the antenna with space of 65cm and move the tag along horizontal and vertical directions, i.e., y-axis and z-axis. Theoretically, when the tag passes by the phase center, the distance of signal transmission reaches minimum, that is, the unwrapped phase measurement is smallest. However, the measured valleys appear about 2-3cm away from the origin. Although the deviation seems small, localization applications requiring high precision are very sensitive to such deviation. Therefore, we need to calibrate the phase center for achieving higher accuracy.

B. Phase Offset

The phase reported by RFID reader can be expressed as:

\[ \theta = (\theta_d + \theta_T + \theta_R) \mod 2\pi, \]

where \( \theta_d = \frac{2\pi}{\lambda} \times 2d \), depending on the signal transmission distance \( d \) and wavelength \( \lambda \). \( \theta_T \) and \( \theta_R \) refer to the phase offsets caused by the tag’s reflection characteristics and the reader’s transmitter/receiver circuits, respectively. To intuitively show the hardware interference, we use four Laird S9028PCL directional antennas and four ImpinJ E41-B tags to collect phase values from different pairs of antenna and tag. The tag position is fixed in front of the antenna position with space of 1m. We replace one antenna or tag at a time, and collect 500 phase values for each pair. Fig. 3 plots the phase measurements of different antenna-tag pairs. We can see that
both antennas and tags have intrinsic hardware differences, leading to additional phase shifts when other factors remain unchanged. Besides the hardware interference, it is still hard to leverage the raw absolute phase measurement to estimate the distance due to the modulo operation. Therefore, to reduce the hardware interference and the effect of modulo operation, we prefer the phase difference to calculate the distance variation, rather than directly using the raw absolute phase measurement.

**C. Hologram-based Localization**

The intuitive solution to phase calibration is to locate the antenna with tags using existing localization methods. The most general method is based on the likelihood, i.e., the grid with highest likelihood is taken as the target position. To eliminate the phase offset among different antennas and tags, Tagoram [2] proposes to leverage the phase difference to build the hologram. Moreover, it introduces the weight to enhance the likelihood and reduce the candidate positions with high likelihood. Fig. 4 displays an example hologram generated by the simulated phase measurements collected from two positions. The grid size is 1mm×1mm. The two tag positions are (−0.3m, 0m) and (0.3m, 0m), the antenna position is (0.5m, 0.5m). We can find that the grids with high likelihood determined by two phase values, i.e., phase difference, distribute along hyperbolas. Meanwhile, Fig. 4(b) shows the effectiveness of adding weights for improving the accuracy. With more phase measurements collected from different positions, more virtual hyperbolas will generate, and the target just locates at the intersection of these hyperbolas. However, the generation of such a simple hologram takes about 0.8s, let alone when encountering larger area, smaller grid size, or much more phase measurements.

In summary, we obtain the following lessons in this part:

- The actual phase center of antenna is inconsistent with its physical center, so we need to eliminate such approximation for achieving higher accuracy.
- The hardware characteristics can lead to different phase offsets for antennas and tags, so it is necessary to calibrate or eliminate the phase offset.
- The appropriate weight added to the phase difference is likely to help improve the localization accuracy.

**III. LINEAR MODEL OF LOCALIZATION**

In this section, we first present our light-weight localization model in the 2D space. Then, we explain how to extend it to 3D localization. Next, we discuss the lower-dimension issue of our model.

**A. 2D Localization**

Let the position of antenna $A$ be $(x, y)$, the position of a moving tag $T$ at time $t$ be $(x_t, y_t)$, then the distance $d_t$ between antenna $A$ and tag $T$ can be calculated as:

$$d_t = \sqrt{(x_t - x)^2 + (y_t - y)^2}.$$  \(2\)

Eq. (2) represents the circle centered at $(x_t, y_t)$ with radius $d_t$. When the tag moves to different positions, we can derive different circles, and the intersection of these circles is the antenna position. Actually, this is just the basic principle of Time-of-Arrival (ToA) localization method, but it is seldom exploited for the RFID-based localization system. The main reason is that due to the modulo operation and phase offset, it is hard to calculate the exact distance $d_t$ based on a single reported phase value $\theta_t$. However, considering the continuous scanning during the tag movement, we have the opportunity to overcome the phase ambiguity, and realize the ToA localization for RFID systems.

**Observation 1:** If more than two circles centered at different tag positions intersect in a single antenna position, this point is also the intersection of their pairwise radical lines.

Herein, the radical line refers to the line determined by the intersections of two circles. For example, as shown in Fig. 5, the circles centered at $T_1$ and $T_2$ determine their radical line $l_{1,2}$, which passes through the antenna position and the other point of intersection. Similarly, $l_{1,3}$ and $l_{2,3}$ are radical lines determined by other pairs of circles. We can see that all radical lines intersect at the antenna position. Based on Observation 1, we can turn the problem of solving quadratic equations into the problem of solving linear equations. Particularly, according to Eq. (2), the equations of circles centered at $T_i$ and $T_j$ are:

$$d_i^2 = (x_i - x)^2 + (y_i - y)^2$$  \(3\)

$$d_j^2 = (x_j - x)^2 + (y_j - y)^2.$$  \(4\)
By subtracting Eq. (3) from Eq. (4), the radical line \( l_{i,j} \) of the two circles can be represented as:

\[
 l_{i,j} : 2(x_i - x_j)x + 2(y_i - y_j)y \\
= x_i^2 - x_j^2 + y_i^2 - y_j^2 - d_i^2 + d_j^2. \tag{5}
\]

As mentioned above, we cannot directly derive \( d_i \) and \( d_j \) from the reported phase measurements. Fortunately, although it is hard to derive the absolute distance \( |AT| \) from antenna to tag, we can easily derive the distance difference between \( |AT| \) and \( |AT| \) based on the consecutive scanning during the tag movement. Hence, take a random tag position as reference position, the instantaneous distance \( d_t \) can be written as:

\[
d_t = d_r + \Delta d_t, \tag{6}
\]

\[
\Delta d_t = \frac{\lambda}{4\pi} (\theta_t - \theta_r),
\]

where \( d_r \) is the reference distance between the antenna and the tag at reference position. \( \theta_r \) is the phase measurement collected at the reference position. \( \Delta d_t \) is the distance difference between the instantaneous distance and the reference distance, which can be calculated with the phase difference. However, the reference distance \( d_r \) is still an unknown parameter, which needs to be estimated along with the antenna position \( (x, y) \).

Substituting Eq. (6) into Eq. (5) gives:

\[
\alpha_{i,j}x + \beta_{i,j}y + \omega_{i,j}d_r = \kappa_{i,j}, \tag{7}
\]

where

\[
\alpha_{i,j} = 2(x_i - x_j), \beta_{i,j} = 2(y_i - y_j), \omega_{i,j} = 2(\Delta d_i - \Delta d_j),
\]

\[
\kappa_{i,j} = x_i^2 - x_j^2 + y_i^2 - y_j^2 - d_i^2 + d_j^2.
\]

Suppose a tag moves along the known trajectory continuously, the antenna can receive large amounts of phase measurements \( \{\theta_i\} \) at different positions \( \{(x_i, y_i)\} \). Define \( \mathbf{A}, \mathbf{B}, \mathbf{W}, \mathbf{K} \) be the column vector formed by \( \{\alpha_{i,j}\}, \{\beta_{i,j}\}, \{\omega_{i,j}\}, \{\kappa_{i,j}\} \), respectively. These column vectors are all known coefficients as they are related to either the tag position or phase measurements. According to Eq. (7), define \( \mathbf{h} = [\mathbf{A} \ \mathbf{B} \ \mathbf{W}]^T, \mathbf{X} = [x \ y \ d_r]^T \), then we have: \( \mathbf{h}\mathbf{X} = \mathbf{K} \). Due to the noise among phase measurements, the equation is probable to have no exact solution, but we can leverage the least square method to determine the optimal solution \( \mathbf{X}^* \).

To show the efficacy of our method LION, we conduct simulation experiments to objectively compare our model with the hologram-based method introduced in Sec. II-C. Assume the tag moves along the circle centered at the origin \((0,0)\) with radius of 0.3m. One antenna locates at different directions but has the same distance to the origin, \(i.e., (1m, 0m), (0.7071m, 0.7071m), \) and \((1m, 0m)\). We generate phase values for each tag position, and add Gaussian noise to mimic real phase measurements. The additional noise follows the Gaussian distribution \( \mathcal{N}(0, 0.1) \), which is default for the following simulations. We repeat the simulation 100 times for each antenna position. The results in Fig. 6 show that LION can achieve the comparable performance as the hologram-based method.

Meanwhile, although the distance error in the 2D space keeps steady when the antenna locates at different positions, the errors along axes change with the direction of antenna position.

**Fig. 6.** Comparison of LION and hologram-based method for locating a single antenna at different directions

**Fig. 7.** 3D localization based on intersection of intersection circles

This phenomenon can be explained with above findings. As mentioned in Sec. II-C, under the phase difference of two positions, the grids of high likelihood will form the hyperbola. When the antenna is not very close to the tag position, the hyperbola can be replaced by the corresponding asymptote, passing through the center of the two tag positions. Therefore, estimated positions of LION will distribute along the line from the trajectory center to the antenna.

**B. 3D Localization**

Similar to the basic idea of 2D localization, the antenna in the 3D space locates at the intersection of different spheres centered at different tag positions. As shown in Fig. 7, the 3D localization can be simplified as the intersection of intersection circles. The equation of intersection line in Eq. (5) can be extended to the equation of intersection circle:

\[
2(x_i - x_j)x + 2(y_i - y_j)y + 2(z_i - z_j)z \\
= x_i^2 - x_j^2 + y_i^2 - y_j^2 + z_i^2 - z_j^2 - d_i^2 + d_j^2. \tag{8}
\]

Substituting Eq. (6) into Eq. (8) gives:

\[
\alpha_{i,j}x + \beta_{i,j}y + \gamma_{i,j}z + \omega_{i,j}d_r = \kappa_{i,j}, \tag{9}
\]

where

\[
\alpha_{i,j} = 2(x_i - x_j), \beta_{i,j} = 2(y_i - y_j), \gamma_{i,j} = 2(z_i - z_j),
\]

\[
\omega_{i,j} = 2(\Delta d_i - \Delta d_j),
\]

\[
\kappa_{i,j} = x_i^2 - x_j^2 + y_i^2 - y_j^2 + z_i^2 - z_j^2 - d_i^2 + d_j^2.
\]
With the phase sequence collected during the continuous tag movement, we can also leverage the least square method to get the optimal solution $\hat{\lambda} = [x^* y^* z^* d^*_r]^T$. In this way, we are able to realize the light-weight 3D localization of a single antenna with one tag moving along the known trajectory.

### C. Lower-Dimension Issue

To solve the presented linear localization model, one key requirement is that the coefficients of coordinates are independent of each other. If the dimension of tag movement is equal to the spatial dimension of antenna position, we can calculate the antenna position by solving the linear equations based on the phase sequence collected during the tag movement. However, it could be hard to perform the trajectory with the same dimension or the scanning cost is expected to be as less as possible. When the trajectory dimension is lower than the spatial dimension, we cannot directly derive all unknown parameters by solving linear equations, denoted as lower-dimension issue.

**Observation 2:** The reference distance $d_r$ can help calculate the tag position with the lower-dimension tag movement.

It is worth noting that the unknown parameters are not totally independent of each other, e.g., the antenna position $(x, y)$ in Eq. (7) is related to the reference distance $d_r$. Therefore, even if we only get part of solutions, we have the chance to further estimate the remaining unknown coordinate.

1) **2D Localization:** The lower-dimension issue for 2D case happens when the tag moves along the linear trajectory, as illustrated in Fig. 8(a). In this situation, $\alpha$ changes linearly with $\beta$, i.e., $\alpha x + \beta y$ can be rewritten as $\alpha(x + ey)$, $e$ is a real number. Hence, the antenna position $(x, y)$ is reduced to a single unknown parameter $x+ey$, so we cannot directly derive $(x, y)$. For example, when the tag moves along the $x$-axis, $\beta$ keeps zeros and the component of $y$ is eliminated. Fortunately, as $d_r$ represents the distance between the unknown antenna position $(x, y)$ and the known reference position $(x_r, y_r)$, we can leverage $x, d_r, x_r, y_r$ to calculate the two candidates of $y$, as: $y = y_r \pm \sqrt{d_r^2 - (x - x_r)^2}$, and further filter the error one based on the actual deployment. Particularly, assume the tag moves from -0.3m to 0.3m along the $x$-axis, the antenna locates at (0.2m, 1m). We repeat the simulation 100 times, and plot the distance error between the actual position and the estimated positions in Fig. 9. It is obvious that LION can work well with the linear trajectory for 2D localization, and achieve the comparable performance as hologram-based method.

2) **3D Localization:** The lower-dimension issue for 3D case happens when the tag moves along the non-linear trajectory in a plane or the linear trajectory. In terms of the non-linear trajectory in a plane, e.g., the circular tag movement in Fig. 8(b), we can use the similar solution to the lower-dimension issue in the 2D case to derive the antenna position in the 3D case. In terms of the single linear trajectory, the antennas can locate at any position on the circles centered at the linear trajectory, such that we cannot exploit the single linear trajectory for 3D case. Therefore, we can perform the 3D localization with the non-linear trajectory in a plane, but not with a single linear trajectory.

### IV. System Design

Fig. 10 illustrates the architecture of LION. One tag moves along the known trajectory, the target antenna keeps interrogating the tag and collecting the phase value $\theta_i$ when the tag is at position $(x_i, y_i)$. With the received phase sequence collected at different positions $\{(x_i, y_i, \theta_i)\}$, we design three modules to locate the actual phase center and calibrate the phase measurements for antennas, including signal preprocessing, antenna localization, phase calibration.

#### A. Signal Preprocessing

1) **Unwrapping:** Due to the modulo operation in Eq. (1), the range of collected phase measurement is $[0, 2\pi]$ radians. When interrogating the moving tag consequently, the collected phase value is likely to change suddenly from 0 to $2\pi$ or vice versa. Considering that the sampling rate of one tag can be over 100Hz while the tag moves at a normal speed like 10cm/s, the tag displacement between two neighbor phase measurements tends to be much smaller than the half-wavelength (about 16cm). Therefore, we have the chance to unwrap these phase segments into a complete phase profile. Specifically, when the jump between two consecutive phase values is no less than $\pi$ radians, we stick these phase values by adding or subtracting multiples of $2\pi$ until the jump is below $\pi$. In this way, the unwrapped phase profile can reflect the continuous variation of distance between the moving tag and the antenna.

2) **Smoothing:** The raw phase measurement generally contains the noise. As shown in Fig. 3, the phase measurement will change slightly even when both the antenna and the tag are static. Therefore, to reduce the white noise, we smooth the unwrapped phase profile using a moving average filter.
B. Antenna Localization

We provide a novel lightweight localization model to overcome the complex computation cost while guaranteeing the high accuracy, as explained in Sec. II-C. Actually, given the known trajectory of either tag or antenna, LION can quickly estimate the target position with high accuracy by solving linear equations. Thus, benefiting from the accurate localization result, we can calibrate the phase center and the phase offset of target antenna by using a moving tag to locate the antenna in the 3D space.

To realize the highly accurate 3D localization, we suggest the dimension of tag trajectory is equal to the spatial dimension, i.e., three. In practice, we can let the tag move along three straight lines to form the 3D trajectory, as shown in Fig. 11. Particularly, denote the three linear trajectories as \( L_1 \), \( L_2 \), and \( L_3 \), which are parallel to each other. \( L_1 \) and \( L_2 \) are in the \( xy \)-plane, while \( L_1 \) and \( L_3 \) are in the \( xz \)-plane. One tag moves along each linear trajectory separately, and we collect phase measurements at different positions. Note that the unwrapping operation deals with the phase jump caused by the modulo operation for the continuous tag movement. As for the separate linear trajectories, it is likely that the unwrapped phase profiles of different trajectories are not consecutive, i.e., the phase difference of two positions at different trajectories is not consistent with their distance difference. Thus, it is significant to adjust the unwrapped phase profiles manually. One simple solution is to let the tag move from the end of one linear trajectory to the start of other trajectory, such that we have the continuous phase variation and then adjust the unwrapped phase profiles to make them consecutive. Based on the processed phase profile, we next leverage the linear model to locate the phase center of target antenna.

1) Generating coefficient matrix: As the core idea of our localization method is to reduce the non-linear problem into a linear model, we need multiple pairs of tag positions to generate linear equations of radical lines or intersection circles. The principle of selecting tag pairs is to guarantee the diversity of displacement along different axes. Assume \( x_i \) refers to the coordinate of \( x \)-axis within the range of tag movement, \( y_o \) refers to the constant space between \( L_1 \) and \( L_3 \), while \( z_o \) refers to the constant space between \( L_1 \) and \( L_2 \). For each \( x_i \), there are three positions with the same \( x_i \) on the 3D trajectory, denoted as \( P_{i,1}(x_i, 0, 0) \) on line \( L_1 \), \( P_{i,2}(x_i, 0, z_o) \) on line \( L_2 \), and \( P_{i,3}(x_i, -y_o, 0) \) on line \( L_3 \). To obtain the expression for each coordinate, we need to select tag pairs along different axes. Specifically, for \( x \)-coordinate, we can select \( P_{i,1} \) and \( P_{i,+1} \) with interval \( x_o \) from the same line \( L_1 \), where \( k \) is a non-zero integer. Moreover, we can leverage \( P_{i,1} \) and \( P_{i,3} \) to derive the expression of \( y \)-coordinate, while leveraging \( P_{i,1} \) and \( P_{i,2} \) to derive the expression of \( z \)-coordinate. Thus, according to Eq. (9), we have:

\[
\begin{align*}
2x_o x_p + \omega_{P_{i,1}, P_{i,+1}} d_r &= \kappa_{P_{i,1}, P_{i,+1}}, \\
2y_o y_p + \omega_{P_{i,1}, P_{i,3}} d_r &= \kappa_{P_{i,1}, P_{i,3}}, \\
2z_o z_p + \omega_{P_{i,1}, P_{i,2}} d_r &= \kappa_{P_{i,1}, P_{i,2}},
\end{align*}
\]

where \((x_p, y_p, z_p)\) is the coordinate of phase center. Let \( \mathbf{X} = [x_p, y_p, z_p, d_r]^T \), then the above equations can be rewritten as:

\[
\begin{bmatrix}
\mathbf{A}_i
\end{bmatrix} \mathbf{X} = \mathbf{K}_i,
\]

where

\[
\begin{bmatrix}
\mathbf{A}_i
\end{bmatrix} = \begin{bmatrix} 2x_o & 0 & 0 & \omega_{P_{i,1}, P_{i,+1}} \\ 0 & 2y_o & 0 & \omega_{P_{i,1}, P_{i,3}} \\ 0 & 0 & 2z_o & \omega_{P_{i,1}, P_{i,2}} \end{bmatrix}, \quad \mathbf{K}_i = \begin{bmatrix} \kappa_{P_{i,1}, P_{i,+1}} \\ \kappa_{P_{i,1}, P_{i,3}} \\ \kappa_{P_{i,1}, P_{i,2}} \end{bmatrix},
\]

which can be easily calculated based on tag positions and unwrapped phase profiles.

2) Calculating phase center: For each \( x_i \), we build equations like Eq. (11). Through combining all equations from different \( x_i \), we obtain large amounts of linear equations:

\[
\begin{bmatrix}
\mathbf{A}_1 \\
\mathbf{A}_2 \\
\vdots \\
\mathbf{A}_n
\end{bmatrix} \mathbf{X} = \begin{bmatrix}
\mathbf{K}_1 \\
\mathbf{K}_2 \\
\vdots \\
\mathbf{K}_n
\end{bmatrix},
\]

where \( n \) is the number of samples. Due to the noise among phase measurements, we cannot get the exact solution, but we
can leverage the least square method to determine the optimal solution $\mathcal{X}^*$. Generally, denote $\mathcal{A} = [a_1, a_2, \ldots, a_n]^T$, $\mathcal{K} = [K_1, K_2, \ldots, K_n]^T$, then the optimal solution is:

$$\mathcal{X}^* = (\mathcal{K}^T \mathcal{K})^{-1} \mathcal{K}^T \mathcal{A}.$$  

(13)

Actually, the ambient noise or multi-path effect is not uniform in the real-world environment, that is, phase measurements are likely to be much cleaner at certain positions than others. Hence, the collected phase measurements are not equally reliable, correspondingly, the equations in Eq. (12) are not equally reliable as well. Therefore, we prefer adding weights to equations, so as to improve the influence of more reliable measurements. Particularly, assume there are $N$ equations in total, the $i^{th}$ equation is represented as $A_i \mathcal{X} = k_i$, $A_i \in R^{1 \times 4}$, $k_i$ is a real number. In this case, the optimal solution is estimated by minimizing the weighted sum of squares, as:

$$\mathcal{X}^* = \arg \min_{\mathcal{X}} \sum_{i=1}^{N} w_i |A_i \mathcal{X} - k_i|^2,$$

(14)

where $w_i$ is the weight of $i^{th}$ equation based on the residual. Define the residual as $r_i = A_i \mathcal{X}^* - k_i$, we use the exponential of residual as the weight:

$$w_i = e^{-\frac{(r_i - \mu)^2}{2\sigma^2}},$$

(15)

where $\mu$ and $\sigma$ are the average value and standard variation of all residuals, respectively. In this way, we can exploit the weight to measure the uncertainties of equations, i.e., the higher weight indicates the less uncertainty, and the corresponding equation plays a more important role in the solution. As a result, denote the diagonal matrix of weights as $\mathbb{W}$, then the optimal solution is estimated by:

$$\mathcal{X}^* = (\mathcal{K}^T \mathbb{W} \mathcal{K})^{-1} \mathcal{K}^T \mathbb{W} \mathcal{A}.$$  

(16)

If seeking the higher accuracy, we can update the estimation iteratively until the difference between the last estimation and the current estimation is less than the given threshold.

3) Calculating unknown coordinate: Although we use three linear trajectories to locate the phase center in the 3D space for improving the accuracy, we can reduce the trajectory dimension in other localization applications for reducing the scanning cost. As explained in Sec. III-C, one linear trajectory is enough for 2D localization, while the non-linear trajectory in one plane is enough for 3D localization. Taking Fig. 11 for example, we are able to locate the phase center in the 2D space with one linear trajectory like $L_1$, and locate the phase center in the 3D space with two linear trajectories like $L_1$ and $L_2$. In the case of using $L_1$ and $L_2$ for 3D localization, the $z$-coordinate of each tag position is zero, thus we cannot estimate the $z$-coordinate directly by solving the linear function. Since $d_r$ is not independent of position coordinates, we can use $d_r$ to solve the remaining unknown $z$-coordinate. Suppose the phase center is above the tag trajectory, the reference position is $(x_r, y_r, z_r)$, $x_p^*, y_p^*$ and $d_r^*$ are estimated from the linear function, then: $z_p^* = \sqrt{d_r^* - (x_r - x_p)^2 - (y_r - y_p)^2} + z_r$.

C. Phase Calibration

1) Calibrating phase center: The physical center of antenna is generally viewed as its phase center, but this is not the case. Given the measured physical center and the estimated phase center, we propose the center displacement to depict their position difference. Note that, arisen from the ambient noise and multi-path effect in practice, different parameters, e.g., scanning range and intervals $x_o/y_o/z_o$, will lead to different estimations of localization. Although the weighted least square method can reduce the impact of noisy data to some extent, the estimation is likely not to keep stable under different parameters. To improve the stability and robustness, we further propose an adaptive parameter selection scheme to automatically adjust the parameters for localization. Specifically, the average residual of normal least square method is around zero, but as we introduce weights for estimation, the average residual will be actually slightly away from zero. The relatively large absolute residual usually implies much ambient noise and serious multi-path effect. Therefore, we select the estimations with absolute residual around zero, and take the average of selected estimations as the actual center.

2) Calibrating phase offset: In some cases, the phase offset among antennas or tags may affect the localization accuracy. For example, when using multiple static antennas to locate a static tag based on the hyperbola-based method, the phase offset among different antennas will make the intersection away from the ground-truth. Therefore, the phase offset is also an important factor for phase calibration, especially for the localization model with multiple antennas or tags.

Given the phase center, the difference between the tag position and the phase center is easily obtained. Assume that for the $i^{th}$ position, the corresponding distance is $d_i$. Theoretically, $d_i$ leads to the phase rotation $\theta_{d,i} = \frac{\lambda}{4\pi}d_i$. However, due to the hardware interference, $\theta_{d,i}$ is usually different from the corresponding measured phase $\theta_{r,i}$. Thus, suppose we collect $n$ samples at the $i^{th}$ position, we can obtain the phase offset by calculating the average difference:

$$\Delta \theta = \theta_T + \theta_R = \frac{1}{n} \sum_{i=1}^{n} (\theta_{d,i} - \theta_{r,i}) \mod 2\pi.$$  

(17)

Herein, the estimated phase offset is the combination of hardware interference from both the tag and the antenna. Since it is difficult to split the phase rotation, we can leverage the difference of phase offset among tag-antenna pairs to eliminate the phase offset among multiple antennas or tags.

V. PERFORMANCE EVALUATION

A. Experiment Setup

Implementation: We have built a prototype system of LION using commercial RFID devices. As illustrated in Fig. 12, we exploit a self-designed integrated RFID machine to transmit and receive signals, containing an ImpinJ Speedway R420 reader, a Laird S9028PCL antenna, and a WiFi router. The reader is set to work at the frequency of 920.625MHz with the transmission power of 32dBm. The antenna is deployed
at the height of 1m. We denote the horizontal direction of antenna plane as x-axis, and the vertical direction as z-axis, respectively. One E51 tag is fixed on a plastic stick, and moves along the linear sliding track parallel to the x-axis. The moving range is 2.5m and the speed is 10cm/s. We use a MacBook Pro with Intel Core i5 to connect the reader through WiFi, and collect RF-signals from the tag based on the LLRP protocol. Our algorithms are implemented with Java and MATLAB.

**Experiments:** We calibrate the phase center of antenna in advance, and leverage the calibrated antenna to locate the initial position of moving tag with a single antenna. We vary the following key parameters to evaluate the performance: 1) **Height and Depth:** The depth refers to the perpendicular distance between the tag and the antenna along the y-axis. For 3D localization, we let the tag move along the x-axis twice with depth interval of 20cm. The height difference between the tag and the antenna is varied from 0cm to 20cm, and the depth is varied from 60cm to 100cm. For 2D localization, the tag and the antenna are at the same height, the depth is varied from 60cm to 160cm. 2) **Weight:** We use the Weighted Least Square (WLS) method and normal Least Square (LS) method to determine the target location, respectively. 3) **Scanning Range:** The moving range of tag is 2.5m, but we only use the collected data within the scanning range for analysis. The scanning range is centered at x = 0, varied from 60cm to 110cm. 4) **Scanning Interval:** The scanning interval refers to x_0 in Fig. 11, varied from 10cm to 35cm. By default, we adopt the WLS method for estimation. The depth between the tag and the antenna is 80cm. The scanning range and interval are determined adaptively according to Eq. (16).

**Metrics and Baseline:** We take the distance error as the main performance metric, i.e., the absolute distance difference between the true position and the estimation. We compare our method with the DAH proposed in Tagoram [2].

### B. Overall Accuracy

**LION can perform the accurate localization with phase calibration in a light-weight way.** We let the tag move along the linear sliding track with different initial positions, and locate the initial tag position using different methods. Fig. 13(a) compares the average distance errors of our method LION and prior work DAH in different cases, including 2D/3D localization with calibration (2D+/3D+) and without calibration (2D−/3D−). It is observed that the phase calibration can greatly improve the localization accuracy, e.g., the accuracy of LION improves by 6× and 2.1× for 2D and 3D localization, respectively. Moreover, LION performs slightly better than DAH, e.g., even if conducting the same phase calibration, the average distance errors of LION and DAH are separately 0.48cm and 0.69cm for 2D localization, 2.33cm and 2.61cm for 3D localization. Meanwhile, we compare the time consuming of LION and DAH in Fig. 13(b). To control the time consuming, we reduce the searching area of DAH to a small size, e.g., (20cm)^2 for 2D case and (20cm)^3 for 3D case. The grid size of DAH is 1mm. It is observed that LION can significantly reduce the computing time, especially for 3D localization. This is because that the number of searching grids for 3D case is much more than 2D case, so the time consuming of DAH increases sharply. Nevertheless, we leverage the weighted linear model to estimate the location, the computing time keeps lightweight, e.g., 0.02s and 1.8s for 2D and 3D cases.

### C. Impact of Height and Depth

1) **3D Localization:** LION can perform the accurate 3D localization within a limited area. We leverage a moving tag to locate the calibrated antenna in the 3D space. The tag moves along the x-axis in the xy plane (z = 0) twice, i.e., one trajectory is at y = 0m and the other is at y = -0.2m. The antenna is put at six different positions where x = 0m, y = 0.6/0.8/1m, z = 0/0.2m, denoted as P_1 \sim P_6. Fig. 14(a) illustrates the distance error of different positions. It is observed that when the depth is less than 0.8m, the distance errors along all axes are smaller than 1.5cm. However, with the larger depth, the distance error increases significantly, especially for y-axis and z-axis. It is because that the same height difference along the z-axis will lead to the smaller distance difference for the larger depth, that is, the phase measurement is not very sensitive to the position difference along the z-axis when the depth is large. As a result, the twice linear scanning with the depth difference of 20cm is insufficient for the accurate
3D localization. Therefore, to ensure the accuracy of 3D localization in a large area, it is better to ensure the sufficient height variation. Anyway, we have the potential to determine the target position in the 3D space with high accuracy.

2) 2D Localization: LION can always perform the accurate 2D localization when varying the depth from 60cm to 160cm.

We let the tag move along the \( x \)-axis to simulate the conveyor scenario, and track the tag position in the 2D space. For comparison, we leverage LION and DAH to estimate the tag position, respectively. The results are plotted in Fig. 14(b). It is observed that when the depth is not larger than 120cm, LION works slightly better than DAH, i.e., the average distance errors of LION and DAH are about 0.45cm and 0.55cm, respectively. While when the depth exceeds 140cm, LION can still achieve the similar accuracy, but the distance error of DAH increases sharply and over 2.5cm. The reason is likely that the power of line-of-sight signal degrades with the increasing depth, so the multi-path effect has more influence on the phase measurement. As DAH takes all measurements as input, the more noise among signals will decrease the localization accuracy. Instead, LION exploits the adaptive parameter selection scheme to reduce the influence of multi-path, in this way, LION can perform the localization robustly with various depth.

D. Impact of Weight

LION can efficiently improve the localization accuracy by leveraging the weighted least square method. Considering that the multi-path effect will degrade the accuracy, we introduce weights to improve the robustness and accuracy for localization. To evaluate the impact of algorithm parameter, we exploit the Weighted Least Square (WLS) method and normal Least Square (LS) method to locate the tag. Let the tag move along the \( x \)-axis, the depth between the tag and the antenna is 0.8m. We select 30 tag positions randomly. This experiment methodology is default for the following evaluations. As shown in Fig. 15, WLS can efficiently reduce the distance error, i.e., the average distance errors of WLS and LS are 0.43cm and 0.92cm, respectively. It is because that the weight enhances the influence of cleaner data with smaller residuals. In this way, the WLS can efficiently reduce the effect of noisy signals for the accurate localization.

E. Impact of Scanning Range and Interval

LION is able to select the appropriate scanning range and interval automatically according to the residual of WLS.

For evaluating the impact of scanning range, we set the scanning interval as 25cm, and vary the scanning range from 60cm to 110cm. Fig. 16 and Fig. 17 illustrate the average residual of WLS and distance error for different scanning ranges. We observe that the scanning range has obvious impact on the performance, i.e., the average residual of range 80cm is closest to zero, corresponding to its minimum distance error. When the range is smaller than 80cm, the larger range can benefit the localization accuracy. It is because that as the tag trajectory is centered at the antenna, the signals within the small beam in front of the antenna can be viewed as plane waves. That is, the small transition parallel to antenna plane, e.g., \( x/z \)-axis, usually can be ignored. Thus, we need extend the scanning range to make it incur sufficient distance difference, so as to reduce the effect of noise on the phase measurement caused by the distance difference. However, it does not mean that the larger scanning range indicates the higher localization accuracy. We observe that when the scanning range is larger than 80cm, the increasing scanning range will lead to the larger distance error instead. It is likely because that the signals beyond the main beam of antenna tend to contain much more noise. Nevertheless, according to the average residual, we can select the optimal scanning range adaptively, and pick up the best estimation.

For evaluating the impact of scanning interval, we set the scanning range as 80cm, and vary the scanning interval from 10cm to 35cm. Fig. 18 shows the distance error of different scanning intervals. It is observed that when the interval increases to 20cm, the distance error decreases significantly. It is because that the large interval usually causes the large phase difference, such that the effect of noise will decrease relatively. Similarly, we also find that the average residual of interval 20cm is closest to the zero, verifying the effectiveness of the adaptive parameter selection scheme.

F. Case Study

1) Tag Localization with Multiple Antennas: The phase calibration is essential for improving the localization accuracy in the case of locating a static tag with multiple antennas. As shown in Fig. 19(a), we deploy three antennas in a line by aligning their physical centers, and employ them to locate a static tag. Suppose the three antennas are \( A_1 \sim A_3 \), here \( A_2 \) is the integrated RFID machine, \( A_1 \) and \( A_3 \) connect to \( A_2 \) through cables. The antennas and the tag are manually deployed at the same height of 1m. The interval between antennas is 0.3m. Before locating the tag, we first perform
the phase calibration for antennas. Specifically, we let the tag move along three linear trajectories as illustrated in Fig. 11, where \( y_0 \) and \( z_0 \) are 20cm, \( L_1 \) and \( L_2 \) are at the same height of the tag position, and the depth of \( L_1 \) is 70cm. Fig. 19(b) shows the center displacement between the manual physical center and the estimated center. It is observed that the three antennas have various center displacements, containing both the manual measurement error and the intrinsic hardware specialization. Moreover, the phase offsets are 3.98, 2.74, 4.07 radians for \( A_1 \), \( A_2 \), \( A_3 \), respectively. The phase offsets of \( A_1 \) and \( A_3 \) are similar, but not close to \( A_2 \). It is because that antenna \( A_2 \) is attached to other metallic objects, so its phase rotation changes a lot with respect to the standalone antenna. Then, we leverage the differential hologram-based method [2] to locate the tag in the 2D space. Particularly, define the center of \( A_2 \) as origin, the tag is placed at (-10cm, 80cm). Fig. 20 shows the holograms generated with different calibration methods, including no calibration, phase center calibration and phase calibration (phase center and offset). The raw distance error without any calibration is 8.49cm, which decreases to 5.76cm after calibrating the phase center and further decreases to 4.68cm after calibrating the phase offset among antennas. That is, our method of phase calibration can improve the accuracy by 1.8×, verifying the necessity and effectiveness of phase calibration for the more accurate localization.

2) Antenna Localization with a Rotating Tag: LION can perform the accurate localization with rotating scanning. In the above experiments, we use one or more linear trajectories to perform the localization. Actually, our method supports any shape of known trajectories, besides the linear trajectories. As it would be inconvenient to perform the multiple linear scanning in certain situations, we can choose the circular scanning to replace the multiple linear scanning. Taking 2D localization for example, we let a tag rotate on the turntable with different rotating radii, as shown in Fig. 21(a). The turntable is in front of the antenna with distance of 70cm. We leverage a calibrated antenna to track the tag position. Fig. 21(b) illustrates the distance error along different axes. It is observed that the error along the \( x \)-axis is smaller than \( y \)-axis. The reason is that the errors tend to distribute along the direction from the scanning center to the target, as mentioned in Fig. 6. Moreover, the error decreases with the increasing radius. Although we perform the 2D localization in this example, the circular trajectory can work for accurate 3D localization if the radius is large enough. Therefore, we can choose other shape of known trajectories to replace the multiple linear scanning, which improves the scanning flexibility for practical localization applications.

VI. RELATED WORK

RSS-based Localization: The feature “Received Signal Strength (RSS)” can be used as the metric of ranging or the fingerprint for localization. Early work [9] depends on the RSS-distance attenuation model for localization. However, RSS is not very sensitive to the distance, their accuracy is usually at decimeter level without dense reference tags, so they cannot satisfy the requirement of high precision for pinpointing the antenna position. Although the dense reference tag array can help improve the accuracy [10–13], it does not fit for locating the antenna.

Phase-based Localization: Due to the high resolution and sensitivity, the feature “phase” has attracted increasing attention for accurate localization. Phase-based RFID localization generally falls into two categories: the hologram-based and the model-based. The basic idea of hologram-based method is to segment the surveillance area into small grids, and build a likelihood image, i.e., hologram, to show the likelihood of a position to be the target position [2–5]. For example, Tagoram [2] leverages the tag mobility to build a virtual antenna array, and builds the Differential Augmented Hologram (DAH) using the phase values collected from different virtual antennas. Based on Tagoram, MobiTagbot [3] further studies the relationship between channel and phase to reduce the interference of multi-path effect. However, their fine-grained localization accuracy depends on the high computation overhead of building the hologram. That is, the high accuracy demands the large searching area and small grid size, but it will multiply the computation cost. Thus, it is hard for these solutions to balance the localization accuracy and computation overhead, especially for the industrial scenarios where storage and computing resources of edge nodes are too limited to run.
hologram-based algorithms efficiently. Meanwhile, the model-based methods are mainly based on the phase difference, including parabola, hyperbola, angle or angle-of-arrival, etc. The parabola-based method [8] exploits the parabola to fit phase measurements for 2D localization, but it requires the linear scanning and cannot realize the 3D localization. The hyperbola-based models [6, 14–19] leverage the phase difference to build hyperbolas, and determine the target position by calculating the intersection of hyperbolas or fitting hyperbolas. But it is still time-consuming to find the optimal estimation for large amounts of quadratic functions during the continuous scanning. The angle or angle-of-arrival based models depend on the relative direction between the tag and the antenna. For example, Tagspin [7] emulates the circular antenna array by letting a tag spin at the turntable to pinpoint the antenna position, but it limits the shape of scanning trajectory to circular. Since scenarios are various, the design of scanning trajectory should depend on the actual environment, not all scenarios can support the linear or circular trajectory. Nevertheless, we propose a novel linear model to realize the light-weight, fine-grained, and robust localization, regardless of the trajectory shape and spatial dimension.

Other-feature-based Localization: Besides the common features of RSS and phase, other features are also well studied for RFID-based localization [20–22]. For example, Pinlt [20] exploits the multi-path profile of reference tag to locate the target tag. RFind [21] leverages the time-of-arrival to accurately estimate the distance, and then determines the target position by estimating the intersection of circles. However, they depend on the specialized hardware like USRP or reference tags, which is expensive or hard to deploy in real scenarios.

VII. Conclusion

In this paper, we present LION, a linear localization solution to support phase calibration for antennas with no need for the complex computation nor strong limitations. By reducing the intersection of circles or hyperbolas into radical lines, we implement LION with commercial RFID devices. Extensive experiments show the necessity of phase calibration as well as the high time efficiency of LION compared with prior localization work.

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