A Phase and RSSI-Based Method for Indoor Localization Using Passive RFID System
With Mobile Platform

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Abstract—In this paper, a phase and RSSI-based method for indoor localization of UHF RFID tags is proposed and demonstrated. The proposed method exploits the received phase and RSSI profile combined with the location of the moving antenna to locate target tags. The phase and RSSI measurements are collected by a mobile robot carrying a RFID reader and antennas. By analyzing the received RSSI, of which the strength can indicate whether the signal is stable or not, a valid phase profile can be obtained. After obtaining valid phase profile according to the received RSSI, the location of the target along the antenna trajectory is calculated from the stationary point of the phase curve. The location orthogonal to the antenna trajectory distance is estimated by finding the integer number of wavelengths at the point of closest approach which fits the phase profile. 2D localization requires only one straight-line trajectory while 3D localization requires an L-shape trajectory. After estimating the x and y coordinate using the stationary point on each trajectory, the height of the target can be calculated by considering the integer number of wavelengths at the point of the closest approach. A 12 cm 2D localization error and 14 cm 3D localization error are demonstrated.

Index Terms—RFID, phase-based, localization.

I. INTRODUCTION

In the recent years, RFID technology has attracted growing attention and has been widely employed in factories [1], [2], warehouses [3], logistics and retail shops [3], [4]. Compared with traditional solutions such as barcodes, RFID tags allow non-line-of-sight (NLoS) detections and hold more data [3]. Meanwhile, the read rate could reach hundreds of tags per second while the read range could reach over ten meters [3]. Moreover, the small and low-cost passive RFID tags are suitable for attaching to any object [5] and for massive deployment in various scenarios. All these benefits make RFID technology one of the indispensable technologies for the Internet of Things [5] and it is being widely employed as a cost-effective and easy-deployable solution for object localization in an indoor environment [5]. However, accurate 3D localization remains challenging.

A smart warehouse is one of the most important scenarios for RFID technology. Accurate localization of items is the basic and crucial requirement in many applications such as in a smart warehouse [9]. In an indoor scenario such as a warehouse, the environment is complex due to distributed obstacles including shelves, products and people [4]. Finding and accessing items from the shelves is costly and time-consuming [4]. In order to improve the efficiency and reduce cost, a stable and accurate localization method is required. There have been many methods proposed for localization using RFID technology using various physical quantities including received signal strength indicator (RSSI)-based [11]–[13], angle of arrival (AoA)-based [15], time of arrival (ToA)-based [15] and phase-based [16], [17], [23]–[31] techniques. Compared with the RSSI, the phase value is less affected by the environment so a phase-based method is comparatively robust and stable in complicated indoor environments [9], [18]–[22].

Synthetic Aperture Radar (SAR) is one of the most popular phase-based methods which could provide accurate position of targets with minimal radio hardware [19], [20]. In [23], [26], [27], [30], an RFID reader and multiple antennas are installed on a mobile platform. SAR-based algorithms compare the received phase values with the hypothetical values to calculate the location of target tags. A major disadvantage of a typical SAR algorithm is that the accuracy depends on the calculation of the ambiguity function over a fine spatial grid of possible locations. Since the ambiguity function is computationally intensive, a fine grid leads to a high computational load.

Some other phase-based methods are focus on spatial ordering of tags rather than finding their absolute location. The method proposed by Spatial-Temporal Phase Profiling (STPP) infers the order of target tags by using the “V-zone” in the phase profile [22]. As shown in Fig. 1, the received phase will change periodically between [0, 2π] along the reader trajectory. When the robot moves from Loc1 to Loc2, the change in distance between the tag and the antenna will be less than half a wavelength. The shape of the corresponding received phase during this period is like a “V” as shown by the blue

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RSSI-based localization method is another common method for indoor positioning. This method exploits the relationship between the received power and the distance. In [32], a new indoor localization method for passive UHF RFID tag has been proposed. The method investigate the relationship between radar cross section (RCS) of the maximum effective reading distance and any measured distance by RSSI. The estimated RCS can be used to compensate tag unknown parameters for distance estimation. This could reduce the environmental effect without using reference tags.

In this paper, which is an extended version of the conference paper [31], a novel localization approach is proposed. Combined with the known antenna trajectory, the V-zone of the phase profile is used to estimate the location of target tags. Both cross range (or the distance along the track) and down range (or the distance perpendicular to the track) distances of a tag relative to the antenna trajectory can be found using only a single straight trajectory for 2D localization. In 3D space, the received RSSI and phase information from multiple antennas at various heights is used to estimate the location of tags using a L-shape trajectory.

The remainder of the paper is organized as follows. Some related methods are included for comparison in Section II. In Section III, the RFID robotic system is introduced. The localization algorithm is explained in Section IV which is followed by experimental setup and results in Section V. The conclusion is presented in Section VI.

II. RELATED WORK

Some related work such as STPP [22], RFScanner [7] and RLLL [9], achieve relative localization or spatial ordering of tags as would be required for a library scenario. In an environment such as a library, there will be passageway between shelves of tagged books. The reader antenna moves along the passageway parallel to the tags collecting phase information. By analysing the V-zone in the profile of the received phase of each tag, the order of tags can be determined. However, these methods can only provide ordering information rather than the absolute location.

Tzitzis et al. introduce a phase-unwrapping process eliminating the local minima in their Phase ReLock method [24]. The trajectory of the moving antenna is obtained by a Simultaneous Localization And Mapping (SLAM) procedure. They compared a SAR-based method with their method. The results show that both can achieve a 2D localization accuracy of around 17 cm and that the accuracy is affected by the error from the measurement of the trajectory by SLAM, which could be reduced by exploiting reference tags with known locations. In [29], an extension of Phase ReLock is presented in 3D space. After measuring the phase using multiple antennas and unwrapping the received phase measurements, a confidence metric is introduced to identify measured data and remove the faulty data which reduces the accuracy of the localization. The filtered data are used to create a multi-antenna synthetic aperture to locate target tags. This method can achieve a mean 3D localization error of less than 20 cm using four antennas on top of a SLAM-enabled robot.

In [23], a drone carrying a reader and an antenna is used to perform a SAR method to locate target tags. The mean 2D localization error is of the order of decimetres. Since the localization accuracy is affected by the accuracy of the measurement of the trajectory. A high-accuracy vision system, with an accuracy on the order of 1mm, is employed to obtain the trajectory of the moving robot [26]. The SAR-based method with a high-accuracy trajectory can reduce the 2D localization error to be smaller than 10 cm. Although the high-accuracy vision system can improve the performance, the hardware cost will be high. In [27], the proposed method integrated an Unmanned Grounded Vehicle (UGV) with a reader and two antennas. The UGV is controlled remotely to collect the phase information of tags and the trajectory is measured by SLAM. Experimental results show that both the mean localization errors along two-axis are around 9 cm respectively.

While SAR has the potential to provide a high resolution, the calculation of the ambiguity function over a fine grid required for a high resolution can be problematic (particularly in 3D). Due to this, a number of works focus on more efficient algorithms to find the tag location.

In [30], a SAR-based method is proposed for the 3D localization of tags. In contrast to conventional SAR methods which traverse grids in 3D space to find the maxima, the particle swarm optimization approach is employed to reduce the computational burden. This method can obtain a centimeter-order 3D localization error in the considered scenario and it suggests that a decimeter-order localization error can be achieved regardless of the application scenario. E3DinSAR [5] proposed an optimized interference synthetic aperture radar (InSAR)-based 3D localization approach. The proposed method extends the aperture of the moving robot to an arbitrary trajectory which is divided into multiple linear apertures. Instead of generating a 3D holographic image, several 2D holographic images are created at different heights. Thus, a group of candidate locations can be estimated and the final position can be determined by the density-based spatial clustering of applications with noise (DBSCAN) clustering.
method. E3DinSAR achieves a mean localization accuracy of 18.4 cm in 3D space.

Other methods localize target tags by the similarity between target tags and reference tags. Mo and Li use both the received phase and RSSI information from 64 reference tags to perform a 2D localization [28]. Virtual reference tags have been generated by natural neighbor interpolation to reduce the number of reference tags without deteriorating the accuracy. The Laiyite criterion with variable coefficient is introduced to mitigate the effect of multipath. This method can achieve a localization accuracy of 10 cm. The main limit of methods based on reference tags is that the localization accuracy is highly dependent on the number of reference tags.

The key contribution of this paper is to demonstrate a high accuracy 3D localization method based on the received RSSI and the unwrapped phase profile without requiring reference tags. The distance along the track can be found from the inflection point of the phase profile, while the distance perpendicular to the track can be determined from the shape of the profile, effectively the rate at which $k_2 \pi$ must be added to the observed phase to achieve unwrapping.

III. SYSTEM DESIGN AND IMPLEMENTATION

Fig. 2 shows the structure of the system [25]. The system consists of an Impinj R420 RFID reader, multiple linearly polarized antennas, a Turtlebot3 Waffle Pi robot, and two Raspberry Pi controller boards. The reader and the robot are remotely controlled and their timestamps are synchronized through a WLAN to allow alignment of the tag reads with the robot LiDAR as shown in Fig. 3. The speed of the robot is approximately 5 cm/s. The position of the robot is measured by a LiDAR sensor integrated with the robot.

IV. LOCALIZATION ALGORITHM

Fig. 4 shows the coordinate system used in the algorithm. 2D localization requires only one straight-line trajectory while 3D localization requires an L-shape trajectory. In terms of 2D localization, the cross-range, which is the distance along the trajectory1, and the down-range, which is the distance perpendicular to the trajectory1 are shown by the green arrows in the figure. For 3D localization, both x and y coordinate are estimated by cross-range estimation and the height of the target is estimated by down-range estimation. (Although trajectory2 is shown to be perpendicular to trajectory1, this isn’t a requirement of the algorithm, however, it will provide the best accuracy).

A. Cross-Range Estimation

As the robot moves along a straight-line trajectory past a tag the distance between the tag and the moving antenna decreases and then increases. This results in a V-zone in the phase profile which is shown by the blue line in Fig. 1. The corresponding location of the bottom of the phase in the V-zone represents the location along the trajectory where the antenna to tag separation reaches the minimum. The cross-range of the tag can be estimated using the known location of the moving robot.

As shown in Fig. 1, the received phase will change periodically between $[0, 2\pi]$ along the reader trajectory. In order to estimate the cross-range, the received phase is required to unwrap firstly. To ensure correct identification of the minima point, the phase must be sampled at least every half wavelength to allow correct unwrapping. The method assumes that multipath effect will not severely affect the received phase so that the shape of the V-zone will not be totally distorted.

The phase value received by the reader is affected by the noise and multipath effect, as a result, the received phase profile, shown in Fig. 5, is not a perfectly smooth curve, which
would occur in free space. The location of the real minima can be better approximated by applying a least-squares curve fitting and then finding the location of the minima of the fitted curve.

The distance can be expressed as

$$d = \sqrt{(x - m)^2 + (y - n)^2}$$

where \((x, y)\) represents the location of the robot and \((m, n)\) is the location of the tag.

And the phase can be written as

$$\phi = \frac{4\pi}{\lambda} \sqrt{(x - m)^2 + (y - n)^2}$$

Since the robot is moving along a straight-line trajectory, we can assume that the y-coordinate of the robot remains unchanged and the distance can be written as

$$\phi = B\sqrt{(x - m)^2 + C^2}$$

where \(C^2 = (y - n)^2\) and \(B = \frac{4\pi}{\lambda}\) are constant.

The phase could be expressed by Taylor series.

$$\phi = A_0 + A_2(x - m)^2 + A_4(x - m)^4 + \ldots$$

where \(A_0 = B|C|\) and \(A_2 = \frac{B}{2\pi}\).

And the fourth and higher orders of the Taylor series can be ignored which makes the distance approximately a quadratic so that the quadratic fitting could be used.

While curve fitting improves the accuracy, there is an implicit assumption that the variance of the error in the phase at all locations is the same when a simple LMS fit is used. Fig. 6 shows an example phase profile where the real cross range of the tag is close to 0 m. It can be seen that the received phase values appear less reliable when corresponding RSSI is low. This is probably due to two effects. As the RSSI decreases, the effect of random noise in the receiver adding phase noise to the phase measurements will increase. The effect of multipath over longer paths which have lower RSSI will also be greater. When the distance increases, there is a greater chance that the amplitude of the LoS and multipath signals will be similar which leads to greater impact on phase measurements. Since RSSI tends to decrease with path length, excluding low RSSIs will tend to eliminate longer path lengths.

While multipath can increase RSSI, this will only occur when the LoS and multipath signals sum in phase, so only a small phase error is introduced, whereas decrease in RSSI implies anti-phase between the LoS and multipath, and for similar magnitude signals can result in very large phase errors. Therefore, valid phase data can be determined according to the received RSSI. Phase data with RSSI larger than the average of RSSI (in dB) would be used as valid dataset, and only this data used for curve fitting.

**B. Down-Range Estimation for 2D Localization**

The distance variation between the tag and the interrogating antenna as it traverses the trajectory, is typically larger than half wavelength. As a result at each location the recorded phase is related to the unwrapped phase by

$$\phi_{\text{rec}} = \phi_{\text{unwrap}} + 2(n + k)\pi$$

where \(n\) and \(k\) are the integer number of \(2\pi\) phase required such at \(\phi_{\text{rec}} \in [0, 2\pi]\). In the unwrapping process, \(n\) increases or decreases by 1 each time the phase is wrapped such that \(n\) varies along the trajectory. However \(k\) is the residual number of \(2\pi\) required at the point of the closest approach which we term the k-parameter. After unwrapping the phase profile only \(n\) is removed and \(k\) remains. The k-parameter will be constant over the whole trajectory and the unwrapped received phase plus a k-parameter is equal to the true phase delay. The residual k-parameter can therefore be used to calculate the range at the point of the closest approach.

The trajectory can be expressed as a vector of \(N\) locations

$$Q = [q_1, \ldots, q_i, \ldots, q_N]^T$$

where

$$q_i = [m_i, n_i]$$

Are the coordinates of the antenna at each observation point where the phase is recorded.

The actual location of the target tag is expressed as

$$A = [x, y]$$
The distance between the location of the target tag and the location of the reader antenna at point $i$ can be calculated by

$$d_i^2 = (x - m_i)^2 + (y - n_i)^2$$  \hspace{1cm} (9)

So the y-coordinate of the tag is

$$y = \sqrt{d_i^2 - (x - m_i)^2} + n_i$$  \hspace{1cm} (10)

The relationship between the unwrapped phase $\phi_i$ at each observation point and the distance can be expressed by the following equation

$$\phi_i + 2k\pi = \phi_0 + \frac{4\pi d_i}{\lambda}$$  \hspace{1cm} (11)

where $k$ is an unknown integer and $\phi_0 \in [0, 2\pi]$ is offset caused by equipment and cable length (which can be calibrated).

Equation (11) can be rewritten as

$$d_i = \frac{\lambda}{4\pi} (\phi_i - \phi_0) + k \frac{\lambda}{2}$$  \hspace{1cm} (12)

As a result, the relationship between y-coordinate and phase is

$$y = \sqrt{\left(\frac{\lambda}{4\pi} (\phi_i - \phi_0) + k \frac{\lambda}{2}\right)^2 - (x - m_i)^2} + n_i$$  \hspace{1cm} (13)

The phase offset $\phi_0$ can be calibrated and removed, leaving the integer number $k$ as the only unknown in equation (13). As mentioned above, after phase unwrapping, the k-parameter will be constant over the whole trajectory. Since $y$ and $k$ should both be independent of the location where the measurement is taken, the correct value of $k$ can be found by using multiple phase measurements at different locations. The value of $k$ is iterated until $y$ remains constant. If the $k$ is not correct, the shape of the resulting $y$ would be a curve as shown in Fig. 7(a). When the $k$ is the correct number, since the tag is stationary, a straight line which has the smallest standard deviation would be obtained as shown in Fig. 7(b). In practical cases, the real shape will not be a perfect straight line due to errors in the phase measurement and the effects of multipath. The final estimated location would be the average of calculated results.

**C. Estimation for 3D Localization**

Multiple antennas and an L-shape trajectory are required to estimate 3D location of target tags. As shown in Fig. 4, the robot is moving along a L-shape trajectory. By using the cross-range estimation method, combined with two known straight-line trajectories, the x-coordinate and y-coordinate of the target tag can be obtained using the highest antenna. The highest antenna is used since we observed the signal received by the highest antenna is comparatively stable so the phase obtained by the highest antenna will be comparatively more reliable this is likely due to the large multipath from the floor affecting the other antennas more.

In order to calculate the height of the target tag and improve the accuracy, RSSI received by multiple antennas is used to determine the approximate range of height for the target tag. By calculating the largest and second largest received RSSI by the four antennas, the range of height can be estimated. Fig. 8 shows received RSSI values of one target tag with x, y coordinates of 1.615 m and 1.2 m and height of 1.15 m by four antennas with height of 1.3 m, 1.0 m, 0.7 m, 0.4 m respectively. Since the RSSI received by antenna 1 and antenna 2 are similar to each other and larger than the RSSI received by the other two antennas, it can be deduced the target is located between the height of antenna 1 and antenna 2.

After obtaining the approximate range of the height, the span of which is 0.3 m, the z-coordinate can be calculated by finding the integer number of wavelengths which fits the x, y location and phase profile.

The relationship between the received phase and the distance can be written as

$$\phi_i + 2k\pi = \phi_0 + \frac{4\pi}{\lambda} \sqrt{(x - m_i)^2 + (y - n_i)^2 + (z - h_i)^2}$$  \hspace{1cm} (14)

where $k$ is an unknown integer, $\phi_0 \in [0, 2\pi]$ is offset caused by equipment and cable length, $(m_i, n_i)$ is the location of the moving robot at time $t$ which is measured by LiDAR, $h_i$ is the height of the antenna, $(x, y, z)$ represents the location of the target tag and $x$ and $y$ are estimated by cross-range estimation.

The z-coordinate is expressed as

$$z = h_i \pm \sqrt{\left(\frac{\lambda}{4\pi} (\phi_i - \phi_0) + k \frac{\lambda}{2}\right)^2 - (x - m_i)^2 - (y - n_i)^2}$$  \hspace{1cm} (15)

The height can be estimated by adjusting k-parameter. However, as shown in equation (15), there would be two
ambiguous heights if only a single antenna is used. This can be resolved by using more than one antenna in a vertical arrangement to determine the range of the height as described above so that only one solution is left. The final z-coordinate of the target would be the average of heights estimated by four antennas. Although two antennas are sufficient to solve the problem of ambiguity, in practice, both the multipath effect and the error of \(x\)- and \(y\)-coordinate estimation will lead to large errors in the estimation of \(z\). Using RSSI to determine the approximate range of \(z\) can reduce the occurrence of large errors. For example, consider a target tag where the real \(z\) is 1.15 m. Without setting the range for the height of the tag, the estimated heights, using the k-parameter method, for antenna 1 are 1.39 m and 1.21 m while the estimated heights by antenna 4 are 0.69 m and 0.11 m. The reason for this large error is the selection of the wrong \(k\) parameter, due to the geometry this results in a large error in \(z\).

Fig. 9 shows the steps for 3D localization. After collecting and unwrapping received phase values, \(x\) and \(y\) coordinate are calculated by cross-range estimation. RSSI is used to determine the range of the height and the final height of the target tag is estimated by down-range estimation.

V. RESULTS

A. 2D Localization Results

The setup of the experiment is shown in Fig. 10(a). The position of the moving robot is obtained by LiDAR which is measuring the distance between the robot and some boards placed at the edges of the area as references. Anechoic materials were used in the lab to partially reduce the influence of the equipment and metal objects as shown in Fig. 10(b).

After estimating the cross-range by calculating the minimum of the V-zone combined with the corresponding location of the robot, the down-range estimation algorithm is applied. One example of results finding the correct k-parameter is shown in Fig. 11. By adjusting \(k\), the shape of the curve for \(y\)-coordinate of the target tag gets straighter and reaches optimal when \(k\) is three which is shown by the purple line and has the lowest standard deviation of values, the average value is the final estimate \(y\)-coordinate.

Table I summarizes the results of five tests each locating 8 target tags. The average value of the mean localization errors for five tests is around 12 cm which is smaller than the results obtained using traditional phase-based SAR processing [25] and Phase Relock [24] but slightly larger than some phase-based methods [26]–[28]. One source of error in cross-range estimation is the error incurred by the trajectory measurement. The trajectory is obtained by measuring the distance provided by LiDAR, of has an accuracy on the order of centimeters (\(\pm 15\) mm within 500 mm and \(\pm 5.0\%\) when the distance is 500~3500 mm [33]). By employing a higher accuracy system
for trajectory estimation, the cross-range error could be further reduced. Moreover, both cross-range and down-range estimation is affected by the environment such as multipath effects which results in inaccurate received phase values.

B. 3D Localization Results

Fig. 12 shows the setup of the experiment. Passive UHF tags are attached to plastic boxes as targets to locate. The mobile robot is carrying four antennas with heights of 1.3m, 1.0m, 0.7m and 0.4m respectively. Tags are placed in two layers with heights of 1.15m and 0.75m as shown in Fig. 11(a). Black dashed lines represent the trajectories of the four antennas. Anechoic materials are used to partially reduce the effect of the metal objects and other tags in the lab as shown in Fig. 11(b).

Fig. 13 plots the CDF of the localization error using four antennas for all tags along each axis as well as the total error magnitude. The total mean localization error, which is shown by the purple line, is around 15cm. Both the mean errors in the x- and y-axis are around 5 cm as shown by the blue and the red line. The majority of the error is from the vertical, z-axis, of which the mean error is around 12 cm as shown by the yellow line.

Fig. 14 plots the estimated location, which is shown by the red cross, and the actual location, which is shown by the black circle, for all tags. The tags in the upper layer have a smaller localization error than the tags in the lower layer. And most of the tags in the lower layer are predicted to be lower than their locations.

Since the RSSI is used to determine the range of height for targets, the larger errors imply that the RSSI determines incorrect range of height in some cases. Tags in the upper layer are located between the heights of two higher antennas (antenna 1 and 2) as shown in Fig. 8 so the received RSSI can determine the range of height accurately. The height of the lower layer is close to antenna 3 rather than in the middle of two antennas as shown in Fig. 14(b). The location of this tag, for example, is (1.615 m, 0.4 m, 0.75 m). The theoretical RSSI received by antenna 3 should be the largest and the RSSI received by antenna 2 should be the second largest. This can be used to determine the range of the height for the tag. However, in practice, due to the imperfect antenna pattern and stronger multipath effect from the ground reflection, the RSSI received by antenna 4 can be as large as that received by antenna 3 as shown in Fig. 15(a) which leads to wrong estimated ranges of height for the tag. As a result, tags at the lower layer have larger localization error. Moreover, tags located further from the trajectory have larger localization error on the z-axis which could be the result of the larger ground reflection.

VI. Conclusion

This paper proposes a computationally simple phase and RSSI-based localization method. In 2D space, only a straight-line trajectory is required to estimate the location of the
target tag. The cross range of the target tag can be estimated by combining the location of the moving robot and the minimum point of the unwrapped phase curve. The down range can be calculated by adjusting the k-parameter. The 2D localization accuracy is around 12 cm. In 3D space, the x and y-coordinate of the target tag can be calculated by the minimum point of the unwrapped phase curve using an L-shape trajectory. A possible range of the height of the target tag can be estimated by RSSI received by multiple antennas. After obtaining the possible range of the height, the actual height can be calculated by adjusting the k-parameter. The mean 3D localization error is around 14 cm using four antennas.

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