A fast phase and RSSI-based localization method using Passive RFID System with Mobile Platform

Zheng Liu
Centre for Photonic Systems, Electrical Division, Department of Engineering
University of Cambridge
Cambridge, U.K.
zl390@cam.ac.uk

Zhe Fu
Centre for Photonic Systems, Electrical Division, Department of Engineering
University of Cambridge
Cambridge, U.K.
zf233@cam.ac.uk

Tongyun Li
Centre for Photonic Systems, Electrical Division, Department of Engineering
University of Cambridge
Cambridge, U.K.
tl299@cam.ac.uk

Ian White
University of Bath
Bath, U.K.
ihw3@cam.ac.uk

Richard Penty
Centre for Photonic Systems, Electrical Division, Department of Engineering
University of Cambridge
Cambridge, U.K.
rvp11@cam.ac.uk

Michael Crisp
Centre for Photonic Systems, Electrical Division, Department of Engineering
University of Cambridge
Cambridge, U.K.
mjc87@cam.ac.uk

***Abstract*—A novel localization method is proposed and demonstrated which exploits the phase profile combined with the location of the moving robot to locate target tags using only a single straight-line interrogator antenna trajectory. A system that integrates a mobile robot with an integrated RFID reader and antenna is used to obtain phase measurements of target tags when the robot is moving along its trajectory. The cross-range location of the target is obtained from the stationary point of the fitted phase curve. The down range distance is estimated by finding the integer number of wavelengths which fits the cross-range location and curve shape. The proposed method could reduce the localization error to around 12 cm which is similar to the SAR method using a straight-line trajectory, but with much lower computational complexity.**

Keywords—RFID; phase-based; Localization;

I. INTRODUCTION

Many RFID applications require accurate position information of materials and products in various scenarios such as inventory interrogation in warehouses and automatic manufacturing on an assembly line in factories [1, 2]. Recently, passive Ultra High Frequency-Radio Frequency Identification (UHF-RFID) technology has attracted increasing interest and been widely adopted in object localization [3-5] since it has many advantages such as contactless communication which is essential in a complicated environment, multi-object recognition providing the ability to track a large number of objects which is crucial in many applications [6], and low-cost which increases profitability and enables large-scale applications [1, 7].

There have been many methods on localization using RFID technology such as received signal strength indicator (RSSI)-based [8-10], angle of arrival (AoA)-based [12], time of arrival (ToA)-based [12] and phase-based [13, 14, 20-25] techniques. Phase-based methods have been shown to be comparatively robust and stable in complicated indoor environments [6, 15-19].

Synthetic Aperture Radar (SAR), which exploits the mobility of a mobile platform, is one of the most popular algorithms to estimate the position of target tags with minimal radio hardware [16, 17]. However, the major disadvantage of SAR-based methods is the large computational load required to calculate the ambiguity function over a wide area with a high resolution. This problem becomes even greater when 3D localisation is required.

Other phase-based methods focus on relative localization. Spatial-Temporal Phase Profiling (STPP) proposed a method utilizing the “V-zone” in the phase profile to infer the order of tags. As the phase changes between [0, 2π], the received phase will change periodically as shown by the blue line in Fig. 1. When the antenna moves from Loc1 to Loc2, the change in distance will less than half a wavelength, the shape of received phase during this period is like a “V” and is referred to in this paper as the V-zone of the phase profile.

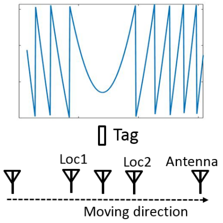


Fig. 1. Relative motion and V-zone

In this paper, a novel approach with a low computing burden is proposed to provide the absolute 2D location of targets. The method exploits the V-zone of the phase profile combined with the known antenna trajectory to estimate the location of target tags. By fitting a curve to the phase data, both cross range (x-coordinate) and down range (y-coordinate) can be found using only a single straight trajectory. In order to analyse the performance, the results of the proposed method are compared with the SAR processing using the same data from a single straight-line trajectory.

The remainder of the paper is organized as follows. Some related methods are included 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

The most recent related work includes STPP [19], RFScanner [4] and RLLL [6] which all exploit the concept of the V-zone. All these methods are designed to perform the relative localization or achieve the ordering of tags which could be used in a library scenario. In such an environment, the reader’s antenna follows a straight-line trajectory parallel to the tags. By analysing the V-zone or using the symmetric shape of the phase profile, the order of tags could be determined. However, it is difficult to achieve absolute localization through these methods directly.

Tzitzis et al. compared the SAR-based algorithm with their Phase Relock method which introduces a phase-unwrapping process eliminating local minima [21]. Both methods could provide a localization accuracy of around 17cm. The accuracy is affected by the error introduced by SLAM which needs reference tags to improve localization accuracy.

Buffi et al. integrated a reader on a drone to carry out a typical SAR method to locate target tags [20]. The mean 2D localization error is of the order of a few tens of centimetres. In [23], a high-accuracy vision system with uncertainty in the order of around 1mm is employed to measure both the position of the robot. Experimental results show that the 2D localization error could be smaller than 10 cm. The high-accuracy vision system could increase the performance, but the cost will also increase. In [24], an Unmanned Grounded Vehicle (UGV) is controlled remotely and equipped with a reader and two antennas. The proposed method exploits the trajectory of the UGV, which is measured by a Simultaneous Localization And Mapping (SLAM) procedure to achieve a 2D localization for target tags. Both the mean localization errors along two-axis are around 9 cm. These methods [20, 23, 24] are based on the SAR approach which needs large number of grids of the area to achieve high accuracy localization. This will result in high computational complexity.

The localization method proposed by Mo and Li uses 64 reference tags to localize target tags by similarity measurement using both phase profile and RSSI [25]. In order to reduce the number of reference tags, virtual reference tags have been generated by natural neighbour interpolation. To mitigate the effect of multipath, the Laiyite criterion with variable coefficient is presented. Results show that error of 90% of tags is within 10 cm. The localization accuracy high depends on the number of reference tags which is one main limit of the method.

The key contribution of this paper is to demonstrate a high accuracy localization with a low computing burden and without using reference tags. Our method is based on the phase profile and k-parameter estimation is proposed.

III. SYSTEM DESIGN AND IMPLEMENTATION

The structure of the system is shown in Fig.2 [22]. It consists of an Impinj R420 RFID reader with a linearly polarised antenna which is mounted on a wooden pole attached to the robot, a Turtlebot3 Waffle Pi robot, and two Raspberry Pi controller boards. The RFID reader and the Turtlebot3 Waffle Pi are remotely controlled, and their timestamps are synchronised by using a WLAN (See Fig. 3) to allow alignment of robot position data with the tag reads. The RFID reader interrogates the passive tags and records the EPC, phase information and timestamps offline processing. The speed of the robot is approximately 5 cm/s. A LiDAR sensor is used to determine the robot position.

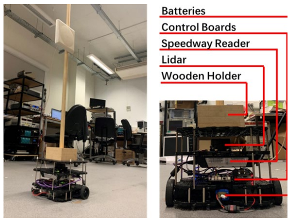


Fig. 2. RFID Robot [22]

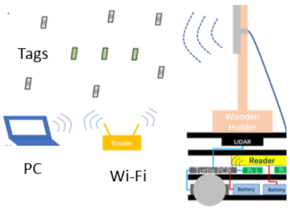


Fig.3.Diagram of the system [22]

IV. LOCALIZATION ALGORITHM

As shown in Fig.4, when the robot moves forward along the trajectory, the distance between the tag and the robot decreases firstly and then increases. The distance could be expressed by Taylor series. And the high orders of Taylor series could be ignored which makes the distance approximately a quadratic so that the quadratic fitting could be used. As shown by the blue line, there is a V-zone in the phase profile. The corresponding time when the phase reaches the bottom of the V-zone represents the time when the antenna to tag distance reaches the minimum. By combining this time and the known trajectory of the robot, the x-coordinate of the tag could be estimated (or the distance along the track known as cross range in radar). The unwrapped phase profile is also related to the y-coordinate of the tag (or distance perpendicular to the track known as down range in radar). Combining with the known trajectory of the moving robot, the location of the tag can be estimated.

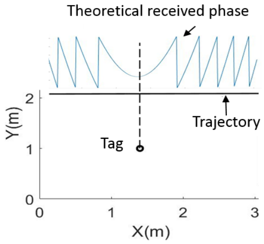
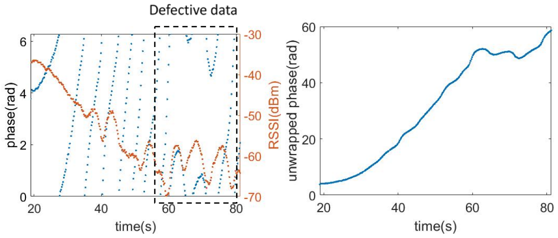


Fig. 4. X-coordinate estimation by V-zone

The distance variation between reader and tag is typically larger than half wavelength, resulting in phase wrapping and an unknown integer number of 2π (k-parameter) in addition to the recorded phase which varies along the path. The received phase sequences need to be unwrapped firstly such that the unwrapped phase plus a k-parameter which is constant over the whole trajectory is equal to the true phase delay. The unwrapped phase could be used to estimate the x-coordinate of the target tag. However, as shown in Fig.5(a), one problem is the defective data which results in defective unwrapped phase profile as shown in Fig.5(b) which is clearly not quadratic at t>60s. A straight forward way to solve this problem is to use only part of phase values.



(a) Received phase RSSI values (b) Unwrapped results

Fig. 5. The problem of unwrapping

As shown in Fig.5(a) blue points show the phase while red points represent RSSI. When RSSI decreases into low levels, the phase signal becomes unreliable. This is most likely due to smaller multipath effects having a great impact on recorded phase over longer wireless path lengths which also have smaller RSSI. Therefore, RSSI can be used to determine the range of valid data. In the new method, phase data with RSSI larger than the average of RSSI would be considered as valid data and this valid dataset is used to estimate the location of the target tag.

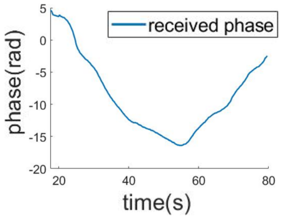


Fig. 6. Received phase values after unwrapping

Because the phase value received by the reader is affected by noise and multipath effect, the received phase profile is not a perfect smooth curve as shown in Fig.6. In order to find the lowest point of the phase profile, the least squares regression is used to calculate its fitting curve.

The coordinate system is be defined so that the x-axis of the coordinate system is along the straight-line trajectory of the robot to simplify the equations. After obtaining the curve fitting, the corresponding time of the minimum of the fitting curve would be the time when the distance between the robot and the tag reaches the minimum. The x-coordinate of the robot, which is measured by LiDAR, at this time is the estimated x-coordinate for the target tag. When the x-coordinate of the target is obtained, the y-coordinate can be calculated by following steps.

At time t, the location of the reader antenna is expressed as

$$\boldsymbol{q_t} = [m_t, n_t] \tag{4}$$

The trajectory can be expressed as a vector of locations

$$\mathbf{Q} = \left[\boldsymbol{q_1}, \ldots, \boldsymbol{q_t}, \ldots, \boldsymbol{q_{T_1}}\right]^T \tag{5}$$

Where T is the transpose operator and each element represents a location at which information of the phase for tags is recorded. The location of the target tag is expressed as

$$\boldsymbol{A} = [x, y] \tag{6}$$

The distance between the location of the target tag and the location of the reader antenna at time t can be calculated by

$$d_t^2 = (x - m_t)^2 + (y - n_t)^2 \tag{7}$$

So the y-coordinate of the tag is

$$y_t = \sqrt{d_t^2 - (x - m_t)^2} + n_t \tag{8}$$

The relationship between the phase and the distance can be expressed by the following equation

$$\phi_t + 2k\pi = \phi_0 + \frac{4\pi d_t}{\lambda} \tag{10}$$

Where k is an unknow integer and $\phi_0 \in [0,2\pi]$ is offset caused by equipment and cable length

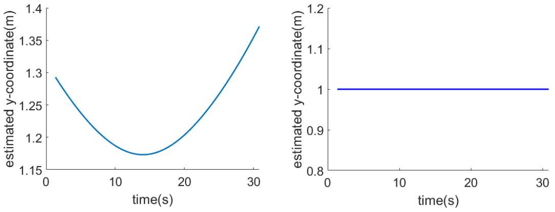
This could be rewritten as

$$d_t = \frac{\lambda}{4\pi}(\phi_t - \phi_0) + k\frac{\lambda}{2} \tag{12}$$

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

$$y_t = \sqrt{(\frac{\lambda}{4\pi}(\phi_t - \phi_0) + k\frac{\lambda}{2})^2 - (x - m_t)^2 + n_t} \tag{13}$$

The ϕ_0 can be calibrated, and the only unknown number is the integer number k. By using the equation above and multiple measurement of the returned tag phase at different m_t, a series of estimated y-coordinates for the tag can be obtained as the robot moves along the trajectory. The shape of y-coordinates would be a curve if the k is not correct as shown in Fig.7(a). By adjusting k, the shape will change and finally when the k is the correct number which results in a static value (or nearly static value) for y as shown in Fig.7(b). In practical cases, the real shape of y-coordinates may not be a straight-line due to errors in the phase measurement. The final estimated y-coordinate of the target tag would be the average of calculated y-coordinates.

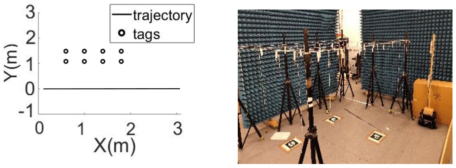


(a) With wrong k (b) With correct k

Fig. 7. Simulated results of y-coordinate estimation with different k

V. RESULTS

Fig. 8(a) shows the setup of the experiment. The location of the robot is estimated by placing some boards with known locations at the edges of the area as references for LiDAR. Using the shortest distance measured to each board, a 2D position of the moving robot can be obtained by LiDAR. The trajectory, which is parallel to the x-axis and around 1m away from the nearest row of tags, is 3 m long. The distance between each row and column of tags is 40 cm. Anechoic materials were used in the lab to partially reduce the influence of the equipment and metal objects as shown in Fig. 8(b).



(a) Configuration of tags (b) Picture of the environment

Fig. 8. Experiment setup

After obtaining the x-coordinate by calculating the minimum of the fitting curve, the algorithm of adjusting the value of k is applied to estimate y-coordinate. Fig.9 shows one example of results with different k. By adjusting the value of k, the curve of results becomes straighter and reaches optimal when the k is 3. And the estimated y-coordinate will be the average of the purple curve.

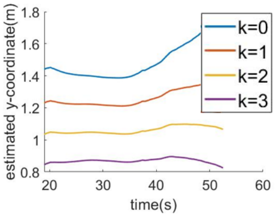


Fig. 9. Y-coordinate estimation results with differnet k

Five tests are carried out each locating 8 tags and results are summarized in Table I. The mean value of the five tests is around 12 cm which is smaller than the results obtained using SAR processing [22] and Phase Relock [21] and slightly larger than some phase-based methods [23-25]. However, compared with the SAR-based method which commonly requires grids, the proposed method could locate target tags faster with much lower computational complexity. Moreover, the proposed method only uses one antenna and the trajectory of the antenna is measured by LiDAR, of which the accuracy is in order of centimeters. By using more antennas and high-accuracy system for trajectory estimation, the localization error could be further reduced.

TABLE I. MEAN LOCALIZATION ERROR OF FIVE TESTS

Mean localization error (cm)		
Test	**SAR [23]**	**Proposed method**
1	17.86	13.75
2	11.91	10.12
3	8.09	13.11
4	8.61	12.23
5	15.33	9.21
Mean	12.36	11.68

VI. CONCLUSION

This paper proposes a localization method requiring only a straight-line trajectory and comparatively low computational load. By combining the location of the moving robot and the minimum point of the fitting curve, the x-coordinate of the target tag could be estimated. By adjusting k-parameter, the y-coordinate could be calculated. The localization accuracy using this new method is around 12 cm which is similar to the accuracy achieved by SAR-based method with lower computational complexity.

ACKNOWLEDGEMENT

The authors would like to thank the Beijing Institute of Aerospace Control Devices (BIACD) for their support through the RFID system Optimization for smart manufacturing using Mobile rEader (ROME) project.

REFERENCES

[1] Baha Aldin, N., Erçelebi, E. & Aykaç, M. An Accurate Indoor RSSI Localization Algorithm Based on Active RFID System with Reference Tags. Wireless Pers Commun 97, 3811–3829 (2017).

[2] K. Nur, M. Morenza-Cinos, A. Carreras, and R. Pous, "Projection of RFID-Obtained Product Information on a Retail Stores Indoor Panoramas", *IEEE Intelligent Systems*, vol. 30, no. 6, pp. 30-37, Nov.-Dec. 2015.

[3] L. Shen, Q. Zhang, J. Pang, H. Xu and P. Li, "PRDL: Relative Localization Method of RFID Tags via Phase and RSSI Based on Deep Learning," in *IEEE Access*, vol. 7, pp. 20249-20261, 2019.

[4] Jiaqing Luo and Kang G Shin. Detecting misplaced rfid tags on static shelved items. In *Proceedings of the 17th Annual International Conference on Mobile Systems, Applications, and Services (Mobisys)*, pages 378–390, 2019

[5] S. Zhang, Y. Fu, D. Jiang and X. Liu, "RFID Localization Based on Multiple Feature Fusion," *2018 15th Annual IEEE International Conference on Sensing, Communication, and Networking (SECON)*, 2018, pp. 1-2.

[6] X. Liu, Q. Yang, S. Zhang and B. Xiao, "RLLL: Accurate Relative Localization of RFID Tags with Low Latency," *2020 IEEE/ACM 28th International Symposium on Quality of Service (IWQoS)*, 2020, pp. 1-10.

[7] H. Ding et al., "Trio: Utilizing Tag Interference for Refined Localization of Passive RFID," *2018 IEEE INFOCOM 2018 - IEEE Conference on Computer Communications, Honolulu, HI, USA*, pp. 828-836.

[8] E. L. Berz, D. A. Tesch, and F. P. Hessel, "RFID indoor localization based on support vector regression and k-means," in *2015 IEEE 24th International Symposium on Industrial Electronics (ISIE)*, pp. 1418–1423, 2015.

[9] H. Ma and K. Wang, "Fusion of RSS and Phase Shift Using the Kalman Filter for RFID Tracking," in *IEEE Sens. J.*, vol. 17, no. 11, pp. 3551–3558, 2017.

[10] X. Wu, F. Deng, and Z. Chen, "RFID 3D-LANDMARC Localization Algorithm Based on Quantum Particle Swarm Optimization," in *Electronics*, vol. 7, no. 2, pp. 1–11, 2018.

[11] S. Azzouzi, M. Cremer, U. Dettmar, R. Kronberger and T. Knie, "New Measurement Results for the Localisation of UHF RFID Transponders Using an Angle of Arrival (AoA) Approach," in *2011 IEEE International Conference on RFID*, pp.91,97, 12-14 April 2011

[12] Y. Ma, K. Pahlavan, and Y. Geng, "Comparative Behavioral Modeling of POA and TOA Ranging for Location-Awareness Using RFID," in *Int. J. Wirel. Inf. Networks*, vol. 23, no. 3, pp. 187–198, 2016.

[13] L. Yang, Y. Chen, X.-Y. Li, C. Xiao, M. Li, and Y. Liu, "Tagoram: Real-time Tracking of Mobile RFID Tags to High Precision Using COTS Devices," in *Proceedings of the 20th Annual International Conference on Mobile Computing and Networking*, pp. 237–248, 2014.

[14] A. Povalac and J. Sebesta, "Phase difference of arrival distance estimation for RFID tags in frequency domain," in *2011 IEEE International Conference on RFID-Technologies and Applications*, pp. 188–193, 2011.

[15] Li, C., Tanghe, E., Plets, D., Suanet, P., Hoebeke, J., Poorter, E., & Joseph, W. (2019). RePos: Relative Position Estimation of UHF-RFID Tags for Item-level Localization. *2019 IEEE International Conference on RFID Technology and Applications (RFID-TA)*, 357-361.

[16] Bernardini, F., Motroni, Nepa, Buffi, Tripicchio, & Unetti. (2019). Particle Swarm Optimization in Multi-Antenna SAR-based Localization for UHF-RFID Tags. *2019 IEEE International Conference on RFID Technology and Applications (RFID-TA)*, 291-296.

[17] A. Buffi, A. Motroni, P. Nepa, B. Tellini, and R. Cioni, "A SAR-Based Measurement Method for Passive-Tag Positioning With a Flying UHFRFID Reader", *IEEE Transactions on Instrumentation and Measurement*, vol. 68, no. 3, pp. 845-853, March 2019.

[18] Tzitzis, A., Megalou, S., Siachalou, S., Tsardoulias, E., Yioultsis, T., & Dimitriou, A. (2019). 3D Localization of RFID Tags with a Single Antenna by a Moving Robot and "Phase ReLock". *2019 IEEE International Conference on RFID Technology and Applications (RFID-TA)*, 273-278.

[19] Longfei Shangguan, Zheng Yang, Alex X. Liu, Zimu Zhou, and Yunhao Liu. Relative localization of RFID tags using spatial-temporal phase profiling. In *Proceedings of 12th USENIX Symposium on Networked Systems Design and Implementation (NSDI)*, pages 251–263, 2015.

[20] A. Buffi, P. Nepa, and R. Cioni, "SARFID on drone: Drone-based UHF-RFID tag localization," in *2017 IEEE International Conference on RFID Technology & Application (RFID-TA)*, 2017.

[21] A. Tzitzis et al., "Localization of RFID tags by a moving robot, via phase unwrapping and non-linear optimization," IEEE J.Radio Freq. Identif., vol. 3, no. 4, pp. 216–226, Dec. 2019, doi: 10.1109/JRFID.2019.2936969.

[22] Z. Liu, Z. Fu, T. Li, I. H. White, R. V. Penty and M. Crisp, "An ISAR-SAR based Method for Indoor Localization using Passive UHF RFID System with Mobile Robotic Platform," in *IEEE Journal of Radio Frequency Identification*.

[23] A. Motroni et al., "SAR-Based Indoor Localization of UHF-RFID Tags via Mobile Robot," 2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN), 2018, pp. 1-8.

[24] A. Motroni, P. Nepa, A. Buffi, P. Tripicchio and M. Unetti, "RFID Tag Localization with UGV in Retail Applications," 2018 3rd International Conference on Smart and Sustainable Technologies (SpliTech), 2018, pp. 1-5.

[25] L. Mo and C. Li, "Passive UHF-RFID Localization Based on the Similarity Measurement of Virtual Reference Tags," in IEEE Transactions on Instrumentation and Measurement, vol. 68, no. 8, pp. 2926-2933, Aug. 2019.