ReLoc 2.0: UHF-RFID Relative Localization for Drone-based Inventory Management

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Abstract—Radio frequency identification (RFID) technology attracts extensive attention for industrial applications, especially supply chain businesses and inventory management. In this paper, a passive RFID localization scheme based on unmanned aerial vehicle (UAV) or drones is established for inventory management in warehouses. In case of the major challenge of the on-board antenna tracking errors in practical scenarios, the state-of-the-art numerical methods rely on accurate antenna positions, such as synthetic aperture radar-based algorithms, which will introduce large positioning errors and become unreliable. To this end, we propose a new relative RFID localization method based on phase, received signal strength indicator (RSSI), and readability, which is little affected by antenna tracking errors. In the proposed method, the tagged items on the racks are located laterally through pinpointing the minimum of the unwrapped phases, which have been unwrapped based on the hybrid random forest model. RSSI differences and the read count of each patch antenna's beam are utilized to distinguish the rack level of tagged assets via a boosting tree classifier. The experimental results in a real warehouse show that the proposed method achieves 27.1-cm mean lateral positioning accuracy, and orders the tagged items horizontally and vertically with more than 96.7% and 98.0% accuracy, respectively.

Index Terms—Radio frequency identification (RFID), indoor localization, industrial Internet-of-Things (IIoT), inventory management, unmanned aerial vehicle (UAV), received signal strength indicator (RSSI), phase unwrapping.

I. INTRODUCTION

THE increasing complexity in supply chain businesses requires feasible logistical solutions at every stage of operations, especially inventory management. Presently, warehouses management builds on barcode, Quick Response (QR) code, and radio frequency identification (RFID) based solutions for item-level identification [1]–[4]. However, even with these, the inventory management in warehouses remains labor-intensive and time-consuming, involving forklifts or scissor-lifts, manual operations, and hundreds of man-hours. To this end, unmanned robot-based scheme have been proposed for the automated inventory positioning in the warehouses, where the stocks are bulky and stored vertically. Tiemann *et al.* [4] utilized unmanned aerial vehicles (UAVs) for the fast and

automated stocktaking in a mimicked warehouse based on QR-code detection. Kalinov *et al.* [5] proposed the drone-based barcode scanning system for the on-board assets identification. Compared to vision-based solutions (QR code, barcode, etc.), passive ultra-high frequency (UHF) RFID-based inventory management has also attracted extensive attention thanks to its low-cost, easy-deployment, and the absence of the requirement of light. Buffi *et al.* [6] exploited a drone-mounted RFID reader to locate the tagged assets for the outdoor storage, in which the drone was tracked by global navigation satellite system (GNSS).

According to [7], [8], the available commercial off-the-shelf (COTS) RFID reader can provide low-level user data (LLUD), such as radio frequency phase, received signal strength indicator (RSSI), and Doppler shift, which can be used to identify (or localize) the RFID tag. Upon the underlying idea of synthetic aperture radar (SAR), Miesen *et al.* [9], Buffi *et al.* [6] and Zhao *et al.* [10] achieved decimeter-level (even centimeter) positioning accuracy based on the holography at the targeted area via a moving reader. Liu *et al.* [11], and Ma *et al.* [12] adopted a hyperbolic positioning method based on the phase difference of arrival (PDoA) in case of satisfying spatial sampling constraint, and obtained decimeter-level accuracy as well. To reduce the computation cost of the grid searching methods, Huang *et al.* [13] proposed to utilize the Levenberg–Marquardt (L-M) algorithm to solve the localization problem after the phase unwrapping. Even though this localization problem is non-convex, it locally exhibits a strong convexity at an optimal solution [14]. So the performance of the L-M algorithm highly depends on the initialization.

Instead of the absolute locations of targets, several relative localization algorithms were proposed for the logistics, retailing, and warehouses management. Shangguan *et al.* [15] proposed a RFID tag sorting algorithm (STPP), which ordered the tags horizontally and vertically based on the core V-zone of the measured phase profiles as the antenna moves along the tags. Instead of only using the core V-zone in STPP, Liu *et al.* [16] utilized all the phase profile data to form a super V-zone after the phase unwrapping (RF-scanner), then hyperbola fitting was used to pinpoint the locations of the tags. However, both STPP and RF-scanner require sufficient phase records to obtain a satisfying performance. Instead of absolute positioning, Shangguan *et al.* [2] proposed a multi-frequency enhanced SAR-based method (MobiTagbot), which achieved fine-grained ordering accuracy, even in multipath-prevalent scenarios. The main drawback is that MobiTagbot dwells at

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Fig. 1. RFID-based inventory management scenario, in which the RFID reader and antennas are mounted on the drone, and the drone flies along the middle line of the aisle (left and right racks) with a given speed v and trajectory: (a) aisle view, (b) rack view.

each sampling position and collects the measured phases of all selected channels. Otherwise, it would degenerate into a naive SAR-based method. Considering some practical challenges including phase and radiation characteristic, material of the tagged objects, and multipath, Li *et al.* [17] proposed a relative localization method (ReLoc) for warehouse management based on hybrid phase and RSSI, which localized the lateral position via phase-based variant maximum likelihood estimation (MLE), and distinguished the rack level through two tilted COTS antennas (upwards and downwards) after the logical judgment on RSSI differences.

Motivation and requirement: For the inventory management in warehouses, the positioning platform (e.g., commercial drones) moves between the vertical racks along the straight aisle with a given speed and trajectory (parallel to the plane of racks), as shown in Fig. 1. Considering the flying drone may not be fully controlled along the predefined trajectory, it is usually required to track the drone's location during the RFID interrogation. Furthermore, for safety reasons, the inventory operation should be launched during the night when no one is still working in the warehouse. To this end, vision-based methods (e.g., QR code) may not work due to no (or low) light level. On-board lighting can be a potential choice, but this also introduces an additional payload and energy consumption for the drones. So RFID-based solutions have an advantage as they do not require any lighting. To further improve the efficiency, the customers usually demand that the drone-based RFID systems can handle multi-layer management, so the drone does not need to scan each layer of the racks. On the scale of altitude (z -axis in Fig. 1), it is generally not required to achieve a centimeter-level accuracy, but only to support layer-granularity, corresponding to one to two meters in real-world warehouses.

Novelty: In this paper, a drone-based relative RFID localization algorithm for inventory management is proposed based on the above practical situation in warehouses. The main contributions of this article are as follows,

- 1) Considering the case of antenna tracking errors, we have proposed a lateral positioning algorithm based on the unwrapped phase, which is robust to the tracking errors compared to other numerical algorithms [2], [6], [9],

[10], [17]. Specifically, a phase unwrapping algorithm based on the hybrid formula and random forest classifier has been proposed, which mitigates the antenna spatial sampling constraint. Moreover, we have introduced subsequence dynamic time warping (sDTW) to extract the critical region of the phase profile, which helps to increase the lateral positioning accuracy further.

- 2) We have proposed a rack level distinguishing method based on the designed multi-beam patch antenna (electrically). Compared to the two tilted antennas (mechanically) adopted in [17], it is light-weight and feasible. Regarding the level distinguishing as a multi-class problem, a boosting tree classifier has been trained based on the RSSI differences of multiple beams and RFID readability (record count), and pinpoints the rack level.
- 3) We have mounted two antennas on both sides of the drone platform, so the RFID management system can handle two rows of racks (left and right) simultaneously (e.g., rack 1 and 2 in Fig. 1).
- 4) We have evaluated the proposed indoor drone-based UHF-RFID inventory management solution in a real large warehouse, which has been rarely reported in the literature according to the authors' best knowledge (barcode-based solution [5], and [6], [18] for outdoor storage positioning).

The remainder of this paper is organized as follows. In Section II, the high-level overview of the drone-based RFID inventory management solution is introduced. Based on the given system design, the major challenges for practical application are discussed in this section. In Section III, the considerations and technical details of the proposed relative localization algorithm are presented, including lateral positioning and rack level distinguishing. Section IV presents and discusses the experiments in a real logistical warehouse, and the validated results of the proposed method. Section V concludes this paper.

II. OVERVIEW OF DRONE-BASED RFID SYSTEM

A. System Design for Inventory Management

The assets are stored on the pallets vertically in the warehouses, as shown in Fig. 2(a), with attached identification labels (RFID tags). The drone with UHF-RFID reader and antennas mounted, flies along the planned trajectory (i.e., along Y -axis in Fig. 1) to gather inventory information. In order to obtain the location information of the tagged assets, the drone's trajectory during the interrogation is required. In spite of flying along the given trajectory, the drone needs accurate tracking to guarantee the performance of the second-stage positioning (RFID localization). In the proposed system, we have utilized a sensor fusion-based scheme to track the drone with centimeter-level accuracy, as presented in Fig. 2(a). The collected inventory information is sent to the access points deployed in warehouses via WiFi, and then stored by the local server. The server conducts the processing of RFID localization and asset management based on the launched inventory mission.

Fig. 2. Drone-based inventory management in warehouses via UHF-RFID: system design and setup.

Fig. 2(b) presents the drone-based RFID localization setup. The drone involved in this system is a quadcopter DroneMatrix Yacob v2.3 with the size 109.6 cm×109.6 cm×39.3 cm (including the rotor wings), which supports no less than 2-km remote control and 20-min autonomy. It also carries the power storage, drone control and tracking modules, wireless connection modules, etc. on board. Considering the endurance and payload of drone, the weight of each module requires careful consideration. In our previous work [17], we adopted two COTS antennas (Advantenna-SP11 with weight 200 grams). To handle two rows of racks (left and right, in Fig. 1 (a)) simultaneously through one flight, four antennas (two antennas for each side) are required, and the weight of the antennas will reach 800 grams. This makes a practical realization difficult when taking the weight of other modules into account. In the proposed system design, we utilize two self-designed light-weight patch antennas weighing 135 grams each (further description in Section III-B), which helps to improve the endurance of drone. For the RFID interrogation, a light-weight reader module, ThingMagic M6E-Micro [8]), is adopted. For the overall system, the mass weight is 6454 grams, including the DroneMatrix Yacob drone 4725 grams, RFID module 734 grams, sensor fusion and other supporting components 995 grams. It should be noted that the ThingMagic M6E-Micro module, unlike other COTS RFID readers (for instance, Impinj R420 with phase located between $0 \sim 2\pi$ rad), reports the measured phase being unwrapped between $0 \sim \pi$ rad. Therefore, the measured phase can be given as

$$\phi_m = \text{mod}(\varphi_d + \underbrace{\varphi_{Tx,Rx} + \varphi_{Tag}}_{:=\varphi_0} + \omega), \quad (1)$$

where $\text{mod}(\cdot)$ is the modulo- π operator. $\varphi_d = 4\pi \frac{d}{\lambda}$ is the phase due to the two-way propagation delay, and d , λ represent the one-way propagation distance and wavelength,

respectively. φ_0 denotes the total phase shift caused by the transceiver and tag. ω is the phase noise.

To locate the tagged assets on the racks, it is required to track the on-board RFID reader (drone) during interrogation. Under the GNSS-less indoor environment, laser- or vision-based equipment can achieve extremely fine-grained drone tracking accuracy (even millimeter level errors). However, they introduce additional payload and high cost to the whole drone-based RFID system. To realize fine-grained indoor UAV tracking for practical applications, a number of radio frequency- and sensor fusion-based solutions have been proposed in [4], [19], [20]. Considering the advantage of high time resolution, UWB was utilized to track the flying drone and achieved 13-cm accuracy with more than 90% in laboratory environment [4]. Besides UWB, monocular simultaneous localization and mapping (SLAM) was added to enable autonomous flight in [19]. Based on extended Kalman filter (EKF), [20] developed a sensor fusion framework using multiple low-cost sensors, including an inertial measurement unit (IMU), a laser scanner, a range sensor, and three cameras (forward, downward, upward), which achieved centimeter-level mean localization errors. In our inventory management system, to track the drone in warehouses with high accuracy, we fuse the positioning results from multiple sensors based on EKF. The involved sensors include a Decawave UWB chipset, altitude sensor, and other directional sensors (IMU and magnetometer) from the drone itself. The EKF establishes separate observation functions for each sensor input, which deals with asynchronous sensor inputs (different sampling frequencies) by keeping track of a buffer of the last measurements and compensating the delays. Moreover, CasADi [21] has been introduced to derive the system model, observation functions and Jacobian matrices for EKF with low computation time. According to experimental results, the sensor fusion-based method has achieved 6 – 10-cm mean absolute errors (MAEs). In this paper, we will focus on the RFID localization algorithm design on top of the drone-based RFID system technically. So the detailed discussion of sensor fusion for drone tracking is out of the scope.

B. Practical Challenge: Antenna Trajectory Errors

Even though drone-based RFID localization is definitely a potential solution for inventory management due to feasibility, low cost and easy-deployment, it still faces technical challenges when it comes to practical applications. In our previous work ReLoc [17], we mainly discussed the impact of tag's or antenna's orientation, material of the tagged assets, tag distortion, and multipath effect on RFID LLUD collection. We recommend the readers to obtain more details in [17]. In this paper, we will mainly discuss the impact of antenna tracking errors for the second-stage RFID localization on top of the proposed drone-based system: drone tracking errors and phase center effects. Note that we will focus on the analysis of measured phase in case of antenna tracking errors, since it is much more sensitive than the coarse-grained RSSI.

1) *Drone Tracking Errors*: As mentioned above, we utilize sensor fusion to track the drone (RFID antenna), and achieve 6 – 10-cm MAEs in the warehouse. The tracking errors can

Fig. 3. UHF-RFID antenna center tracking errors.

Fig. 4. Relative phase offsets with 180-degree Y/Z-axis antenna or tag rotation (the transmitted power: 25 dBm, antenna-to-tag distance: 85 cm, and Alien G tag). (c)-(d): standalone tag, different materials (liquid and metal) behind the tag, different spaces (5 or 10 cm), and postures (rotate asset 45° or 90° clockwise).

be presented as in Fig. 3(a). Even though the accuracy is quite high from the perspective of indoor drone tracking, it will also cause unacceptable errors for the phase-based RFID positioning methods via numerical calculation (such as hologram-based algorithms [2], [6], [9], [10], [17]).

2) *Phase Center Effect*: The antenna phase center is defined as the apparent source of radiation, which is not necessarily the geometric center of the antenna, especially for the short-range wireless connection, as shown in Fig. 3(b). When it comes to passive UHF-RFID backscatter communication, the phase center effect of both reader antenna and tag antenna should be taken into account. Fig. 4(b) presents the relative phase offsets with ± 90 -degree Y/Z-axis tag/antenna rotation in an anechoic chamber compared to the initial position (the planes of antenna and tag are aligned with each other in Fig. 3(a)). When the rotation angle increases, the phase offsets will be up to about 1.2 rad in case of the maximum antenna rotation. According to the results in [22], the distance offsets between RFID antenna physical center and mean phase center can be up to 15 cm. An intuitive idea is to measure the phase center of the antenna and the tag, and calibrate the phase at the offline stage. But it is not practical and convenient because the phase center of the

Fig. 5. Positioning results based on SAR with the antenna's tracking errors when the measured phases are wrapped between $(0, \pi)$ rad. The ground truth of the tag is (2.1, 3.1) m, and two antennas are adopted with the heights 2.7 and 3.3 m, respectively.

on-board antenna is different from the standalone antenna. To cover this, a reference tag [22] or iterative compensation [23] was utilized to calibrate the measured phases, which improved the accuracy to some extent. But when considering the cases of different materials and postures (shapes) behind the tagged assets, the phase offsets due to the phase center effect will be heterogeneous and more distinct (up to 3.9 rad), as shown in Fig. 4(c)-(d), which leads to additional errors in practical applications.

Overall, drone tracking errors and the phase center effect can be come down to the antenna trajectory accuracy during interrogation. To evaluate the impact of antenna tracking errors on RFID tag positioning, we adopt a differential SAR method in this section. However, the reported phases in our system are wrapped between 0 to π rad, so the SAR methods in [6], [10] for modulo- 2π phases cannot be used directly. We have modified the differential SAR method for modulo- π phase (see the derivation in Appendix A). As shown in Fig. 5, we analyze the RFID positioning results of the modified differential SAR method in cases of different simulated antenna tracking errors. According to [22], it is effective to assume that the phase center has a constant offset towards antenna physical center considering a dm-level accuracy requirement. In Fig. 5(a), we set a constant antenna tracking bias (10 cm) to mimic the phase center effect. It causes about 8.7-cm errors, which is consistent with the experimental results in [22], [23]. So when taking the phase center offsets into account merely, the antenna errors have slight impact on the differential SAR, which is effective for the usages without requirement of high resolution. But when combining with drone tracking errors, the negative effect cannot be neglected anymore. When we set the standard deviation (STDev) and mean bias of antenna trajectory as 5 cm (mimic drone tracking errors) and 10 cm, respectively, as shown in Fig. 5(b), the positioning results are totally incorrect with about 1.2-m errors. To this end, even though we have achieved 6 – 10-cm MAEs for the antenna trajectory via sensor fusion, SAR-based and other numerical algorithms that highly depend on the antenna tracking accuracy cannot be implemented directly for our drone-based RFID system.

III. RELOC 2.0 RFID SYSTEM DESIGN

For the drone-based RFID inventory management system, the localization of assets on the racks consist of three parts:

rack number, tag lateral location, and rack level distinguishing. The rack number (left or right), as shown in Fig. 2, can be distinguished via identifying the tag that is detected by which antenna. However, during the experiment, we found that sometimes the tags on the left rack can be detected by the right mounted antenna and vice versa due to the side-lobe or back-lobe effect. According to experimental validation, one simple but effective method is to compare the record count of the antennas mounted on the two sides of drone. In the following of this section, we will focus on tag lateral positioning and rack level distinguishing. As discussed above, SAR-based methods [2], [6], [9], [10], as well as our previous work ReLoc [17], cannot be used in case of antenna trajectory errors (5-cm MAEs and larger). So a new and practical localization scheme is required for our drone-based RFID system. In this section, we will discuss the whole algorithm design of the proposed relative localization method (ReLoc 2.0) for inventory management, in which the tagged assets' lateral position is pinpointed by the unwrapped critical phase profile, while the rack vertical level is identified via the RSSI and readability of RFID reader.

A. Lateral Positioning

The RSSI reflects the strength of the backscattered signal, which decays as $1/d^4$ [17]. When the antenna moves along the RFID tag, as shown in Fig. 3(a), the RSSI should increase and then decrease with the decreasing and increasing distance. The maximum is reached when the antenna is right in front of the tag. So we can determine the lateral location of the tag based on the trajectory of antenna in theory. But the RSSI is sensitive to the absorption, scattering, and multipath effect, which turns out to be a coarse-grained metric for localization compared with phase [15], [17]. As presented in (1), the phase is proportional to the distance d , which pinpoints the tag's position at its minimum. But the measured phase is wrapped between 0 and π rad, and cannot be utilized directly. Core V-zone of the measured phases was detected for lateral positioning in [15], but this requires sufficient samples to guarantee the accuracy which may be impossible in many practical cases. According to [13], we can use the unwrapping algorithm to get the reconstructed unwrapped phase $\psi_m[n]$, ($n = 1, 2, \dots, N-1$)*,

$$\begin{cases} \psi_m[1] = \phi_m[1] \\ \psi_m[n+1] = \phi_m[n+1] - \pi \left\lfloor \frac{\phi_m[n+1] - \psi_m[n]}{\pi} + \frac{1}{2} \right\rfloor \end{cases}, \quad (2)$$

where $\lfloor \cdot \rfloor$ denotes the round-down operator. Equation (2) takes effect only when the measured phase satisfies spatial sampling theory $\frac{4\pi}{\lambda} |d[n+1] - d[n]| = \frac{4\pi}{\lambda} |\Delta d_{(n+1,n)}| < \frac{\pi}{2}$, namely $|\Delta d_{(n+1,n)}| < \frac{\lambda}{8}$ (for instance, $\frac{\lambda}{8} \approx 4.1\text{cm}$ for frequency 917.5 MHz). This constraint is difficult to satisfy, especially when the projected drone-to-tag distance along the direction of moving is large and the distance along the perpendicular direction is small (see the proof in Appendix B). To this end,

*Notice that (2) is modified by replacing the periodic term 2π with π for modulo- π measured phases, which also decreases the spatial sampling constraint from $\frac{\lambda}{4}$ to $\frac{\lambda}{8}$.

Fig. 6. The proposed random forest with memory for the phase unwrapping.

Fig. 7. Two examples of the measured phases and unwrapping results via (2) and the proposed hybrid random forest predictor.

unwrapping via (2) is not effective for practical applications in case of sparse sampling.

1) *Phase Unwrapping*: To unwrap the measured phases, we need to clarify the following questions: (i) *to compensate or not when unwrapping the phase compared with the previous state?* (ii) *how many instances of π rad should be compensated to unwrap the phase?* Based on the analysis above, these two questions can be answered by the adjacent phase difference $\Delta\phi_m^{[n+1,n]}$ and adjacent antenna distance of two sampling positions $\delta_{(n+1,n)}$. However, it is unclear how they related to each other when the sampling constraint is not satisfied. In this section, we propose a new hybrid model- and machine learning-based phase unwrapping method, which considers the amount of π -instances to be compensated as a multi-class classification problem. We utilize (2) to unwrap the phase if the sampling constraint is satisfied, otherwise machine learning is used for this purpose. Compared to only using machine learning, the hybrid method will decrease not only the computation time but also the overall predicted errors. According to triangle inequality, an enhanced constraint of adjacent sampling distance can be given by $\delta_{(n+1,n)} \leq \frac{\lambda}{8}$. But when taking the phase noise, antenna's position errors, and other interference into account, we add a more strict constraint to the sampling distance, namely $\delta_{(n+1,n)} \leq \eta \cdot \frac{\lambda}{8}$, ($0 < \eta < 1$). In this paper, we set $\eta = 0.8$. When adopting (2) to unwrap the measured phases, we define the amount of π -compensations $\Upsilon(n)$, ($n = 1, 2, \dots, N-1$) as,

$$\Upsilon(n) = - \left\lfloor \frac{\Delta\phi_m^{[n+1,n]}}{\pi} + \frac{1}{2} \right\rfloor, \quad (3)$$

where $\Upsilon(n) = 0$ means no phase jump. Otherwise, when $\delta_{(n+1,n)} > \eta \cdot \frac{\lambda}{8}$, we train a random forest (RF) prediction model. The output label is given as $\Upsilon = \{0, \pm 1, \pm 2, \dots\}$. Based on the experimental observations, the adjacent phase

compensation is less than 3π generally. Only rarely, samples requiring more than $\pm 3\pi$ compensation are observed, which appear at the beginning or end of the sampling period. Therefore, in this paper, we implement our RF model for $\Upsilon = \{0, \pm 1, \pm 2, \pm 3\}$ as a seven-class classifier. It should be noted that we can train the multi-class model for more than $\pm 3\pi$ compensation definitely, but these cases rarely happen in practice due to the limitation of the RFID working range and the fact of high reading rate of the RFID reader module [7], [8]. Furthermore, the proposed method also can be extended to modulo- 2π measured phases with a minor modification towards the periodic term π . After obtaining $\Upsilon(n)$, ($n = 1, 2, \dots, N-1$), the unwrapped phase can be calculated by,

$$\begin{cases} \psi_m[1] = \phi_m[1] \\ \psi_m[n+1] = \phi_m[n+1] + \pi \sum_{i=1}^n \Upsilon(i) \end{cases} \quad (4)$$

The unwrapped phase is proportional to the distance d , which means that the amount of π -compensations Υ is non-positive when the antenna moves towards the tag, while Υ is non-negative when the antenna moves away. In other words, the predicted result at the n -th stage is closely related with the predicted results of the previous and later stages. In this section, we propose a memory-enhanced random forest model upon the underlying idea of bidirectional recurrent neural network (BRNN), as shown in Fig. 6. The input features of RF by adding the predicted labels of both the previous and later sampling period can be given as

$$\tilde{\chi}(n) = \left\{ \frac{\Delta\phi_m^{[n+1,n]}}{\pi}, \frac{\delta_{(n+1,n)}}{\lambda/8}, \Delta x(n), \Delta y(n), \Delta z(n), \hat{\Upsilon}(n-\varepsilon), \dots, \hat{\Upsilon}(n-1), \hat{\Upsilon}(n+1), \dots, \hat{\Upsilon}(n+\varepsilon) \right\}, \quad (5)$$

where the first and the second features are the normalized phase difference and distance, respectively. $\Delta x, \Delta y, \Delta z$ represent the antenna's coordinate differences considering the possible fluctuations of drone trajectory. ε is the memory step. The model without the input features of adjacent predicted labels is defined as naive RF. To input the adjacent unknown labels of the n -th prediction as the features, we implement an iterative random forest algorithm with the predicted results of naive RF as an initialization. We train the naive RF and memory-enhanced RF model via the training sets, which were generated by the simulated and collected samples (small part with about 20%). The memory step ε is set as 2 in this paper, since we have observed that the prediction accuracy became saturated gradually on the training sets when $\varepsilon \geq 2$. Meanwhile, larger ε values introduce more input features, which also increase the computation time. For the random forest training, depth of the trees in the forest $\alpha_{\min LS}$ and the number of predictors to sample at each node α_{PTS} are two major hyperparameters needing to be tuned. We have implemented Bayesian optimization to tune the hyperparameters and obtained that $\alpha_{\min LS} = 1$ and $\alpha_{PTS} = 4$.

The detailed algorithm of the hybrid RF-based unwrapping model is presented as follows (Fig. 6),

Fig. 8. Pinpoint the lateral position of tag via unwrapping phase.

Fig. 9. Subsequence dynamic time warping of unwrapping phase for critical region searching: (a) optimal warping path on the accumulated cost matrix, (b) sDTW matching result.

- Step 1:** Utilize the naive RF and (3) to predict the amount of π -compensations $\hat{\Upsilon}(n)$ based on the judgment of sampling space, namely $\delta_{(n+1,n)} \leq \eta \cdot \frac{\lambda}{8}$.
- Step 2:** Compute the accumulated sum of $\hat{\Upsilon}(n)$, namely, $\sum_{i=1}^n \hat{\Upsilon}(i)$. Find the segment of peaks when the accumulated sum of $\hat{\Upsilon}(n)$ hits the minimum, given by $\langle \nu_{left}, \nu_{right} \rangle$.
- Step 3:** Calibrate the mispredicted labels $\hat{\Upsilon}$ mildly using zeros. If $\hat{\Upsilon}(n) > 0$ when $n < \nu_{left}$, then $\hat{\Upsilon}(n) \leftarrow 0$. Likewise, if $\hat{\Upsilon}(n) < 0$ when $n > \nu_{right}$, then $\hat{\Upsilon}(n) \leftarrow 0$.
- Step 4:** Forward the calibrated $\hat{\Upsilon}$ to the memory-enhanced RF model, and update the prediction of $\hat{\Upsilon}$.
- Step 5:** Repeat Step 2 to Step 4 until the two consecutive estimations of $\hat{\Upsilon}$ remain unchanged or reach the predefined maximum number of iterations. Unwrap the measured phase based on (4).

Fig. 7 presents two examples of measured phases unwrapping results based on (2) merely and the proposed RF model. We can see that the proposed model outperforms the traditional unwrapping method (2) distinctly with fewer estimation errors, especially at the two ends of phase profile.

2) *Critical Phase Profile:* After the phase unwrapping, we can pinpoint the lateral position of RFID tag where the phase profile reaches its minimum. Due to sparse sampling and noisy phase, the point when the antenna is right in front of the tag may be not recorded by the reader. Generally, quadratic fitting techniques can be utilized to reduce such impact [15], [16], [24], [25]. But when it comes to practical implementation, the drone's velocity cannot be fully controlled, when it speeds up (or slows down), the phase profile may be stretched (or compressed) [15]. Furthermore, unwrapping errors will cause fluctuations in the unwrapped phase. Fig. 8 presents a bad case that includes the two problems mentioned above. At the start-

up stage of drone's navigation, the speed is slower than the set velocity, so the unwrapped phase profile is more or less flat. The unwrapping model fails to estimate the correct $\hat{Y}$ at the right end of phase profile. As a result, quadratic fitting on the whole phase profile directly causes errors. If we can truncate the whole phase profile, and just select the segment (critical region) that is less affected, as presented in Fig. 8, we can mitigate the above two problems. Definitely, the critical region is always located where the antenna gets closer to RFID tag, which has more stable drone flight, less multipath effect, and more interrogation due to the shorter distance. In this paper, we introduce the subsequence dynamic time warping (sDTW) algorithm [26] to target the critical region. We define a symmetric reference phase profile $\vartheta = (\vartheta[1], \vartheta[2], \dots, \vartheta[M])$ which is generated via (1), and the unwrapped phase profile $\psi_m = (\psi_m[1], \psi_m[2], \dots, \psi_m[N])$ over the feature space $\mathcal{F}$. Define $c : \mathcal{F} \times \mathcal{F} \rightarrow \mathbb{R}$ be a local cost measure and $\mathbf{C}$ the cost matrix given by $\mathbf{C}(m, n) = c(\vartheta[m], \psi_m[n])$ for $m \in [1 : M]$ and $n \in [1 : N]$ [26]. To this end, we can find the critical region by searching the possible subsequence on ψ_m that minimizes the DTW distance to ϑ ,

$$\langle \hat{a}, \hat{b} \rangle = \arg \min_{(a,b): 1 \leq a \leq b \leq N} \text{DTW}(\vartheta, \psi_m[a : b]). \quad (6)$$

Fig. 9 shows the optimal warping path (green line in Fig. 9(a)) and the sDTW matching results, which truncates the whole unwrapping profile and removes the unexpected segments. Then we perform quadratic fitting towards the critical phase profile $\psi_m[\hat{a} : \hat{b}]$, and pinpoint the lateral position of the tag with respect to drone trajectory.

B. Rack Level Distinguishing

1) *Patch Antenna*: Considering the practical challenges in real-world applications: multipath effect, tag distortion, different materials inside the tagged assets, and not fully occupied racks, our previous work ReLoc [17] proposed to compare the RSSI from two tilted COTS antennas (upwards and downwards), and distinguish the rack level. The tilted angle needs to be carefully designed based on the practical scenario. Compared to the mechanically adjusted antennas' angle in ReLoc, we have designed a 2×1 patch antenna which steers the beam electrically via phase shifting, as shown in Fig. 10. The patch antenna supports at most three beams (up, middle, and down). The designed antenna has a broad azimuth radiation pattern with 70° half power beamwidth (HPBW) aiming for large area interrogation. Differently, to obtain a better resolution of vertical level distinguishing, we set the elevation HPBW as 40° , as presented in Fig. 10(b). The antenna has a 10-dBi gain, which operates at both 865-868 MHz and newly released 916-919 MHz in Europe [27]. To save battery life and increase the endurance of the drone, we have adopted foam board as substrate, which decreases the weight of the patch antenna to 135 grams. The dimension of antenna is $217 \times 430 \times 17$ mm, which is suited for mounting on a drone, as shown in Fig. 2(b).

2) *Level Classification*: Fig. 11 presents the RSSI profiles of three antenna beams, of which the tagged assets are placed on level one and two, and the drone flies along the racks at

Fig. 10. Patch antenna for rack level distinguishing: (a) 2×1 patch array (foam board used as substrate), (b) the normalized radiation pattern in the elevation plane with three distinct beams (HPBW = 40 degrees), (c) on-board steering patch antenna for rack level distinguishing.

Fig. 11. RSSI and read count for level distinguishing.

the height of about level 2, as presented in Fig. 10(c). When we take the tagged asset on level 1 as an example, we clearly observe that beam 1 has a distinct higher RSSI than beam 3, while the RSSI of beam 2 pointing towards the middle is slightly smaller than beam 1. Intuitively, we can distinguish the rack level based on RSSI differences using a simple logical decision like ReLoc [17] using two antenna beams (1-upwards and 3-downwards),

- 1) *Level 1*: $\text{RSSI}_1 \geq \text{RSSI}_3$.
- 2) *Level 2*: $\text{RSSI}_1 \approx \text{RSSI}_3$.
- 3) *Level 3*: $\text{RSSI}_1 \leq \text{RSSI}_3$

where RSSI_i , $i \in \{1, 2, 3\}$ represents the measured RSSI from i -th beam. Or using three antenna beams,

- 1) *Level 1*: $\text{RSSI}_1 \geq \text{RSSI}_2 \geq \text{RSSI}_3$.
- 2) *Level 2*: $\text{RSSI}_2 \geq \text{RSSI}_3 \approx \text{RSSI}_1$.
- 3) *Level 3*: $\text{RSSI}_3 \geq \text{RSSI}_2 \geq \text{RSSI}_1$

Note that we focus on three-level distinguishing here, since the drone can read at most three-level tagged assets according to our experimental results (in case of 1 – 2-m level vertical distance). When it comes to 2-m vertical distance, the drone can only read two-level assets mostly in spite of increasing the transmitted power (< 31 dBm [8]) due to the limitation of elevation beamwidth. In this case, the rack level distinguishing can be simplified to a two-class classification problem (up or down) using three beams (or two beams),

- 1) *Up*: $\text{RSSI}_1 \geq \text{RSSI}_3 \approx \text{RSSI}_2$ (or $\text{RSSI}_1 \geq \text{RSSI}_3$).
- 2) *Down*: $\text{RSSI}_3 \geq \text{RSSI}_1 \approx \text{RSSI}_2$ (or $\text{RSSI}_3 \geq \text{RSSI}_1$).

To distinguish more than three levels, we can fly the drone at one or more altitudes as shown in Fig. 2(a). Three-level distinguishing is efficient for drone-based inventory management in warehouses.

Furthermore, for the tagged asset on level 1 in Fig. 11(a), the number of the collected RSSI samples from beam 3 is much less than the sampling number of other two beams. For the RFID tag on level 2 in Fig. 11(b), the number of collected RSSI samples from three beams have slight offsets, but we still observe that the count of samples from beam 2 is larger than the other beams. There are also some cases where the tags on level 1 (or 3) cannot be reached by beam 3 (or 1). Then the read count is zero. In these cases, the above criteria based on RSSI merely are not sufficient to distinguish the rack level. As such, the readability (or read count) is a potential metric for these cases. The read count per tag per second (read rate) is closely related with the reader mode setting, transmitted power, antenna, the number of tags within the working distance, etc [8], [28]. But for a specific measurement campaign, as well as the given RFID system setting, read rate is mainly determined by the distance from tag to antenna, and incidence angle. Larger distance and incidence angle generally result in a lower read count [17], [24].

In this paper, we propose to adopt the RSSI and readability as the features to pinpoint the rack level. However, the RSSI is sensitive to multipath effects and polarization mismatch [17]. Instead of comparing the whole RSSI profile, we just utilize the RSSI segment when the antenna is in front of the tag. The critical region $\langle \hat{a}, \hat{b} \rangle$ defined in Section III-A is exactly what we need. So we utilize $\langle \hat{a}, \hat{b} \rangle$ to truncate the whole RSSI profile, given by critical RSSI profile $\text{RSSI}_i[\hat{a}:\hat{b}]$. Due to the random access of the RFID air interface protocol [17], [29], it is not possible to collect the RSSI from three antenna beams at each interrogation simultaneously. Therefore, we divide the critical RSSI profile into K subsequences of equal length with respect to drone's trajectory, and average the RSSI in each subsequence. This also helps to mitigate the impact of noise and multipath effect to some extent. If there is no RSSI collected in some of the subsequences, the average RSSI will be set as the minimal detectable power of the reader, e.g., -85 dBm. So we can define the following metric function,

$$\rho_{i,j} = \sum_{k=1}^K \text{sgn}(\overline{\text{RSSI}}_i[k] - \overline{\text{RSSI}}_j[k]), (i < j) \in \{1, 2, 3\}, \quad (7)$$

where $\overline{\text{RSSI}}[k]$ is the average RSSI in k -th subsequence, and $\rho_{i,j}$ identifies the rack level. $\text{sgn}(\cdot)$ is the sign function operator. For example, if the tag is on level i (or j), then $\rho_{i,j} \rightarrow K$ (or $\rho_{i,j} \rightarrow -K$). How to select K will be discussed in Section IV-B. We model the rack level distinguishing as a multi-class classification problem, and define the read count of three beams as $\gamma_i, i \in \{1, 2, 3\}$, so the input features for the boosting tree can be given as,

$$\Omega = \{\rho_{1,2}, \rho_{1,3}, \rho_{2,3}, \tilde{\gamma}_1, \tilde{\gamma}_2, \tilde{\gamma}_3\}, \quad (8)$$

where $\tilde{\gamma}_i = \frac{\gamma_i}{\max\{\gamma_1, \gamma_2, \gamma_3\}}$ is the normalized read count. To train the classifier, we utilized a part of measured datasets (about 20%), because with simulated data, it is difficult to mimic the comprehensive impact of antenna beamwidth, polarization mismatch, reader mode, multipath, physical environment etc. on RSSI and readability. For level distinguishing, a boosting tree (ensemble of weak decision tree predictors)

Fig. 12. ReLoc 2.0 algorithm design.

has been trained, which outperforms RF in case of small training sets. The maximal number of branch node splits for the boosting tree are optimized via cross validation, namely $\alpha_{\text{MaxNS}} = 4$.

C. Putting Things Together

The algorithm design details for the drone-based RFID inventory management have been presented in this section, including rack identification, lateral positioning, and vertical level distinguishing. The overall algorithm structure is shown in Fig. 12. When the drone (on-board RFID setup) flies along the racks, it collects the RSSI and phases of the tagged assets. The number of single metric (RSSI or phase) per tag is labeled as read count. We can identify the rack number (left or right) directly through comparing the read count of each antenna, as the yellow line shown in Fig. 12. The measured phases are unwrapped via the iterative hybrid random forest model. The lateral positions of the tagged assets are determined via quadratic fitting over the critical phase profile with respect to drone's trajectory, of which the procedure is marked by the blue lines. Meanwhile, RSSI differences in the critical region and the read count are fed to the boosting tree model to predict the vertical level of the tagged assets with respect to drone's altitude (presented as green lines).

IV. EXPERIMENT AND RESULTS

A. Measurement Campaign

To validate the proposed algorithm (ReLoc 2.0), we have conducted a measurement campaign in a logistic warehouse in Belgium (with the aisle length from 70 meters to 135 meters, and the ceiling height about 10 meters), as shown in Fig. 13. The vertical rack level separation varies from one meter to two meters. Considering the weight limitation of the whole RFID setup, a small RFID reader, ThingMagic M6E-Micro module, has been selected for LLUD collection. Two patch antennas (2×1 elements) have been installed on the two sides of the drone. A low-complexity phase shifting circuitry has been designed for the antenna beam steering, which is soldered on the ThingMagic M6E-Micro module. The lateral distance between each pallet is about 1.2 meters. RFID tags, Avery Dennison AD661-R6P (with dimension $22 \text{ mm} \times 93 \text{ mm}$, working at 860-960 MHz), are attached on the assets arbitrarily (the minimal tags' lateral separation is 0.2 m). The RFID reader collects the LLUD and sends them to the

Fig. 13. Measurement campaign in a warehouse of ID Logistics Company in Belgium. The pilot is operating the drone along the predefined trajectory to scan the RFID tagged assets on the racks.

TABLE I
CONFIGURATIONS OF RFID MEASUREMENT WITH DIFFERENT DRONE'S VELOCITIES AND TRANSMITTED POWER

Configuration	#1	#2	#3	#4
Drone velocity (m/s)	0.75	1.0	1.5	1.0
Transmitted power (dBm)	20	20	23	27

local controller via WiFi under the low-level reader protocol (LLRP). The drone is located and tracked via sensor fusion, as mentioned in Section II-A, of which the mean tracking accuracy is about 6 – 10-cm for different drone's velocities (varying from 0.75 to 1.5 m/s). The working frequency is set as 917.5 MHz. We have investigated the system performance for different transmitted powers (varying from 20 to 27 dBm). The configurations are given in Table 1.

B. Performance and Evaluation

1) *Lateral Positioning*: To localize the lateral position of the tagged assets in case of antenna trajectory errors, we have proposed to unwrap the measured phases via the hybrid RF model, and pinpoint the positions with respect to drone's trajectory. In this section, we compare the positioning accuracy of the proposed method with some state-of-the-art (SOTA) methods via the cumulative distribution function (CDF). As shown in Fig. 14, the proposed method outperforms the other methods in our cases, which achieves less than 27.1-cm MAEs in all the four configurations. SAR-based (hologram) methods [6], [9] and lateral positioning part of ReLoc [17] have the worst positioning results with MAEs larger than one meter, which are just slightly better than randomly guessing. This is because SAR methods and ReLoc (lateral positioning) are hologram-based schemes that highly depend on the tracking accuracy of the moving antenna. L-M method in [13] is also a numerical positioning method, which utilizes iterative optimization instead of grid searching. When only considering

Fig. 14. CDF of lateral positioning errors, and comparison between SOTA methods and the proposed algorithm (ReLoc 2.0).

Fig. 15. Lateral localization results: (a) absolute positioning errors, (b) lateral ordering accuracy.

one-dimensional positioning (lateral direction), it achieves relatively good results with less than 1.2-m errors generally, except for some outliers. It is surprising to find that OTrack based on RSSI [24], achieves quite good and robust results in all configurations (less than 1.1 m). RSSI is a coarse-grained metric for localization, but it presents the advantage of insensitivity on antenna's tracking errors in our cases. STPP was designed for the fine-grained ordering based on the phase profile [15]. However, its accuracy is not satisfactory in our cases, especially in configuration 3 and 4. It can be interpreted by the sparse sampling in configuration 3 (more sparsely sampled due to a larger drone's speed), while the accuracy of STPP highly depends on a sufficient number of phase samples to detect the core V-zone correctly. In configuration 4, the measured phases were severely affected by multipath because of a larger transmitted power (27 dBm). Fig. 15(a) shows the statistical errors of the proposed method in the four configurations. The proposed method in configuration 4 also has larger errors than the other three configurations due to more severe multipath effect. The larger transmitted power indeed increases the working distance and have more records, but deteriorates the quality of LLUD (RSSI and phase). To this end, the transmitted power control should be carefully

considered for the RFID positioning system design in case of specific applications. As shown in Fig. 15, we also find that the lateral accuracy decreases slightly as the velocity of the drone increases in configurations 1-3.

To evaluate the ordering performance, we use the Kendall's rank coefficient to define the accuracy [16], [30]

$$\text{Accuracy} = \frac{2}{M(M-1)} \sum_{i < j} \text{sgn}(o_i - o_j) \text{sgn}(\hat{o}_i - \hat{o}_j), \quad (9)$$

where $\mathbf{o} = \{o_1, o_2, \dots, o_M\}$, and $\hat{\mathbf{o}} = \{\hat{o}_1, \hat{o}_2, \dots, \hat{o}_M\}$ represent the correct order and the predicted order, respectively. For example, the correct order of tags is 1-2-3-4-5-6-7, while the predicted order is 1-2-4-5-3-6-7. Then the ordering accuracy is $17/21 \approx 81.0\%$ instead of $4/7 \approx 57.1\%$ adopted in [15], [17], [24]. This is more reasonable since the Kendall's rank coefficient accepts the correct inner order of subsequence 4-5. As shown in Fig. 15(b), we compare the ordering accuracy between the proposed method (ReLoc 2.0) and several SOTA methods which achieve relatively good positioning results in Fig. 14. We can see that ReLoc 2.0 has the best performance for all configurations with ordering accuracy 94.1%-99.0%. L-M and OTrack achieve 90.1%-94.2% accuracy for the four configurations, while STPP fails in configurations 3 and 4 (less than 80%). As mentioned in Section IV-A, the lateral separation of pallets (center distance) is about 1.2 m. Even though we have attached the RFID tags arbitrarily (minimal lateral distance 0.2 m), most of the lateral distances are still larger than 0.5 m. So the proposed ReLoc 2.0, L-M, and OTrack all obtain high ordering accuracy. But the proposed method has a better positioning resolution, which can handle more fine-grained requirements.

2) *Level Distinguishing*: To identify the rack level of the tagged assets, we combined the RSSI differences in the critical region and the read count of each beams. As mentioned in Section III-B, the critical RSSI profile has been divided into K segments of equal length. Fig. 16 discusses the impact of K -selection for level distinguishing. We compare the ordering performance of only RSSI and combining RSSI and read count. The accuracy begins to decrease when the increasing K reaches a large value in cases when only the RSSI is used, as well as some fluctuations for a large K value in Fig. 16(a)(c). In the proposed algorithm, the RSSI profile has been divided in K equal subsequences based on the drone's trajectory along the racks, as mentioned in Section III.B-2. But the RSSI was not collected evenly along the time scale due to the RFID reader setting and antenna pattern. So the RSSI profile is unevenly sparse. For a specific K value (especially a large one), some of the RSSI subsequences may have not any sample. In this case, according to the algorithm design in Section III.B-2, the average RSSI will be set as the minimal detectable power, namely -85 dBm, which may introduce errors and uncertainty for the RSSI-based level distinguishing. A smaller K results in a reasonable selection. But if we add the feature of read count, as the black lines presented in Fig. 16, the ordering accuracy becomes stable with any K selection (accuracy larger than 96.7%). To this end, the concern of K selection can be mitigated. Furthermore, we also find that the drone's

Fig. 16. K selection for rack level distinguishing accuracy (w: with read count, wo: without read count).

Fig. 17. Level ordering accuracy comparison for different configurations, and the datasets in [17] (three cases: normal, different material, and tag distortion).

velocity and transmitted power have no distinct impact on level ordering according to the results in Fig. 16.

Fig. 17 compares the level ordering accuracy between ReLoc 2.0 and our previous work ReLoc [17]. The other STOA methods mentioned above are not discussed here since they are not feasible for our RFID setup or application scenario (rack level distinguishing). We set the same K for both ReLoc and ReLoc 2.0, namely, $K = 4$ which was suggested in [17]. Fig. 17 shows that ReLoc achieves about 86.7%-93.6% ordering accuracy for the four configurations while ReLoc 2.0 more than 98.0%. The level distinguishing accuracy of ReLoc is decreased by the lateral positional accuracy, since it compares the truncated RSSI segment around the estimated lateral position. But on the other side, it also shows robustness towards lateral accuracy because it still obtains relatively high accuracy in cases of worse lateral results. Furthermore, we also compare these two methods using the datasets in [17], in which the vertical distance between rack levels is about 0.66 m. We find that ReLoc 2.0 achieves more than 95.8% ordering accuracy, which also outperforms ReLoc (93.7%). In cases of different materials and tag distortion, ReLoc 2.0 shows its robustness, as it is built upon the idea of ReLoc for level identification, and inherits the merits of immunity to

different materials and tag distortion, as well as mutipath.

V. CONCLUSION

In this paper, we have proposed a RFID relative localization method for drone-based inventory management in warehouses. The measured phase, RSSI, and readability are incorporated for the lateral positioning and rack level distinguishing.

- 1) Concerning the impact of on-broad antenna tracking errors, we implement a hybrid random forest model to unwrap the measured phases, and pinpoint the lateral position of the tagged assets within the critical phase profile. According to experimental validation, the positioning accuracy is better than 0.5 m in general, and the ordering accuracy is larger than 96.7%.
- 2) To distinguish the vertical level, two 2×1 patch antennas are designed and mounted on the two sides of the drone. Through comparing the RSSI differences in critical profiles and the read count of each antenna beam, the level of the tagged assets is determined via the boosting tree classifier. The level distinguishing accuracy is larger than 98.0% (or 95.8%), based on the experimental results in warehouses (or the datasets in [17]).

Overall, ReLoc 2.0 can be an effective solution for drone-based inventory management, especially for the case of inaccurate on-board antenna tracking. As future work, incorporating RSSI to improve lateral positioning via deep learning can be a potential direction, thanks to its advantage of insensitivity to drone's tracking errors.

APPENDIX A

DERIVATION OF DIFFERENTIAL SAR-BASED AND RELOC FOR THE MODULO- π MEASURED PHASES

To mitigate the phase uncertainty, differential mitigation was utilized in SAR-based methods [6], [10], [31] and ReLoc (lateral positioning part) [17]. But all these algorithms were designed for modulo- 2π phases. When they come to modulo- π measured phases, they may be not able to be used directly.

1) *SAR*: Select the r -th sampling location as the reference, so the calculated phasor sequence in SARFID [6], [31] can be given as

$$\mathbf{a}_{\mathbf{P}_{tag}} = \left[\exp \left(-j \frac{4\pi}{\lambda} \Delta d^{[n,r]} \right) \right] \in \mathbb{C}^{N \times 1}, \quad (10)$$

where $\mathbf{P}_{tag}$ denotes the tag's position, and $\Delta d^{[n,r]} = d[n] - d[r]$. The modulo- π measured phasor sequence is given by

$$\mathbf{y}_{\mathbf{P}_{tag}} = \left[\exp \left(-j \left(\Delta \phi_m^{[n,r]} + K_n \pi \right) \right) \right] \in \mathbb{C}^{N \times 1}, \quad (11)$$

where $\Delta \phi_m^{[n,r]} = \phi_m[n] - \phi_m[r]$, and $K_n \in \mathbb{Z}$, ($n = 1, \dots, N$). Since the existence of $K_n \pi$ in (11), the matching function (or positioning function) in [6], [10] cannot be used directly. So we modify the cross-correlation function in [6], [31], and the position of tag can be estimated by

$$\begin{aligned} \mathbf{P}_{tag} &= \arg \max_{\mathbf{P}_{tag}} \frac{(\mathbf{a}_{\mathbf{P}_{tag}} \odot \mathbf{a}_{\mathbf{P}_{tag}})^H (\mathbf{y}_{\mathbf{P}_{tag}} \odot \mathbf{y}_{\mathbf{P}_{tag}})}{\|\mathbf{a}_{\mathbf{P}_{tag}}^H\| \cdot \|\mathbf{y}_{\mathbf{P}_{tag}}\|} \\ &\triangleq \arg \max_{\mathbf{P}_{tag}} \sum_{n=1}^N \left| \exp \left(2j \left(\frac{4\pi}{\lambda} \Delta d^{[n,r]} - \Delta \phi_m^{[n,r]} \right) \right) \right|. \end{aligned} \quad (12)$$

where $\odot$ denotes the element-wise product operator. $\square$

2) *ReLoc*: Based on MLE, the estimated tag's position in ReLoc [17] can be given as

$$\mathbf{P}_{tag} = \arg \max_{\mathbf{P}} \sum_{n=1}^N \left[- \left(\Delta \phi_m^{[n,r]} - \Delta \varphi_d^{[n,r]} \right)^2 \right], \quad (13)$$

where $\Delta \varphi_d^{[n,r]} = \text{mod} \left(\frac{4\pi}{\lambda} d[n] + \varphi_0 \right) - \text{mod} \left(\frac{4\pi}{\lambda} d[r] + \varphi_0 \right)$. When it comes to modulo- π measured phases, $\Delta \varphi_d^{[n,r]}$ can be converted to

$$\Delta \varphi_d^{[n,r]} = \begin{cases} \text{mod} \left(\frac{4\pi}{\lambda} \Delta d^{[n,r]} \right) - \pi, & \Delta \varphi_d^{[n,r]} \in (-\pi, 0) \\ \text{mod} \left(\frac{4\pi}{\lambda} \Delta d^{[n,r]} \right), & \Delta \varphi_d^{[n,r]} \in [0, \pi) \end{cases}. \quad (14)$$

Substituting (14) to (13), we have

$$\begin{aligned} \mathbf{P}_{tag} &= \arg \max_{\mathbf{P}_{tag}} \sum_{n=1}^N \left[- \left(\Delta \phi_m^{[n,r]} - \Delta \varphi_d^{[n,r]} \right)^2 \right] \\ &\triangleq \arg \max_{\mathbf{P}_{tag}} \sum_{n=1}^N \left[-\sin^2 \left(\Delta \phi_m^{[n,r]} - \frac{4\pi}{\lambda} \Delta d^{[n,r]} + K_n \pi \right) \right] \\ &= \arg \min_{\mathbf{P}_{tag}} \sum_{n=1}^N \sin^2 \left(\Delta \phi_m^{[n,r]} - \frac{4\pi}{\lambda} \Delta d^{[n,r]} \right). \end{aligned} \quad (15)$$

So we can see that ReLoc variant maximum likelihood positioning can be used for modulo- π measured phase without any modification. $\square$

APPENDIX B

DISCUSSION OF SPATIAL SAMPLING CONSTRAINT

Suppose that the location of the antenna at n -th and $(n+1)$ -th sampling positions are $\mathbf{P}_{ant}^{(n)}$ and $\mathbf{P}_{ant}^{(n+1)}$, respectively, and the location of the RFID tag is $\mathbf{P}_{tag}$. The antenna moves parallel to the racks, with h the distance from the tag to the antenna trajectory. The distance of the two adjacent antenna positions is $\delta_{(n,n+1)}$, ($n = 1, \dots, N-1$). The projected distance from $\mathbf{P}_{ant}$ to $\mathbf{P}_{tag}$ along the direction of antenna moving is $d_0[n]$. When the distance difference reaches the spatial sampling constraint, $|\Delta d_{(n+1,n)}| = \frac{\lambda}{8}$. According to the geometry relationship, we can obtain

$$(d_0[n] - \delta_{(n,n+1)})^2 + h^2 = \left(\sqrt{d_0^2[n] + h^2} - \frac{\lambda}{8} \right)^2. \quad (16)$$

Namely,

$$\delta_{(n,n+1)}^2 - 2d_0[n]\delta_{(n,n+1)} + \frac{\lambda}{4}\sqrt{d_0^2[n] + h^2} - \frac{\lambda^2}{64} = 0. \quad (17)$$

So the distance of the two adjacent antenna positions can be given by $\delta_{(n,n+1)} = d_0[n] \pm \sqrt{d_0^2[n] - \frac{\lambda}{4}\sqrt{d_0^2[n] + h^2} + \frac{\lambda^2}{64}}$, where $'-'$ means that the two adjacent antenna positions are the same side with respect to the RFID tag (namely $d_0[n] > \delta_{(n,n+1)}$), while $'+'$ represents one of the sampling positions is on the other symmetric location (namely $d_0[n] < \delta_{(n,n+1)}$).

1) Assume $d_0[n] > \delta_{(n,n+1)}$, so $\delta_{(n,n+1)} = d_0[n] - \sqrt{d_0^2[n] - \frac{\lambda}{4}\sqrt{d_0^2[n] + h^2} + \frac{\lambda^2}{64}}$. Omit the augment $n, n+1$, and take the partial derivative

$$\begin{aligned} \frac{\partial \delta}{\partial d_0} &= 1 - \frac{d_0 - \frac{\lambda}{8} \frac{d_0}{\sqrt{d_0^2 + h^2}}}{\sqrt{d_0^2 - \frac{\lambda}{4}\sqrt{d_0^2 + h^2} + \frac{\lambda^2}{64}}}, \left(d_0 > \delta > \frac{\lambda}{8} \right) \\ &= 1 - \frac{\sqrt{d_0^2 - \frac{\lambda}{4}\sqrt{d_0^2 + h^2} + \frac{\lambda^2}{64}} + \frac{\lambda}{4} \left(1 - \frac{\lambda}{16} \frac{1}{\sqrt{d_0^2 + h^2}} \right)}{\sqrt{d_0^2 - \frac{\lambda}{4}\sqrt{d_0^2 + h^2} + \frac{\lambda^2}{64}}} \quad (18) \\ &< 0, \end{aligned}$$

$$\frac{\partial \delta}{\partial h} = \frac{\frac{\lambda}{8} \frac{h}{\sqrt{d_0^2 + h^2}}}{\sqrt{d_0^2 - \frac{\lambda}{4}\sqrt{d_0^2 + h^2} + \frac{\lambda^2}{64}}} > 0. \quad (19)$$

Therefore, to satisfy the spatial sampling constraint, the distance of the adjacent antenna position $\delta_{(n,n+1)}$ decreases as d_0 increases or h decreases.

2) Assume $d_0[n] < \delta_{(n,n+1)}$, so $\delta_{(n,n+1)} = d_0[n] + \sqrt{d_0^2[n] - \frac{\lambda}{4}\sqrt{d_0^2[n] + h^2} + \frac{\lambda^2}{64}}$. Take the partial derivative, and we have

$$\begin{aligned} \frac{\partial \delta}{\partial d_0} &= 1 + \frac{d_0 - \frac{\lambda}{8} \frac{d_0}{\sqrt{d_0^2 + h^2}}}{\sqrt{d_0^2 - \frac{\lambda}{4}\sqrt{d_0^2 + h^2} + \frac{\lambda^2}{64}}}, \left(\sqrt{d_0^2 + h^2} > \frac{\lambda}{8} \right) \quad (20) \\ &> 0, \end{aligned}$$

$$\frac{\partial \delta}{\partial h} = - \frac{\frac{\lambda}{8} \frac{h}{\sqrt{d_0^2 + h^2}}}{\sqrt{d_0^2 - \frac{\lambda}{4}\sqrt{d_0^2 + h^2} + \frac{\lambda^2}{64}}} < 0. \quad (21)$$

Therefore, the distance of the adjacent antenna position $\delta_{(n,n+1)}$ has an inverse tendency with respect to $d_0[n]$ and h compared with the cases of $d_0[n] > \delta_{(n,n+1)}$.

However, when two adjacent sampling positions satisfy $d_0[n] < \delta_{(n,n+1)}$, it means that the antenna is closely in front of the tag, which generally has sufficient samples and easily satisfies the sampling constraint compared with the case of $d_0[n] > \delta_{(n,n+1)}$. So in general, the spatial sampling constraint is difficult to satisfy when the projected drone-to-tag distance along the direction of moving d_0 is large and the distance along the perpendicular direction h is small. $\square$

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