Accurate Localization Using Augmented UHF RFID System for Internet-of-Things

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***Abstract*—This work addresses the problem of accurate indoor localization with an augmented ultra-high-frequency (UHF) radio-frequency-identification (RFID) system. In augmented UHF RFID system, a semi-passive component, called ST (from sense-a-tag), can communicate with the RFID reader as a passive tags, and can also capture the backscattering communication between RFID reader and passive tags within its proximity. The system requires that a grid of passive RFID tags is deployed and ST is attached to object of interest. As such it allows for fine-grained proximity-based localization. ST is localized based on the aggregated binary measurements according to localization algorithms, such as weighted centroid localization (WCL). The aforementioned algorithm assumes that the aggregated binary measurements simply depends on the distance between landmark tags and ST. However, it is not the case for ST-to-tag backscattering communication. To improve the localization accuracy, this paper proposes to use a Monte Carlo-based estimation with the detection probability model of ST-to-tag. The performance of the proposed algorithm is demonstrated by extensive computer simulation.**

Keywords–Internet-of-Things; augmented UHF RFID system; indoor localization; WCL; Monte Carlo estimation.

I. INTRODUCTION

The concept of Internet-of-Things (IoT) is simple but powerful, which envisages the infrastructure of ubiquitous wireless sensing and identification of IoT nodes to connect anything from anywhere at anytime [1]. The IoT nodes, such as radio tags, can be embedded into objects, monitoring their status and surrounding environment, as well as acquiring geographical information. Since the popular satellite-based positioning system are restricted to outdoor environment, academic and industrial communities have carried out intense research work to build indoor localization system to realize the vision of IoT [2]. Ultra-high-frequency (UHF) radio-frequency-identification (RFID) has been widely recognized as enabling technology for IoT indoor localization application due to its miniature size, easy deployment, low-cost and ultra-low power consumption [3].

The majority of state-of-art UHF RFID localization approaches is based on the fusion of multiple pieces of relevant information of RF signals, which are either angle-of-arrival (AoA), time-of-arrival (ToA), time-difference-of-arrival (TDoA) or received-signal-strength (RSS) returned to RFID readers from tags [3]. The major problem with the aforementioned methods is that they are easily affected by the non-line-of-sight (NLoS) conditions, severe multi-path distortions and fast temporal change of indoor environment [4]. One direction to resolve this problem is to apply proximity-based method, which is to deploy passive tags at fixed positions as landmarks and attach RFID reader to target of interest [10]–[12], and vice versa [6]. However, these approaches are not realistic solutions for IoT indoor localization application considering size, cost and energy.

The objective of this paper is to analyze and improve a novel augmented UHF RFID system, which includes a semi-passive UHF RFID component, called ST (from sense-a-tag) [5] and off-the-shelf UHF RFID components, reader and tag. The augmented UHF RFID system can be used for fine-grained proximity-based localization for IoT application by keeping both landmark and target tags simple and inexpensive. In the same way as passive tags, ST applies envelope detection to extract the baseband signal in the receiving path, and applies backscattering modulation to talk back in the transmitting path. The difference is that in the receiving path ST does not only capture the RFID reader's command signal, but also passive tag's backscattering signal. ST is fully compatible with EPCGlobal Class 1 Gen 2 RFID protocol. The augmented UHF RFID system requires that RFID reader is installed and a grid of passive tags is deployed as landmarks in the environment. In [7], we showed how to use weighted centroid localization (WCL) to localize ST in augmented UHF RFID system. Strictly speaking, WCL is not fully range-free localization method, since it depends on aggregated binary measurements aside the simple communication link connectivity of ST and landmark tags. However, the aggregated binary measurements of ST-to-tag depends on numerous factors other than the distance between ST and tag, such as the distance from RFID reader antenna, the orientation of antennas and phase cancellation [8]. In this paper, we propose a method where we apply a Monte Carlo estimation based on the probability detection model of ST-to-tag. In Monte Carlo framework, the proposal distribution of ST locations is assumed to be uniformly distributed over a circle area around WCL estimation.

We have calibrated our newly developed UHF RFID simulator PASS based on the real experiment data [8][9]. In PASS, we could simulate various scenarios with all components of the augmented UHF RFID system. The localization algorithms are evaluated in the simulator. The paper is organized as follows: in Section 2, we introduce the background and related work. The localization algorithms are presented in Section 3. In Section 4, we provide the simulation results which show the

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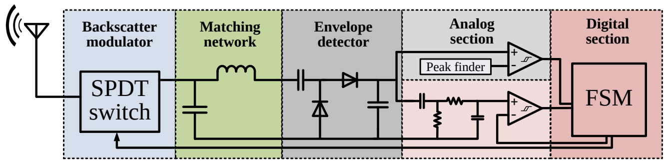

Figure 1. Block diagram of ST hardware.

performance of the proposed localization algorithms, followed by the conclusion with future discussion in Section 5.

II. Background and prior work

In this section, we will discuss the state-of-the-art in proximity-based localization approaches, augmented UHF RFID system, and UHF RFID simulation framework specified for indoor localization research.

A. Proximity-based localization

Proximity-based localization techniques exploit symbolic relative location information related to the presence or absence of the target within a small range of reference points [4]. Conventional approaches of proximity-based UHF RFID localization solutions are based on deploying passive tags at fixed locations as landmarks and attaching RFID reader to target and vice versa. Usually, the former approach is referred to as reader-based method while the latter as tag-based method.

In [10], researchers deployed a grid of UHF RFID tags on the ceiling of the building. The read region of each tag is well defined, thus the floor environment is subdivided into a set of cells. When the target equipped with reader enters into the read region of UHF RFID tag, the tag ID or the equivalent tag coordinates are retrieved. Based on the similar fashion, multiple indoor localization systems have been proposed [11][12]. In [6], the area is covered by a mesh grid of a large set of RFID readers and associated antennas, whose locations are known. The objects with attached UHF RFID tags are localized and tracked using particle filter based inference algorithm.

However, these approaches are strictly constrained by energy, cost and size. For example, the former approaches is limited to relatively large and expensive objects that justify carrying the RFID reader, such as human or robot. In the latter approach, it is not cost-efficient to densely deploy RFID readers merely for connectivity information.

B. Augmented UHF RFID system

In order to keep both targets and landmarks simple and inexpensive, a novel UHF RFID component, referred to as ST, is developed to augmented the off-the-shelf UHF RFID system [7]. Figure 1 depicts the block diagram of ST hardware. The antenna is followed by a backscatter modulator, a corresponding matching network and a conventional diode envelope detector circuit. The output of envelope detector is fed into the analog section, which can process both reader's pulse-interval-encoding (PIE) command signal and the tag's backscattering signal. The analog section for processing reader's PIE signal is the same as the standard passive tag, which employs a hysteresis comparator to generate digital signal. The processing circuit of tag's backscattering signal is more complex, which consists of a band-pass filter for removing the DC offset, followed by a comparator serving as one-bit A/D converter. The output of analog section is the input of digital section, which runs finite state machine (FSM) for Gen2-based ST locator protocol. As for rapid prototyping, the latest version of digital section is implemented on FPGA Xilinx Spartan 3AN chip.

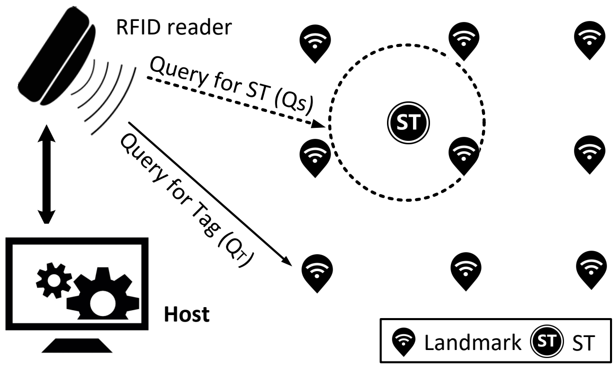

Figure 2. Augmented UHF RFID system.

Figure 2 shows a typical deployment of augmented UHF RFID system for fine-grained proximity-based localization. The system consists of a grid of passive tags as landmarks, ST attached to the target of interest, a standard RFID reader and a computer hosting localization algorithm. The host computer can control RFID reader to send out two distinct query signals, Q_S and Q_T. A query Q_T drives ST to *Listening* state. In this state, ST does not respond but listens to the backscattering communication between RFID reader and passive tags. Upon receiving the tags' ID, ST stores a hash value corresponding to the IDs temporarily. A query Q_S drives ST to *Responding* state. In this state, ST works as a standard passive tag, and backscatters the information of the detected tags' IDs to the RFID reader. Based on such aggregated binary measurements of ST-to-tag, the host determines the location of ST according to the embedded localization algorithm, such as WCL.

C. PASS simulator

Proximity-based **A**ugmented UHF RFID **S**ystem **S**imulator (PASS) is a system-level time-domain UHF RFID simulator. PASS simulator inherits the hierarchical software structure, the behavioral model of NXP UCODE G2XM tag and wireless propagation channel from PARIS simulation framework [14]. While PARIS mainly focuses on indoor wireless channel modelling, PASS completes the functionality of RFID reader and tag according to EPCglobal Class1 Gen2 protocol. The behavior model of ST is developed to emulate the specific ST hardware. The channel model consists of large-scale model and statistical model. Besides that, the channel model also includes the virtual transmitter model for the surface reflection. Various characteristics of implemented models can be configured, such as scenario deployment, parameters of wireless channel, tag, reader and ST, etc. With the simulator-provided functions and basic functions, behaviors of implemented components in simulator can be measured, such as wireless signal delay and attenuation. The simulator and user guide are available on GitHub [15].

III. LOCALIZATION USING AUGMENTED UHF RFID SYSTEM

In this section, we will describe our proposed detection probability model of ST-to-tag, as well as the localization algorithm based on Monte Carlo estimation.

A. The detection probability model of ST-to-tag

The detection probability of ST-to-tag depends on numerous factors, which include the distance between ST and tag, the distance from RFID reader, antenna orientation and phase cancellation, etc [8]. The existing localization algorithms assume that the detection probability of ST-to-tag simply depends on the distance between ST to tag [7][13]. In order to improve localization accuracy, a more realistic detection probability model of ST-to-tag is developed based on the research on the ST-to-tag backscattering communication link. First, the detection probability model of ST-to-tag is modelled as a function of distance between ST and tag, as well as the distance and orientation from reader to tag. Secondly, while fitting the detection probability model of ST-to-tag, the phase cancellation effect is considered by augmenting phase cancellation-reducing technique to ST.

The proposed probability detection model of ST-to-tag is formulated as a logistic regression model as shown in (1). Figure 3 depicts the model features. D is the distance from RFID reader to passive tag. θ represents the azimuth (the relative orientation between (X, Z) plane with antenna to tag vector), while ϕ represents elevation (the relative orientation between (X, Y) plane with antenna to tag vector). d is the distance between ST with tag. $\{a_i, i = 1, \ldots, 4\}$ are the model parameters.

$$p(D, d, \theta, \phi) = \frac{1}{1 + e^{a_0 + a_1 D + a_2 d + a_3 |\theta| + a_4 |\phi|}} \quad (1)$$

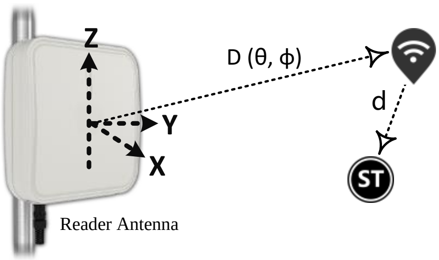

Figure 3. The pictorial depiction of model features.

We fit the detection probability model of ST-to-tag with data obtained from the PASS simulator. In the simulation, the host controls a standard UHF RFID reader to sends out the queries Q_T and Q_S. We use circularly polarized panel antenna RFMAX S9028PCRJ as the reader antenna, whose radiation pattern is shown in Figure 4. The power level of reader antenna is 30 dBm. The channel model is configured as *"room"*. For the scenario setup, the RFID reader antenna is placed at the origin $(0, 0, 0)$. The locations of passive tag are uniformly sampled from the cuboid space of $x \in [1, 8]$, $y \in [-4, 4]$ and $z \in [-4, 4]$. We obtained 3000 samples of tag locations in the space. The locations of ST is uniformly sampled within a sphere space, whose globe is at tag location

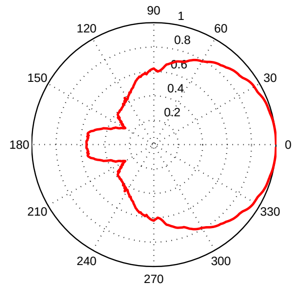

Figure 4. The radiation pattern of reader antenna.

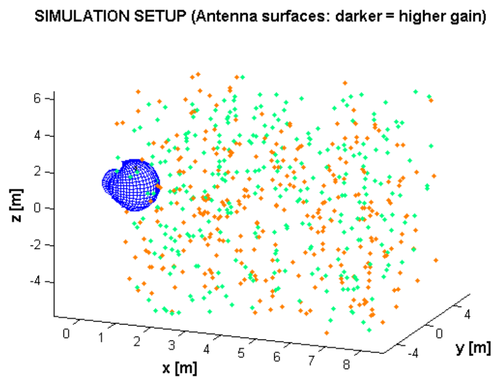

Figure 5. The simulation setup.

with the radius as $2m$. Figure 5 shows the simulation setup, in which the green dots represent tag locations, brown dots represent ST locations.

The logistic regression model is trained with the obtained data set, in which the cost function used is cross-entropy and the optimization method is gradient descent. The parameter estimations are $a_0 = -1.462$, $a_1 = 0.4941$, $a_2 = 2.506$, $a_3 = 0.0126$ and $a_4 = 0.0523$. For comparison, the conventional model, in which the detection probability simply depends on the distance between ST and tag, is presented in (2). With the obtained data set, the parameter estimations are $a_0 = 0.8970$ and $a_1 = 2.4443$. Figure 6 depicts the normalized histogram of the obtained data set, as well as the curves of (1) and (2). Furthermore, we use 1000 newly obtained data set as test data set. The cross entropy cost of (1) 0.1278 is lower than (2) 0.1502. Therefore, (1) possesses higher model accuracy than (2).

$$p(d) = \frac{1}{1 + e^{a_0 + a_1 d}} \quad (2)$$

B. Monte Carlo estimation

Let us assume that there are K landmark tags with known location in 2D cartesian coordinate system, $\{LT_k, k = 1, \ldots, K\}$. ST is attached to target of interest with an unknown location x. Here ST is static. RFID reader sends out the number of N rounds of Q_T. A landmark tag k can be detected by ST with probability p_k. In this work, we use (1) to approximate such probability. Let the number of detection of landmark tag k by ST denote by n_k. Then, the probability of n_k is modelled

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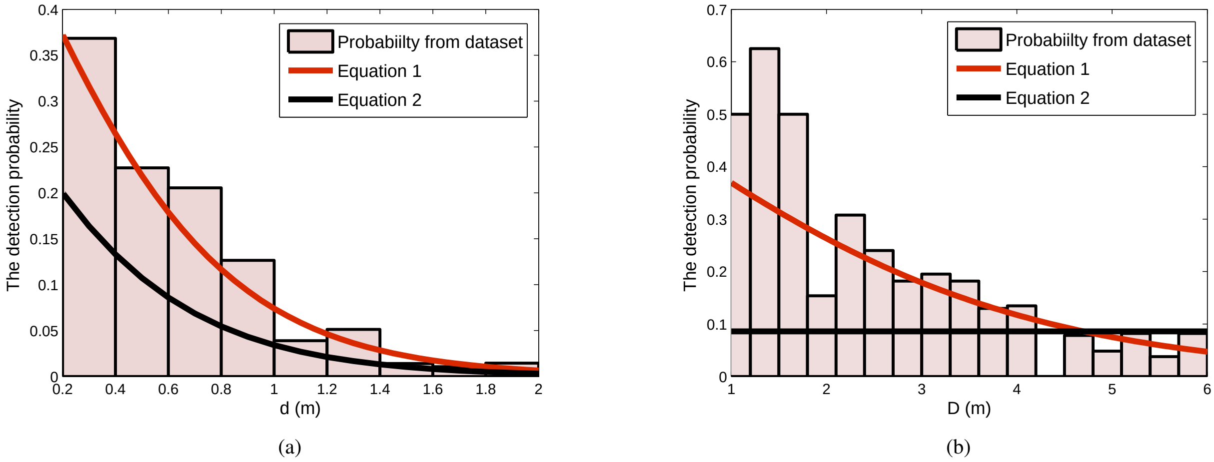


Figure 6. The detection probability histogram versus (a) d with data from the space $D \in [2, 4]$. (b) D with data from the space $d \in [0.4, 1]$. (Since the (2) purely depends on d, the probability is constant along D and the value is based on $d = 0.6$)

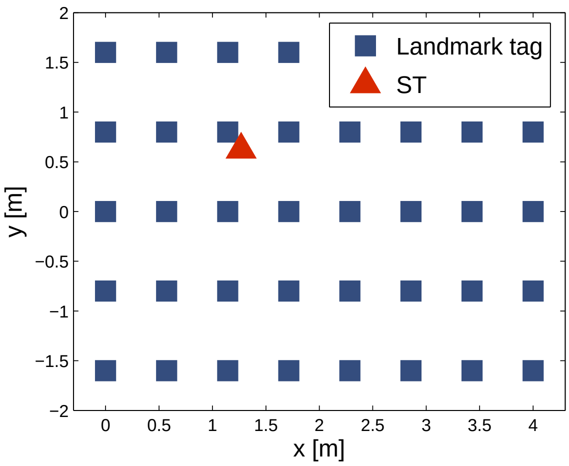


Figure 7. Simulation setup with landmarks tag and ST.

as binomial distribution.

$$P(n_k) = \binom{N}{n_k} p_k^{n_k} (1 - p_k)^{N - n_k} \tag{3}$$

where

$$\begin{aligned} p_k &= p(D, d, \theta, \phi) \\ &= \frac{1}{1 + e^{-1.462 + 0.4941 * D + 2.506 * d + 0.0126 * |\theta| + 0.0523 * |\phi|}} \end{aligned} \tag{4}$$

D, d, θ, ϕ are determined by the location of RFID reader, tag and ST as described in Section III-A. After the reader sends out Q_S query, there are K measurements from landmark tags $\mathbf{y} = \{n_k \in \{0, 1, \ldots, N\}, k = 1, 2, \ldots, K\}$. The likelihood function is given by

$$p(\mathbf{y}|x) = \prod_{k=1}^{K} \binom{N}{n_k} p_k^{n_k} (1 - p_k)^{N - n_k} \tag{5}$$

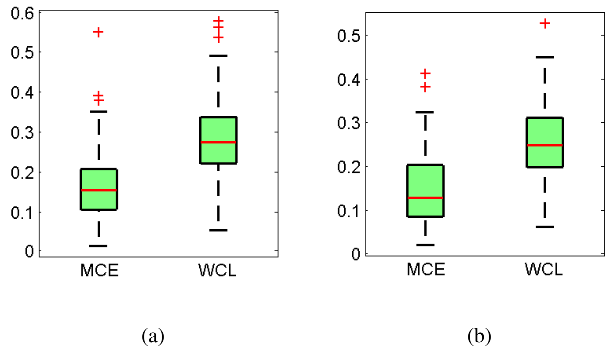


Figure 8. The localization error distribution of Monte Carlo estimation and WCL for two ST locations (a) (3.8804, -0.1470) (b) (1.5443, 0.6334).

Based on Bayes rule, the posterior probability could be written as

$$p(x|\mathbf{y}) = \frac{p(\mathbf{y}|x)p(x)}{p(\mathbf{y})} \tag{6}$$

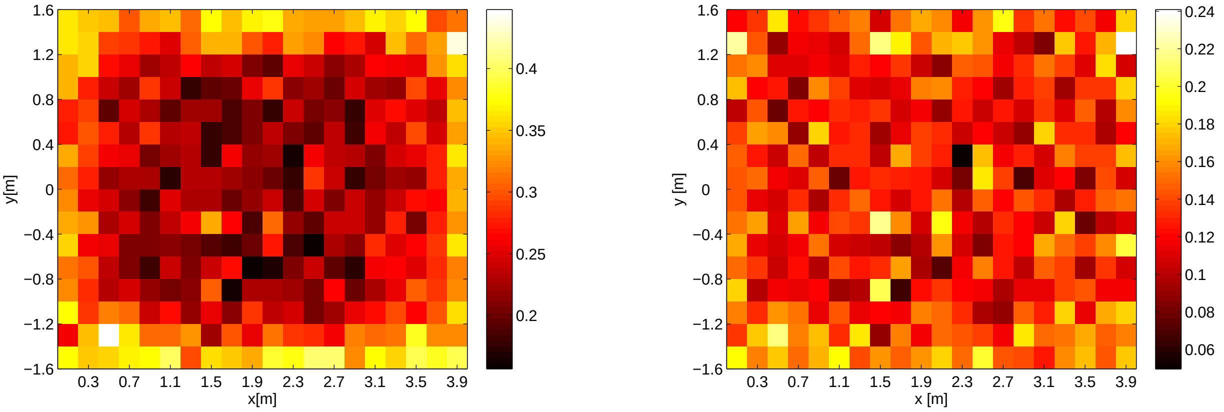
Therefore, the estimation of ST location x is

$$\hat{x} = \int x p(x|\mathbf{y}) dx \tag{7}$$

However, it is difficult to get a close form solution for (7) based on (4) and (6). According to Monte Carlo method, the distribution can be approximated by discrete random measures defined by particles and associated weights [17].

$$p(x|\mathbf{y}) \approx \sum_{m=1}^{M} w^{(m)} \delta(x - x^{(m)}) \tag{8}$$

where $\{x^{(m)}, m = 1, \ldots, M\}$ is a set of particles and $\{w^{(m)}, m = 1, \ldots, M\}$ is its weights. M is the number of particles in the approximation. However, it is difficult to draw samples from the distribution $p(x|\mathbf{y})$. We could generate sample $x^{(m)}$ from a proposal distribution $q(x)$, which is simple enough to generate random samples from it. And the weight



(a) (b)

Figure 9. The heatmap of location estimation error in meters associated with ST true locations applying (a) WCL (b) Monte Carlo estimation (each block is 0.2 m × 0.2 m).

assigned to the particle is

$$w^{(m)} = \frac{p(x^m|\mathbf{y})}{q(x^{(m)})} \tag{9}$$

Then, the weights are normalized by $w^{(m)} = w^{(m)}/\sum_{i=1}^{M} w^{(i)}$.

In this work, the proposal distribution is assumed to be an uniform distribution over the circle region centering WCL estimation. WCL is simple and computationally efficient, the form is as follows

$$x^* = \frac{\sum_{k=1}^{K} n_k * LT_k}{\sum_{k=1}^{K} n_k} \tag{10}$$

Then, a measure $\chi = \{x^{(m)}, m = 1, \ldots, M\}$ is generated from uniform distribution over the region centering at x^* with radius r. The prior distribution $p(x)$ in (6) is assumed as a uniform distribution over the whole target region. $p(\mathbf{y})$ is a constant. Therefore,

$$w^{(m)} \propto p(\mathbf{y}|x^{(m)}) \tag{11}$$

We obtain the estimation of ST location by

$$\hat{x} = \frac{1}{\sum_{m=1}^{M} p(\mathbf{y}|x^{(m)})} \sum_{m=1}^{M} x^{(m)} * p(\mathbf{y}|x^{(m)}) \tag{12}$$

Noteworthily, since the computation task is executed on host computer, the increased computational complexity of Monte Carlo estimation is of little concern.

A pseudo-code description of this algorithm is given by Algorithm 6.

IV. Performance Evaluation

In this section, a number of simulation has been carried out to evaluate the validity of the proposed algorithm. The simulation setup follows the deployment scenario as shown in Figure 7. The area is 4 m $\times$ 3.2 m, and covered by 8×5 UHF RFID landmark tags. RFID reader's panel antenna is placed at the center of the area facing the ground at the height of 2 m. The PASS simulator is configured as in Section III-A. For

ALGORITHM 1: Monte Carlo Estimation

Data: Observations $\mathbf{y} = \{n_k, k = 1, 2, \ldots, K\}$

```
begin
    /* WCL based on observations                                  */
    x* = (Σ_{k=1}^K n_k*LT_k) / (Σ_{k=1}^K n_k) , K landmark tags with known
      location {LT_k, k = 1, ..., K};
    /* Particle generation                                        */
    Sample generation χ = {x^(m), m = 1, ..., M} from
      uniform distribution over the region in circle
      centering x* with radius r;
    /* Weight of particles                                        */
    w^(m) = 1 / (Σ_{m=1}^M p(y|x^(m))) p(y|x^(m)) for all particles;
    /* Location estimation                                        */
    x̂ = Σ_{m=1}^M x^(m) w^(m)
end
```

the proposed algorithm, the size of particles M is set as 200. The number of query Q_T is set as 10. The radius r of circle region for proposal distribution is set to 0.8 m. The localization performance is measured by average root mean square error (RMSE). The RMSE for one realization is calculated as $||x - \hat{x}||_2$.

In the first set of simulations, we place the ST at a fixed location in the region. The location is randomly selected. We conduct 100 independent realizations of simulation with WCL and Monte Carlo estimation. We repeat the aforementioned procedure two times with different ST locations, which are picked randomly. The objective of the simulation is to present the localization performance of WCL and Monte Carlo estimation. Figure 8 shows the localization error distribution of these two scenarios with box-and-whisker plot. In Figure 8a, the ST is placed at $(3.8804, -0.1470)$, the RMSE for Monte Carlo estimation is 0.1641 m, while for WCL the RMSE is 0.2834 m, which is improved by 42.10%. In Figure 8b, the ST is placed

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at $(1.5443, 0.6334)$, the RMSE for Monte Carlo estimation is 0.1488 m, while for WCL is RMSE is 0.2561 m, which is improved by 41.90%. From the distribution and RMSE, we could conclude that Monte Carlo estimation achieves higher localization accuracy than WCL for these two scenarios.

In the second set of simulations, we randomly sample 3000 locations for ST in the region. We collect the data of the true ST location and the location estimation error for Monte Carlo estimation and WCL. The RMSE of ST location estimation is 0.2673 m for WCL and 0.1330 m for Monte Carlo estimation, which is improved by 50.24%. Figure 9 shows the heatmap of location estimation error associated with ST true locations. Each block of the heatmap is 0.2 m $\times$ 0.2 m, whose value is determined by the RMSE of location estimation while ST resides within the block. The overall localization accuracy of Monte Carlo estimation is higher than WCL. in particular, for the region close to the edge. The reason for such effect is that as ST approaches the edge, the landmark tags within ST's proximity are unequally distributed. Monte Carlo estimation utilizes detection probability model of ST-to-tag, which could alleviate the effect of unequally distributed landmarks. From the figure, we could conclude that Monte Carlo estimation achieves higher localization accuracy than WCL.

V. Conclusion

In this paper, we have investigated the problem of locating static object attached with ST, which can detect the presence of UHF RFID landmark tags with its proximity. Based on a more realistic detection probability model of ST-to-tag, we propose a Monte Carlo-based method for achieving higher localization accuracy. We conduct several sets of simulation in our newly developed PASS simulator, and the simulation results show that Monte Carlo-based method achieves higher localization accuracy than the conventional WCL method.

There are several interesting direction to explore in the future work. First, the detection probability model does not consider shadowing effect, which is important while attaching ST to human or metallic vehicle. Second, this work only considers locating one ST. It would be convenient to localize multiple STs using Monte Carlo estimation method independently. However, we could anticipate that the accuracy and robustness of localization method would be improved with extra ST-to-ST detection information. Third, the landmark deployment does not receive much attention in this work. We simply deploy the landmark tags in square pattern, and distance among neighboring landmarks is constant. However, it is beneficial to investigate the relationship between localization accuracy and the deployment density and pattern of landmark tags.

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