HF RFID-based Book Localization via Mobile Scanning

Lin Xu, Jia Liu, Xia Wang, Hualin Gong, Yanyan Wang, Lijun Chen
State Key Laboratory for Novel Software Technology, Nanjing University, Nanjing 210023, China
Email: xlycj@smail.nju.edu.cn, jialiu@nju.edu.cn, {wangxia, netlab428, wangyanyan}@smail.nju.edu.cn, chenlj@nju.edu.cn

***Abstract*—Shelf scanning is one of the most important processes for inventory management in a library, which is able to help library users find the misplaced books and pinpoint where they are. Traditional solutions suffer from intensive manual labor, long scanning delay, or high-cost infrastructure renewal, which is a great barrier to commercial adoption. In this paper, we propose an HF RFID system that can perform the shelf scanning automatically by combining robotics and RFID technology, where the mobile robot is used for replacing the library staff and the RFID is for locating the tagged books on the bookshelves. The biggest challenge is that the commodity HF RFID device cannot capture RF phase, which is a fine-grained metric with high resolution for locating. To address this problem, we break down the task of localization into two stages, tier-level localization and order estimation, and use fuzzy logic to model and estimate the tagged book's position. We implement the system and deploy it into four libraries for practical use. Long-term experiment results show that our system provides a fine-grained book localization with an accuracy of a few centimeters.**

***Index Terms*—HF RFID, Book Localization, Library, Mobile Scanning**

I. Introduction

As the saying goes, "books are the ladder of human progress". A library is a collection of books that provides readers with access to reference and borrowing. These books are placed in a specific bookshelf and sorted in sequence according to the call numbers. If the collection of books is heavily used, the circulating books are likely to be misplaced, i.e., a book is not in the position where it should be. When this happens, the library users can search the books of interest out via the library management systems but cannot pinpoint where they are, especially in a library consisting of hundreds of thousands of books, leading to a great waste of time and library resources. As the literature [1] shows, the ratio of misplaced books in some US school libraries reaches up to 10%; this ratio will appear even higher in public libraries. In other words, more than one tenth of library users cannot find their wanted books even though these books reside in the library indeed. A misplaced book is a 'lost' book and accurately locating each book (including misplaced book) is critical to avoiding the waste of massive book resources and providing good service to the public.

To do so, a shelf scanning over all bookshelves in a library is needed. By traditional means, the library staff first conduct shelf reading, i.e., manually checking each book by observing the call number attached to the book's spine, as shown in Fig.1(a). If a book is misplaced, they need to tip it out, search the position where it would be, and insert it into the correct location. This process is extremely labor intensive and time-consuming, which is almost infeasible for the large-scale library management. In recent years, Radio Frequency Identification (RFID) technology has be widely used in libraries by two ways: handheld RFID scanning [2], [3] or smart bookshelves [4], [5], as shown in Fig.1(b), Fig.1(c). The former improves the scanning efficiency but still needs librarians to manually move the handheld RFID reader to scan each book on the shelves, suffering from long scanning delay and heavy manual labor. The latter requires high-cost infrastructure and complicated system deployment, which is a great barrier to commercial adoption. Hence, both of them are far away from a complete solution to bookshelf scanning.

RF-Scanner [6] is the most recent work that performs the shelf scanning automatically by combining the robot vehicle and the UHF RFID technology. The former is used for replacing librarians and liberating them from intensively manual labor. The later is installed on the robot and moves with the robot to scan the books on the shelves. By collecting, analyzing, and modeling the RF phases of a tag, RF-Scanner is able to pinpoint the tag, so does the book that the tag is attached to. Since the RF phase has fine-grained measure resolution, it is potential for RF-Scanner to achieve high localization accuracy. In spite of this advancement, many libraries have deployed the HF RFID systems rather than UHF RFID systems, which makes RF-Scanner unavailable in these cases. Hence, a new HF RFID-based localization system is required to accommodate the existing HF RFID-enabled libraries. The biggest difference is that we cannot capture the RF phase profile in the commodity HF RFID system any more, which however, is the key vehicle of RF-Scanner for accurate localization in the UHF RFID system. In this paper, we study how to locate the HF tag (book) by one-pass shelf scanning. Unlike existing localization work [7], [8] that estimates the absolute 3D coordinate of a tag, the localization of shelf scanning returns a 3-tuple (shelf #, tier #, order) that respectively indicates in which bookshelf, in which tier, and in which order a book is placed, which helps the library users find out the books of interest quickly. This is however not easy. Two key technical challenges in locating have to be addressed. First, when scanning a specific tier of the bookshelf, the tags (books) on the upper tier, lower tier, and even the backside of the shelf will participate in the response, making the system fail to determine which one is the ground truth. Second, as

(a) Manual Checking (b) Handheld RFID (c) Smart Bookshelves

Fig. 1. Traditional ways of shelf scanning.

aforementioned, the fine-grained RF metric, phase value, is out of the scope of the commodity HF RFID system. We need to achieve the same and even higher localization accuracy as UHF RFID system with other coarse-grained indicators.

To address above challenges, we break down the locating problem into two stages: the *tier-level localization* and the *cm-level sorting*. The tier-level localization first figures out in which tier and which bookshelf a tagged book is placed, i.e., returning (shelf #, tier #). To do so, we find that, two useful metrics rather than RF phase (unavailable in HF RFID systems), the number of reads and the RSSI values, are useful and potential to do the book localization in the HF RFID system. By taking them as the input and using the models of random forest and fuzzy logic, we can predict the shelf and tier, respectively. After that, we do the the cm-level sorting, which aims to return the order of the books in the same tier. We present a sensor model that concentrates the localization on the one-dimension of the reader's moving direction, which helps improve the ordering accuracy, compared with [9]. The contributions of this paper are summarized as follows:

- We revisit the shelf scanning problem in HF RFID system to accommodate the existing HF RFID-enabled libraries and figure out the difference between UHF RFID and HF RFID for scanning.
- We break down the book-localization problem into two stages: the tier-level localization and the cm-level sorting. Two models are proposed to achieve accurate book localization.
- We implement an HF RFID scanning system by integrating a self-designed robot vehicle and a commercial off-the-shelf HF RFID reader equipped with two antennas. Extensive experiment results show that our system can achieve 97% localization accuracy, which outperforms the state-of-the-art RF-Scanner.
- We deploy our HF system in four different school libraries, which has helped more 10,000 users find the books of interest since 2018.

The rest of this paper is organized as follows. Section II details the tier-level localization. Section III shows the cm-level sorting. Section IV implements the system and evaluates the performance. Section V presents the real-world use case. Section VI introduces the related work. Finally, section VII concludes this paper.

II. Tier-Level Localization

In this section, we show how to achieve the tier-level localization, i.e., returning (shelf #, tier #). The key challenge is that when scanning a specific tier of the bookshelf, the tags

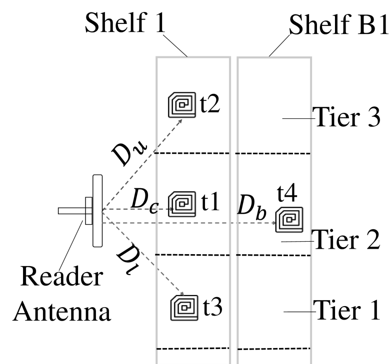


Fig. 2. Side view of a 3-tier bookshelves.

(books) on the upper tier, lower tier, and even the backside of the shelf will participate in the response. It is hard to determine in which tier the scanned tag (book) resides, especially in the case that RF phase cannot be obtained by HF RFID readers. This motivates us to seeks for new useful metrics to do the book localization.

Let us consider a scale-down HF RFID system. As shown in Fig.2, there are two 3-tier bookshelves, back to back. We label the three tiers 1, 2, 3, respectively, from bottom to top. Four tags t_1, t_2, t_3, t_4 are located at (shelf 1, tier 2), (shelf 1, tier 3), (shelf 1, tier 1), (shelf B1, tier 2), respectively. Clearly, when doing a shelf scanning on (shelf 1, tier 2), the distance between the reader antenna and the tag t_1 is closer than those between the reader antenna and other tags. Since the HF RFID communication is based on the principle of electromagnetic coupling. The closer the distance between the antenna and the tag is, the more chances that a tag can be read. Besides, this distance also determines the power strength the tag can receive, so does the power strength emitted by the tag. Hence, based on above two observations, we find two useful metrics, i.e., number of reads and RSSI values, to determine the ground truth of shelf # and tier #.

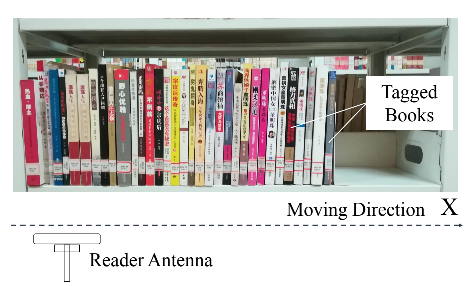


Fig. 3. The way of mobile scanning.

A. Number of Reads

For each tag, the number R of reads represents the total number of tags to be detected by the reader when performing one-pass scanning along the X-axis (AGV's moving direction), see Fig.3. As shown in Fig.2, since the distances D_u, D_l and D_b are greater than D_c, the tag t_1 is likely to get more chances to be read. Hence, the number of reads for t_1 is supposed

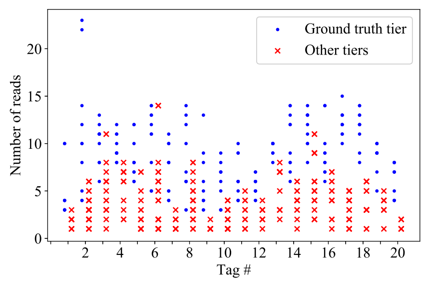


Fig. 4. Number of reads.

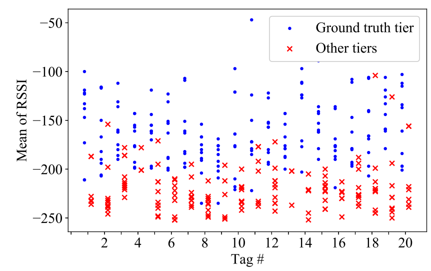


Fig. 5. Mean of RSSI.

to be greater than others'. To validate this conclusion, we conduct a toy experiment with a 3-tier bookshelf filled with 400 tagged books. In the experiment, the reader antenna moves along the X-axis from the most left side to the most right side at a constant speed of 0.1 m/s. Since only one antenna is deployed, each pass scans only one tier of the bookshelf. For the 3-tier bookshelf, three passes are needed. After that, we analyze the collected data and plot the number of reads for each tag. Fig.4 shows the number of reads for 20 tags that are randomly chosen from 400 tags. As we can see, a tag at a specific tier can also be queried by the antenna when the antenna is scanning other tiers ($\times$ symbol). However, in most cases, the number of reads in the specific tier (ground truth) is greater than those when the antenna is located at other tiers where the tag does not belong to. This is consistent with what we expected and validates the correctness of our inference to some degree. However, there are still some violations. Taking tag #8 for example. The tag resides in tier 2. However, one sample of tier 2 (the real position of tag #8) is smaller than some samples of other tiers. There are two reasons for this. The first is the effect of multipath. In RFID communications, the RF signals are likely to be reflected by the metal bookshelf, leading to constructive signal interference or destructive interference. In other words, if the interference is positive to the tag not in the tier where the reader antenna is scanning, the number of reads will be increased, which is prone to get a big number of reads, even through the tag is not in the current scanning tier indeed. The second reason is the interference caused by other tags. Tags in the vicinity introduce a parasitic capacitance that changes the resonance frequency of the RFID tags, which further leads to a reduced read range. Besides, mutual conductance represented by other tags in close proximity have negative effect on read range [10].

B. Mean of RSSI Values

The number of reads, as a useful indicator, gives us some clues to the tier-level localization. However, we cannot just rely on it. This motivates us to explore the second metric: the RSSI value. Received Signal Strength Indication(RSSI) is a indicator that measure the power present in a received radio signal, which is described as follows:

$$P_{recv} = \frac{cP_{tx}}{d^2}, \tag{1}$$

where the parameter c is the path loss involved between the transmitter and the receiver antenna, P_{tx} is defined as the power which is transmitted by the reader's antenna to identify the tags, P_{recv} is the received signal strength indicator value, and d is the distance between tags and reader antenna. According to (1), the smaller the distance d between reader antenna and tag, the greater the RSSI P_{recv}. Since D_c is smaller than D_u, D_l and D_b, the corresponding RSSI value is greater than others. With this characteristic, we can determine in which tier a book is placed. More specifically, in each pass, we collect the RSSI mesurements together with the corresponding timestamps for each tag, which is referred to as RSSI profile, represented as $\{(rssi_1, t_1), ..., (rssi_n, t_n)\}$. After the shelf scanning, we derive the mean of RSSI profile in the same tier. Hence, there might be several means for a tag since the tag can be read by the antenna in different tiers. The tier corresponding to the biggest mean is treated as the tier in which the tag resides.

To validate the performance of the mectic, we repeat the experiment with the same experimental settings as before. Fig.5 shows the mean RSSI value for each tag. As we can see, in most cases, the mean RSSI values of tags on ground-truth tiers are greater than those on other tiers. Similar to the number of reads, there are also a few of violations if we use only a single metric. Taking tag #9 for example, one sample of ground-truth is smaller than some samples of other tiers. Hence, we move one step further, and combine the above two metrics together and expect to get the benefits of them for improving the accuracy.

C. Binary Classification

In fact, the tier-level localization can be treated as a binary classification problem: the tag is in a tier or not. Hence, we can resort to the classic classifier to do the tier-level localization. The basic idea is to connect the two metrics, the number of reads and the mean of RSSI, to form a feature vector $< N, R_m >$, and take the vector as the input of the classifier. More specifically, suppose that a tag is located at (shelf 1, tier 2). When doing the shelf scanning, the tag is very likely to be identified by the reader when the reader performs one-pass scanning on (shelf 1, tier 1), (shelf 1, tier 2), (shelf 1, tier 3), (shelf B1, tier 1), (shelf B1, tier 2), (shelf B1, tier 3), where B1 is the bookshelf back to the bookshelf 1. Since the communication range of HF RFID is less than 100cm, the one-pass scanning on other tiers can hardly query the tag. For

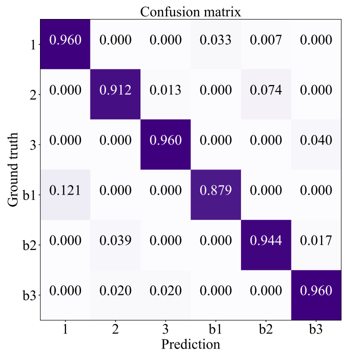


Fig. 6. Tier-level localization accuracy of binary classification.

each tier, we produce a feature vector $< N, R_m >$ and label this vector as '1' if it is produced by the data of (shelf 1, tier 2) and '0' otherwise. After that, we use one of the common classifiers random forest [11] to output the probability that indicates the likelihood of the tag's tier-level position. In this example, we get six probabilities, and we treat the shelf and tier with the highest probability as the tag's position.

As shown in Fig.6, by combining the two metrics, the number of reads and the mean of RSSI, we are able to get a high tier-level localization accuracy in most cases with the random forest algorithm, where 1, 2, 3, b1, b2, b3 indicates (shelf 1, tier 1), (shelf 1, tier 2), (shelf 1, tier 3), (shelf B1, tier 1), (shelf B1, tier 2), (shelf B1, tier 3), respectively. For example, the tier-localization accuracy for tags in (shelf 1, tier 1) and (shelf 1, tier 3) reach up to 96%, which well indicates the high accuracy of this method. However, some tiers, e.g., (shelf B1, tier 1), suffer from low accuracy. This might be due to the fact that our training model is hard to be generalized to all cases. In other words, one group of trained parameters cannot fit well with all different scenarios. In addition, the classification-based solution suffers from tedious data collection and training process, which is a great overhead. In light of this, we seek for another more lightweight and scalable solution: fuzzy logic.

D. Fuzzy Logic

Rather than the usual"true or false" (1 or 0) Boolean logic, fuzzy logic [12] is a form of multi-valued logic, in which the truth value of a variable may be 1 or 0 or any real number between 0 and 1. It is able to simultaneously deal with numerical data and linguistic knowledge. Thanks to this advantage, it has been successfully applied to a wide range problems from different fields presenting uncertainties and vagueness. A typical fuzzy logic system consists of three main parts: fuzzification, rules evaluation, and defuzzification. As shown in Fig.7, fuzzification is the first step in the fuzzy logic system. This involves a domain transformation where crisp inputs are converted into fuzzy inputs representing the membership degree to which an element belongs to a given set by using fuzzy linguistic variables, fuzzy set and membership functions. And then fuzzy inputs are applied to a set of IF $< antecedent >$ THEN $< conclusions >$ control rules for evaluation. The evaluated results of various rules are summed together by fuzzy logic operations. This step is known as rule evaluation. After the evaluation step, the overall result is a fuzzy value. To obtain a crisp output, defuzzication is performed according to the membership function of the output variable. Below, we detail how to use fuzzy logic to do the tier-level localization.

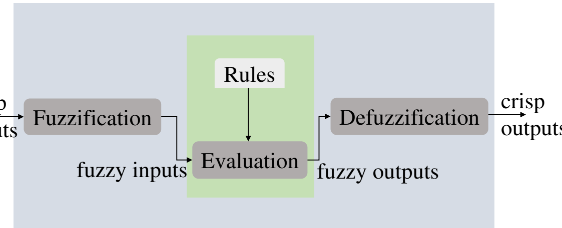


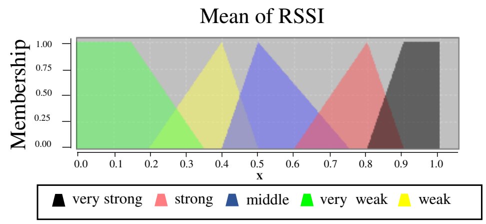
Fig. 7. Fuzzy logic control system architecture.

a) **Fuzzification:** As previously metioned, fuzzification involves a transformation using fuzzy linguistic variables, fuzzy set and membership functions [13]. Linguistic variables are the input or output variables of the system whose values are words from a natural language instead of numerical values. In our case, we define two input variables: n, s that respectively represent the number of reads and mean reading RSSI, and a single output variable: p, indicating the probability of tag in a specific tier. A linguistic variable is generally decomposed into a set of linguistic terms, also known as fuzzy set. For example, the variable n can be decomposed into linguistic terms, such as "high" and "low", which are fuzzy sets. Hence we can define $N = \{$*very high, high, middle, low, very low* $\}$, which are the set of decompositions for the linguistic variable n. Each member of this decomposition covers a small interval of the domain of n. The rest linguistic variables s and p can be done in the similar manner. Namely, we have $S = \{$*very strong, strong, middle, weak, very weak* $\}$, $P = \{$*very high, high, middle, low, very low* $\}$. A membership function is used to do a mapping between the crisp values in the input space and the fuzzy set defined in the universe of discourse of this input. The most common types of membership functions are the triangular shape and the trapezoidal shape [14], which can be described as follows:

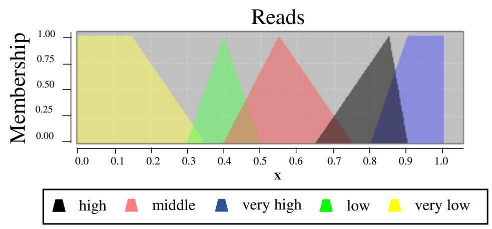
$$f(x) = \begin{cases} \frac{x-a}{m-a} & a < x \leq m \\ \frac{b-x}{b-m} & m \leq x \leq b \\ 0 & otherwise. \end{cases} \tag{2}$$

$$f(x) = \begin{cases} \frac{x-a}{b-a} & a < x \leq b \\ 1 & b \leq x \leq c \\ \frac{d-x}{d-c} & c \leq x < d \\ 0 & otherwise. \end{cases} \tag{3}$$

In this paper, we take the above two as our membership function. For the sake of presentation, we here show only the membership functions for the fuzzy sets of variable n, s. A given value is likely to belong to multiple sets at the same time, with different degrees of memberships. For example, as



(a) Membership functions for S={very strong, strong, middle, weak, very weak}



(b) Membership functions for N={very high, high, middle, low, very low}

Fig. 8. Membership functions for fuzzy set S and N.

shown in Fig.8(a), x is the (normalized) crisp input for input variable s, and $Membership$ indicates the real value of a crisp input value belonging to a given set. Suppose that $x = 0.3$. The $Membership$ value of x belonging to the term $veryweak$ is 0.25, i.e., $\mu_{veryweak}(0.3) = 0.25$, and the $Membership$ value of x belonging to the term $weak$ is 0.5, i.e., $\mu_{weak}(0.3) = 0.5$.

b) **Rules Evaluation:** In a fuzzy logic system, a rule base consisting of m rules is used to determine the output variable. As aforementioned, each rule has the form *IF* $<$ *antecedent* $>$ *THEN* $<$ *conclusions* $>$. For example, a section of our control rules are described as follows:

- *IF s is very strong AND n is very high THEN p is very high*
- *IF s is strong AND n is high THEN p is high*
- *IF s is vey weak AND n is very low THEN p is vey low*

In general, all rules can be expressed in an ensemble form:

$$\bigcup_{i=1}^{m} \textit{IF s is } S_i \textit{ Zadeh Operator n is } N_i \textit{ THEN p is } P_i,$$

where Zadeh Operator can be AND, OR, and NOT operator. The operator AND represents the intersection between the two sets; OR represents the union between the two sets; NOT represents the opposite of the set. Table I contains possible fuzzy operations for OR and AND operators. Since MIN and MAX operators have been extensively used in the membership functions for the intersection and the union of fuzzy sets, we also choose MIN and MAX for OR and AND operators respectively. The i-th rule can be described by a fuzzy relation R_i on a universe of discourse $S \times N \times P$ and its membership function is given by:

$$\mu_{R_i}(s, n, p) = I(\mu_{S_i}(s), \mu_{N_i}(n), \mu_{P_i}(p)), \tag{4}$$

where $\mu_{S_i}(s)$, $\mu_{N_i}(n)$, $\mu_{P_i}(p)$ are respectively the membership functions of the fuzzy sets S_i, N_i, P_i; I is a fuzzy implication operator modeling the fuzzy relation [15]. The choice of an implication operator relies on the context. In our case, we choose MIN operator for I. If all the control rules are put together, the overall fuzzy relation R is then given by:

$$\mu_R(s, n, p) = \mathop{T^*}_{i=1}^{m}[\mu_{R_i}(s, n, p)], \tag{5}$$

where T^* is fuzzy disjunctive operator (t-conorm) [16]. Given S', N', the fuzzy set P' is obtained as a result of the application of the Compositional Rule of Inference (CRI) introduced by Zadeh in [17], denoted by

$$P' = S' \circ N' \circ R,$$

$$\mu_{P'}(p) = \mathop{Sup}_{s,n}\ T[\mu_{S'}(s), \mu_{N'}(n), \mu_R(s, n, p)], \tag{6}$$

where T is fuzzy conjunctive operator (t-norms) [16]. As Zadeh suggested in [17], we use MIN and MAX for T, T^*, respectively. Since evaluation process is applied at the level of individual rules, once the CRI has been applied on the m rules, we can obtain m fuzzy sets P'_i. Hence, we need to aggregate the individual fuzzy sets P'_i for obtaining a final fuzzy set P' by means of a fuzzy aggregation operator AGG, denoted by:

$$\mu_{P'}(p) = AGG\{\mu_{P'_1}(p), ..., \mu_{P'_m}(p)\}. \tag{7}$$

We here choose the most widely used aggregation method, Maximum, i.e., $Max(\mu_S(s), \mu_N(n))$, to combine the results of individual rules.

c) **Defuzzification:** After the evaluation step, the output is just a fuzzy value. This result should be further defuzzified to obtain a final crisp output. By using a defuzzification algorithm, we obtain a crisp value, p_0, which is a global output:

$$p_0 = D(\mu_{P'}(p)). \tag{8}$$

There are different algorithms for defuzzification. We here just borrow one of the most widely used algorithm Center of Gravity (COG), denoted by:

$$p_0 = \frac{\int \mu_{P'}(p) \cdot pdp}{\int \mu_{P'}(p)dp}. \tag{9}$$

The COG algorithm is a method of calculating centroids of sets. More details about COG can be seen in [18]. Due to the space limitation, we omit the introduction on COG here. By running the three stages: fuzzification, rules evaluation, and defuzzification, we can finally determine at which tier a tag is located.

III. CM-LEVEL SORTING

After doing the tier-level localization, the next is to estimate the order of books in a tier. Let x denote the coordinate of a tag along the X-axis. Given two tags t_1 and t_2, if the coordinate of t_1 is smaller than that of t_2, the tag t_1 precedes t_2. Otherwise, the tag t_1 ranks behind. Hence, to get the order of the tagged books is to get the coordinates of the tags. To do so, we propose a probabilistic model that estimates the one-dimension coordinate of each tag on the X-axis. We define a pair of observation values $o = (u, rss)$ which carries two pieces of information, namely that we have detected the tag

TABLE I
FUZZY SET OPERATIONS

OR(Union)	AND(Intersection)
MAX $Max(\mu_S(s), \mu_N(n))$	MIN $Min(\mu_S(s), \mu_N(n))$
ASUM $\mu_S(s) + \mu_N(n) - \mu_S(s)\mu_N(n)$	PROD $\mu_S(s)\mu_N(n)$
BSUM $Min(1, \mu_S(s) + \mu_N(n))$	BDIF $Max(0, \mu_S(s) + \mu_N(n) - 1)$

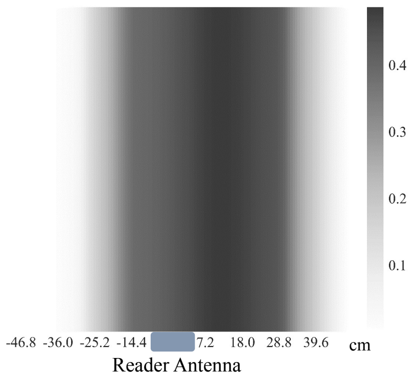


Fig. 9. One-dimension tag detection model.

u in the first and secondly that we received its signal with a signal strength rss. Let r denote the current coordinate of the reader antenna on the X-axis. According to Bayes' rule, the posterior probability distribution of x representing the position of the tag conditioned on the previous observations of this tag $o_{1..t}$ and reader antenna positions $r_{1..t}$:

$$\begin{aligned} P(x|o_{1..t}, r_{1..t}) &= \eta \cdot P(o_t|x, o_{1..t-1}, r_{1..t}) \cdot P(x|o_{1..t-1}, r_{1..t}) \\ &= \eta \cdot P(o_t|x, r_t) \cdot P(x|o_{1..t-1}, r_{1..t-1}), \end{aligned} \tag{10}$$

where η is a normalization constant, and $P(o_t|x, r_t)$ represents the RFID sensor model. Note that the recieved signal strength measurement implicitly condition on the tag detection event, however, we explicitly distinguish tag detection event from recieved signal strength measurement by denoting with d the binary variable representing whether this tag is detected by the reader. Hence, the sensor model $P(o_t|x, r_t)$ can be formalized as follows:

$$\begin{aligned} P(o_t|x, r_t) &= P(rss_t, d_t|x, r_t) \\ &= \beta \cdot P(rss_t|d_t, x, r_t) \cdot P(d_t|x, r_t), \end{aligned} \tag{11}$$

where β is a normalization constant, and d_t denotes whether this tag is detected by the reader. $P(rss_t|d_t, x, r_t)$ is the likelihood that the received signal strength is rss if the tag's position is x and the reader antenna's position is r_t. And $P(d_t|x, r_t)$ is tag detection model.

Unlike prior work [9], [19], we just focus on the one-dimension order along X-axis and evenly choose some points in the X-axis. For each candidate point x, we register a positive event if the tag is detectable by the reader or a negative event otherwise. By counting the numbers of positive events and negative events, we can get the probability P_{x,r_t} that a tag at the point x is read by the reader antenna at the point r_t, i.e., $P_{x,r_t} = \frac{n^+(x)}{n^+(x)+n^-(x)}$, where $n^+(x)$ is the number of positive events and $n^-(x)$ is the number of negative events. By repeating these measurements, we can obtain the tag detection model, which shows the probabilities of a tag at different positions to be read when the reader is fixed on the X-axis. Note that, the positions of the tag and the reader are relative instead of absolute. As we can see in Fig.9, the probability experiences a decline as the relative distance between the reader and tag increases. This does make sense because the field strength in the near field weakens as the distance increases. Besides, we assume that the received signal strength rss of a tag (when the tag and the reader antenna are fixed) follows Gaussian distribution $\mathcal{N}(\mu, \sigma^2)$, and we can get the distribution model for different reader-tag positions by the similar way above. Finally, we get the estimate $P(o_t|x, r_t)$ as follows:

$$\begin{aligned} P(o_t|x, r_t) &= P(rss_t, d_t|x, r_t) \\ &= \beta \cdot P(rss_t|d_t, x, r_t) \cdot P(d_t|x, r_t) \\ &= \beta \cdot \frac{1}{\sqrt{2\pi}\sigma_x} e^{-\frac{(rss-\mu_x)^2}{2\sigma_x^2}} \cdot P_{x,r_t}, \end{aligned} \tag{12}$$

where μ_x, σ_x respectively represents the average received signal strength and the empirical variance for each point x.

IV. EVALUATION

In this section, we implement a shelf scanning system by combining the technologies of HF RFID and AGV, and evaluate the localization performance via extensive experiments, in terms of tier-level localization and order estimation.

A. Implementation

In general, our shelf scanning system is composed of three main components: AGV, HF RFID and camera.

1) AGV: The AGV of our system is self-designed, which integrates the modules of navigation and self-charging. Unlike the magnetic navigation in RF-Scanner [6], our navigation module adopts the laser radar to do the navigation, which has two competitive advantages. First, it can achieve precise positioning without any pre-deployed infrastructures on the ground. Second, the driving path is easy to change, which is scalable to different library environments. The self-charging module helps the robot commute between shelf and home base, ensuring the reliable and continuous scanning.

2) RFID Component: The RFID component consists of one RFID reader and two antennas. The antennas are mounted on the robot arm that is able to move up and down to reach each tier of a bookshelf. When the robot moves along the bookshelf,

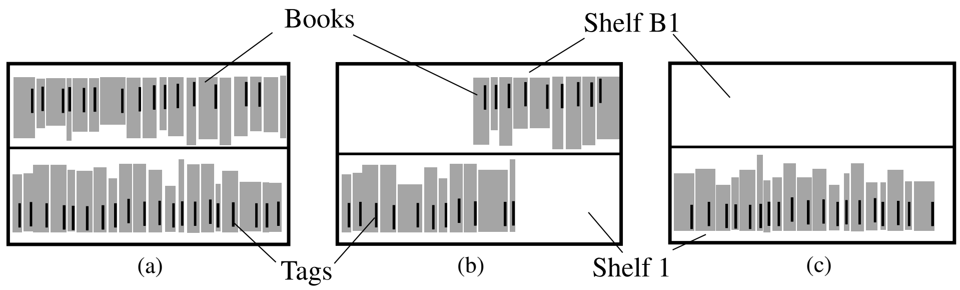
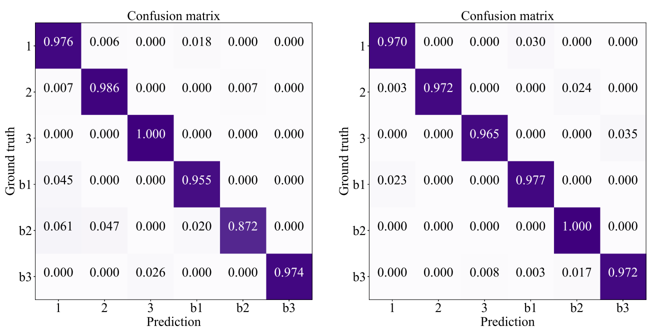
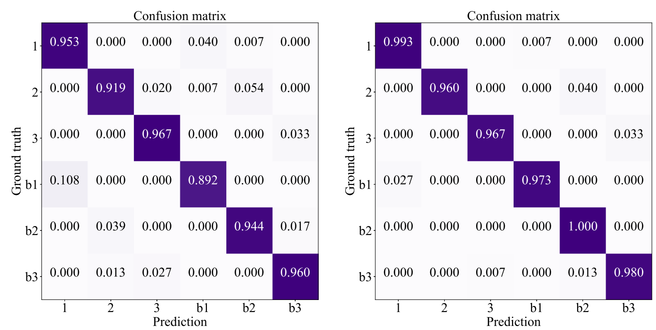


Fig. 10. Top view of shelf with tagged books arranged in three different layouts. (a) The first layout. (b) The second layout. (c) The third layout.



(a) randomf forest (b) fuzzy logic

Fig. 11. Tier-level localization accuracy of two models: random forest and fuzzy logic, with books arranged in the first layout.



(a) random forest (b) fuzzy logic

Fig. 12. Tier-level localization accuracy of two models: random forest and fuzzy logic, with books arranged in the second layout.

the RFID reader (antenna) is activated and starts to scan tags embedded in the books. For a common 6-tier bookshelf in the library, we label these six tiers as tier 1, tier 2,...,tier 6, from bottom to top. The tier information is recorded by the back-end server during each one-pass scanning for the purpose of book localization.

3) Camera: We deploy four depth cameras, Intel RealSense, on the robot arm to detect the obstacle. More specifically, when the book is too large, it will block the shelf scanning. The cameras can detect this exception and avoid any collision. In addition, these cameras can also assist the detection of other barriers, such as pedestrian, desks, chairs in a library.

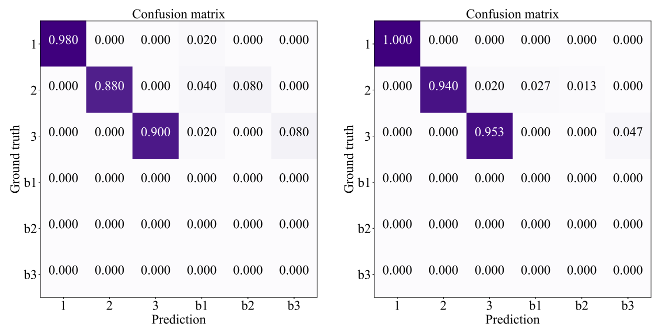
B. Experiment Setting

In the experiment, we randomly picks a bookshelf with about 1000 books filled. The thickness of these books varies from 1cm to 5cm. Moreover, we consider three typical books layouts on the bookshelf, as shown in Fig.10. The first layout is that the same tier of bookshelf 1 and bookshelf B1 is fully loaded by books. The second layout is that the same tier of bookshelf 1 and bookshelf B1 is half loaded by books. The third layout is that a tier of bookshelf 1 is fully loaded, while the same tier of bookshelf B1 is empty (no books). We evaluate the system performance based on these three layouts, in terms of tier-level localization (shelf #, tier #) and the order estimation. Each result is the average output of 20 trials.

C. Tier-level Localization

The information of (shelf #, tier #) can quickly narrow down the search space from a library to a specific tier of a bookshelf, which can help library users find out the misplaced books. For each book, if the predicted (shelf #, tier #) is inconsistent with the ground-truth, this localization is treated as a failure; otherwise it is successful. Hereby, we define the localization accuracy as the ratio of the number of successful localization to the total number of localization. In what follows, we evaluate the tier-localization accuracy of books on (shelf 1, tier 1), (shelf 1, tier 2), (shelf 1, tier 3), (shelf B1, tier 1), (shelf B1, tier 2), (shelf B1, tier 3). Two methods are adopted, i.e, random forest and fuzzy logic.

In Fig.11, we study the tier-level localization performance of the two methods under the first kind of book layout. As we can see, the confusion matrixes show great localization accuracy of these two methods. For example, the localization accuracy is higher than 95% in most cases. Moveover, we observe that fuzzy logic based solution generally outperforms the random forest. For example, as shown in Fig.11, for fuzzy logic model, the probability of books on (shelf B1, tier 1) is correctly classified reaches up to 97.7%, which is superior to 95.5% of random forest model. Besides, it is worth noting that, random forest is not scalable as fuzzy logic due to the tedious data collection and training process. The similar conclusion can also be drawn in the other two layouts in Fig.12 and Fig.13: the tier-localization accuracy of fuzzy logic is higher than that of random forest. We conclude that fuzzy logic



(a) random forest (b) fuzzy logic

Fig. 13. Tier-level localization accuracy of two models: random forest and fuzzy logic, with books arranged in the third layout.

performs better than random forest, in terms of localization accuracy and availability in practice.

D. Order Estimation

Order estimation of books is to give a more fine-grained localization results for better serving the users and helping them find the books of interest more easily. Assume there are N books on a tier of a bookshelf. We label these books as 1 to N in an ascending order. This initial (real) order is referred to as O. After that, we perform our detection model together with the probability distribution to obtain the estimation of the book order, denoted by $\hat{O}$. The ordering accuracy acc is defined as the normalized Kendall tau distance [20], denoted by:

$$acc = \frac{K(O,\hat{O})}{\binom{N}{2}} \tag{13}$$

where K being Kendall tau distance function. Fig.14 compares the ordering accuracy between our system and the first HF RFID based work LibBot [9]. As we can see, the ordering accuracy of our system is more than 90% in all cases. For example, the ordering accuracy reaches up to 94% when speed is 0.08 m/s. This accuracy is higher than LibBot in all cases. That is because, LibBot does not take advantages of the useful metric RSSI for estimating the book order. In addition, it sets up a two-dimension detection model, which is likely to suffer from more noise than the one-dimension model of our method. Moreover, with the increase of speed, the accuracy of LibBot sees a decline tread. In contrast, our system remains stable and even achieve a higher accuracy, which indicates that our model is robust to the moving speed of the AGV.

Besides the book order, we further evaluate the absolute localization error of the tag along the X-axis at different speeds: 0.06 m/s, 0.08 m/s, and 0.1 m/s. Fig.15 shows the CDF of the error distribution. Clearly, the results demonstrate that our method is able to achieve cm-level localization along X-axis. For example, the median localization error is 2.52 cm when the speed is fixed at 0.1 m/s. This high localization accuracy enables the library users to find out book quickly.

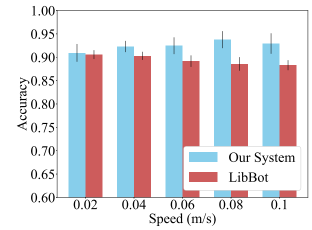


Fig. 14. Ordering accuracy.

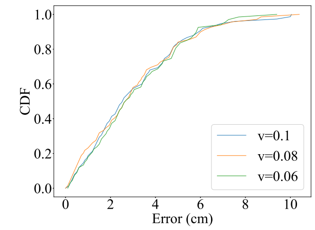


Fig. 15. CDF of localization.

V. Use Case

To date, we have deployed our RFID shelf scanning system in four libraries for practical use, which are Nanjing University, Wuhan university, China Agricultural University, and Chinese University of Hong Kong (Shenzhen), as shown in Fig.16. Our RFID-based robot works every night after closing and returns the latest localization results in the next morning. If a book is misplaced, we report this event and tell the librarian to place it into the correct position. This process works automatically, with no need of any manual intervention.

For the library users, we provide a user interface (UI) to help them find the books in a more straightforward manner. This UI is integrated into the existing library management system. When a library user cannot find a book of interest, he can click a link in the library management system and jump to our UI interface. As shown in Fig.16(d), the UI interface first gives a global map that guides you to the right bookshelf where the wanted book is located at. When the user reaches to the appointed bookshelf, our UI interface further tell you the accurate position of the book, which is shown in Fig.16(e). So far, more than **10,000** users have been served by our shelf scanning system, which avoids a great waste of time and book resources.

VI. Related Work

Existing RFID-based solutions to shelf scanning in libraries generally fall into two ways: handheld RFID readers [2], [3] and smart bookshelves [4], [5]. For the former, librarian needs to move the handheld RFID reader to scan books on the shelves, suffering from long scanning delay and heavy manual labor. For the latter, many RFID readers and antennas are required to deploy on the bookshelves, requiring high-cost infrastructure renewal, which is a great barrier to commercial adoption.

RF-Scanner [6] is the most recent related work that performs the shelf scanning automatically by combining the robot vehicle and UHF RFID technology. The robot is used for replacing librarians and liberating them from intensively manual labor. The UHF RFID readers and antennas are deployed on robot and move with robot to scan the tagged books on the shelves. By using the RF phase, RF-Scanner is able to pinpoint each tagged book and achieve high localizaion accuracy. Many libraries, however, have deployed the HF RFID system rather than UHF RFID system, which makes RF-Scanner unavailable in these cases. The most related works that choose HF RFID technology as vehicle are LibBot [9] and AuRoss [21]. LibBot

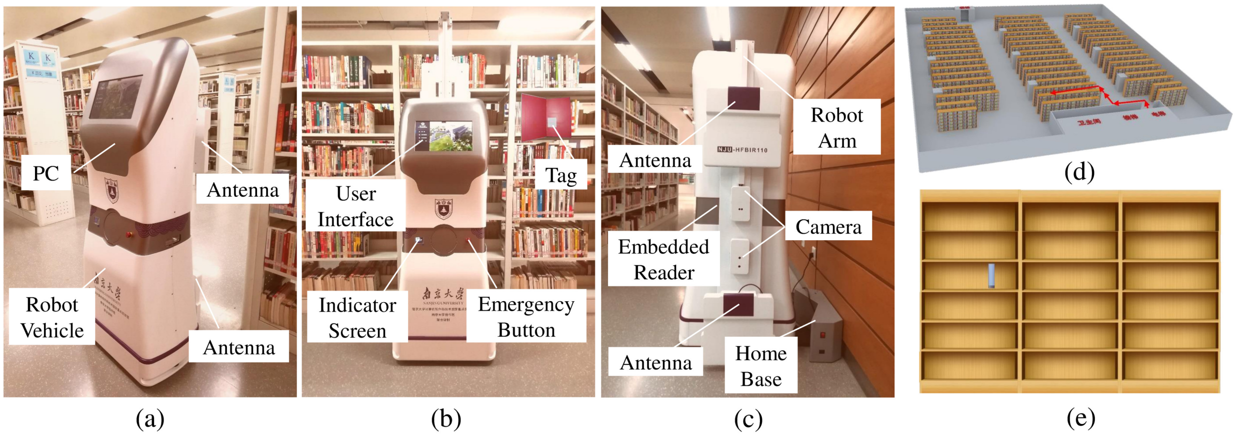


Fig. 16. Our shelf scanning system. (a) Robot vehicle. (b) Front of robot. (c) Back of robot. (d) The global map that guides users. (e) The UI of a bookshelf.

is the first work that presents a mobile robot platform equipped with an HF RFID reader for the purpose of automating the manual shelf reading and finding misplaced books autonomously. However, LibBot cannot achieve the localization of (shelf #, tier #), which is a useful information to help the library users find out the wanted books quickly. Although AuRoSS achieves fully-automated scanning, it focuses on the key robotic technology, i.e., surface tracking which makes RFID antennas move parallel to the shelf with high accuracy. In light of this, We in this paper propose a new HF RFID-based robot system to detect misplaced books effectively and accurately. We formulate the new problems under the new case and give the solutions to them. The real-world experiments show high performance of our system.

VII. Conclusion

In this paper, we present an HF RFID system that performs the shelf scanning automatically by combining robotics, RFID technology, and computer vision. By breaking down the book-localization problem into two stages: the tier-level localization and the cm-level sorting, our system is able to achieve accurate book localization in the case of mobile scanning. We have implemented the shelf scanning system and extensive experiments show that our system can achieve 97% localization accuracy, which is superior to the state-of-the-art. Besides, our system has been deployed in four school libraries for practical use, which has served more than 10,000 users since 2018.

Acknowledgment

This work is supported by the National Natural Science Foundation of China (No.61702257), Natural Science Foundation of Jiangsu Province (BK20170648), National Natural Science Foundation of China (No.61771236), US National Science Foundation CNS-1718708.

References

[1] R. Poll and P. Te Boekhorst, *Measuring quality: Performance measurement in libraries*. Walter de Gruyter, 2007, vol. 127.

[2] A. P. Renold and R. J. Rani, "An internet based RFID library management system," in *Proc. of IEEE ICT*, 2013, pp. 932–936.

[3] T. Kim, J. J. Song, and J. Ri, "Localization of handheld uhf rfid reader using reference tags in 3d environment," pp. 1–4, 2014.

[4] P.-Y. Lau, K. K.-O. Yung, and E. K.-N. Yung, "A low-cost printed cp patch antenna for RFID smart bookshelf in library," *IEEE Transactions on Industrial Electronics*, vol. 57, no. 5, pp. 1583–1589, 2010.

[5] I. Markakis, T. Samaras, A. Polycarpou, and J. Sahalos, "An RFID-enabled library management system using low-sar smart bookshelves," in *Proc. of IEEE ICEAA*, 2013, pp. 227–230.

[6] J. Liu, F. Zhu, Y. Wang, X. Wang, Q. Pan, and L. Chen, "Rf-scanner: Shelf scanning with robot-assisted rfid systems," pp. 1–9, 2017.

[7] L. Ni, Y. Liu, Y. C. Lau, and A. Patil, "LANDMARC: Indoor location sensing using active RFID," in *Proc. of IEEE PerCom*, 2003, pp. 407–415.

[8] 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 *Proc. of ACM MobiCom*, 2014, pp. 237–248.

[9] I. M. Ehrenberg, C. Floerkemeier, and S. E. Sarma, "Inventory management with an rfid-equipped mobile robot," *conference on automation science and engineering*, pp. 1020–1026, 2007.

[10] C. Floerkemeier and M. Lampe, "Issues with rfid usage in ubiquitous computing applications," *international conference on pervasive computing*, pp. 188–193, 2004.

[11] L. Breiman, "Random forests," *Machine learning*, vol. 45, no. 1, pp. 5–32, 2001.

[12] G. J. Klir and B. Yuan, *Fuzzy sets and fuzzy logic: theory and applications*. Prentice Hall PTR New Jersey, 1995, vol. 574.

[13] Z. L. A, "The concept of a linguistic variable and its application to approximate reasoning—ii," *Information Sciences*, vol. 8, no. 8, pp. 301–357, 1975.

[14] A. Barua, L. S. Mudunuri, and O. Kosheleva, "Why trapezoidal and triangular membership functions work so well: Towards a theoretical explanation," *Journal of Uncertain Systems*, vol. 8, 2014.

[15] C.-C. Lee, "Fuzzy logic in control systems: fuzzy logic controller. ii," *IEEE Transactions on systems, man, and cybernetics*, vol. 20, no. 2, pp. 419–435, 1990.

[16] M. M. Gupta and J. Qi, "Design of fuzzy logic controllers based on generalized t -operators," *Fuzzy Sets and Systems*, vol. 40, no. 3, pp. 473–489, 1991.

[17] L. A. Zadeh, "Outline of a new approach to the analysis of complex systems and decision processes," *systems man and cybernetics*, vol. 3, no. 1, pp. 28–44, 1973.

[18] M. M. S. M. S. A. Dr. Sadia Husain, Mr. Yasir Ahmad, "Comparative analysis of defuzzification approaches from an aspect of real life problem," *IOSR Journal of Computer Engineering*, pp. 19–25, 2017.

[19] D. Joho, C. Plagemann, and W. Burgard, "Modeling rfid signal strength and tag detection for localization and mapping," pp. 1213–1218, 2009.

[20] R. Kumar and S. Vassilvitskii, "Generalized distances between rankings," in *Proceedings of the 19th international conference on World wide web*. ACM, 2010, pp. 571–580.

[21] R. Li, Z. Huang, E. Kurniawan, and C. K. Ho, "AuRoSS: an autonomous robotic shelf scanning system," in *Proc. of IEEE/RSJ IROS*, 2015, pp. 6100–6105.