REAL TIME INDOOR TRACKING OF TAGGED OBJECTS WITH A NETWORK OF RFID READERS

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ABSTRACT

We propose a method for accurate real time indoor tracking of tagged objects in Ultra High Frequency (UHF) Radio Frequency Identification (RFID) systems. The method is based on aggregated binary measurements and a model that captures the uncertainty in the number of times that a tag is read while it is in the reading range of an RFID reader. The measurements represent numbers of readings of the tags in short time intervals. The implementation of the method is based on particle filtering and its performance is demonstrated by extensive computer simulations.

***Index Terms*—** Radio Frequency Identification (RFID), real time tracking, particle filtering, binary sensors

1. INTRODUCTION

Radio Frequency Identification (RFID) is a technology for transferring of data from a tag attached to an object with the purpose of its automatic identification and tracking. In this paper the interest is in the use of Ultra High Frequency (UHF) RFID systems for indoor tracking of objects with attached passive tags and based on aggregated binary measurements.

For more than a decade, the RFID technology has seen continuous technical advances combined with decreased cost of equipment and tags, increased reliability in performance, and a stable international standard around UHF passive RFID [1]. An important application of the RFID technology is accurate real time tracking of tagged objects in indoor environments. This remains a very challenging problem due to a number of reasons including missed detections in existing systems. An important class of approaches to localization and tracking of tagged objects is distance-based and relies on measurements that are either received signal strength (RSS), time-of-arrival (TOA), or time-difference-of-arrival (TDOA). The main difficulty of these approaches is the quality of the measurements, which are often distorted due to multipath and other interferences existing in indoor environments [2].

Some recent efforts on real time tracking in indoor environments include [3] and [4]. In [3], the authors use the RFID system to estimate the trajectory of a robot by using passive UHF RFID measurements. There, the tracking is "reader-based" meaning that the RFID tags are placed at fixed, known locations, and the mobile object has a portable reader [2]. In [4], the authors present a UHF RFID location tracking system that exploits the measured phases of the backscattered signals from RFID tags using multiple spatially distributed antennas, and they implement the tracking by extended Kalman filtering.

In our paper, the tracking of the tagged objects is performed by particle filtering [5]. This is a methodology that is applied to nonlinear problems with possibly non-Gaussian noises. The main objective of particle filtering is to track distributions of unknowns, which in our case are the posterior distributions of the locations and velocities of the tagged objects. This is achieved by propagating a set of particles of the possible values of the unknowns and associating with them weights, thereby obtaining random measures that approximate the desired distributions. The nature of the problem of real time tracking of tagged objects in RFID systems allows for the use of as many particle filters as there are tags in the system. This is due to the fact that the source of the signal (backscattered by the tag) is clearly known to the readers. Thus, each tagged object is tracked by a dedicated particle filter, and all the particle filters used in the system operate independently.

In a previous work, we studied the problem of indoor UHF RFID tag tracking with particle filtering [6]. There, the tracked objects were tagged with semi-passive tags, which compared to standard RFID tags had additional functionality. These tags could both sense backscatter communication between commercial passive tags and RFID readers and communicate the sensed information to the reader after they were queried [7]. The advantage of the system in [6] is that with a set of many tags with fixed and known locations, one could gather additional information about the location of the tagged

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objects and use it for improved tracking. In [8], we showed how to use novel semi-passive tags for improved localization of tagged objects, and we introduced a model for the probability of reading a tag that is a function of the distance from the tag to the reader. In this paper, we make this model more realistic by extending it to include variability of the probability of detection of a tag.

The paper is organized as follows. In the next section, we formulate the problem. In Section 3, we propose the solution and describe its implementation. We present simulation results which show the performance of the method in Section 4. In Section 5, we conclude the paper with some final remarks.

2. PROBLEM FORMULATION

Objects with attached RFID tags move in an area covered by a mesh grid of L RFID readers with known locations. The state vector of a tag at time instant t, where $t = 1, 2, \cdots$, is denoted by $x_t \in \mathbb{R}^{4\times 1}$, and $x_t = [x_{1,t}\ x_{2,t}\ \dot{x}_{1,t}\ \dot{x}_{2,t}]^\top$. The first two elements of the vector denote the coordinates of the object at time instant t, and the remaining two elements are the components of the velocities of the object. The tagged object moves according to the model

$$x_t = Ax_{t-1} + Bu_t, \quad (1)$$

where $u_t \in \mathbb{R}^{2\times 1}$ is a noise vector with a known distribution, and $A \in \mathbb{R}^{4\times 4}$ and $B \in \mathbb{R}^{4\times 2}$ are known matrices given by

$$A = \begin{pmatrix} 1 & 0 & T_s & 0 \\ 0 & 1 & 0 & T_s \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \quad \text{and} \quad B = \begin{pmatrix} \frac{T_s^2}{2} & 0 \\ 0 & \frac{T_s^2}{2} \\ T_s & 0 \\ 0 & T_s \end{pmatrix}.$$

RFID readers are located on a mesh grid as displayed by Fig. 1. Each reader has antennas with a field of view of 120°, so that with three sets of antennas, an RFID reader can read tags in a circular area with radius r.

In the time interval between $t-1$ and t, the readers send N queries for reading the tags and in N attempted readings, the readers in the proximity of the tag read it $n_{ij,t} \le N$ times, where $i \in \mathcal{S}_t$ is the index of the reader that has detected the tag during the time interval $(t-1, t)$, $j = 1, 2, 3$ denotes which particular antenna of the three antennas of the reader has detected the tag, and $\mathcal{S}_t$ is the set of readers that have detected the tag at time t.

For each t, the overall system has a set of readings for a particular tag given by $y_t = \{< n_{ij,t}, ij >: i \in \mathcal{S}_t, j \in \{1, 2, 3\}\}$ where ij indicates the ID number of the specific antenna that reads the tag. The objective is to obtain for every t, the posterior distribution of x_t, $p(x_t|y_{1:t})$, where $y_{1:t} \equiv \{y_1, y_2, \cdots, y_t\}$.

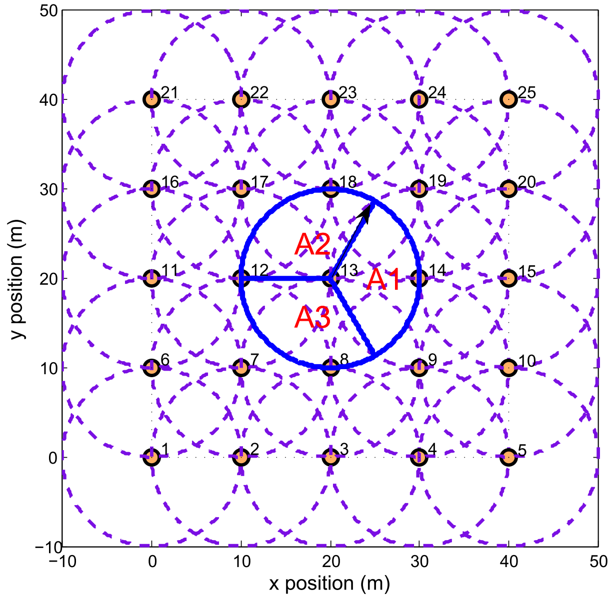

Fig. 1. A network of RFID readers. Each node has tree sets of antennas, each with a field of of view of 120°.

3. PROPOSED METHOD

As already pointed out, each reader sends a number of queries in a fixed time interval, denoted by N, and the tag of the object is read $n \le N$ times (here we drop all the subscripts to simplify the notation). The number n depends on many factors including distance from the antenna, orientation of the tag, and the multipath created by the indoor environment.

For a given distance from the reader, we assume that the probability of the tag being detected by a reader is a random variable, $p(d)$, where d is the distance between the tag and the reader. We model the distribution of $p(d)$ by a Beta distribution with parameters $\alpha(d) > 0$ and $\beta(d) > 0$, i.e.,

$$\pi(p(d)) \propto p(d)^{\alpha(d)-1}(1-p(d))^{\beta(d)-1}. \quad (2)$$

The mean of the probability of detection of a tag at distance d from the reader is assumed to have the form

$$\mathbb{E}(p(d)) = \frac{1}{1+e^{a(d-d_0)}}, \quad (3)$$

where $a > 0$, and $d_0 > 0$ is the distance from the reader at which the probability of detection is equal to 1/2. Since the mean of a Beta random variable is given by $\alpha(d)/(\alpha(d) + \beta(d))$, we must have

$$\frac{\alpha(d)}{\alpha(d)+\beta(d)} = \frac{1}{1+e^{a(d-d_0)}}. \quad (4)$$

In addition, if we assume that the variance of $p(d)$ is $\sigma^2(d)$, we can uniquely obtain the parameters $\alpha(d)$ and $\beta(d)$ of the Beta with mean as in (3) and variance $\sigma^2(d)$.

When the object is at a distance d from the reader, the number of times that it is read by the reader is modeled by a binomial distribution, that is, the probability that the number of reads is n is given by

$$P(n|p(d), d) = \binom{N}{n} p(d)^n (1 - p(d))^{N-n}. \quad (5)$$

Since $p(d)$ is random, we would like to obtain the probability of n by averaging over all random $p(d)$ values using the Beta distribution in (2). It can readily be shown that $P(n|d)$ then follows the Beta-binomial distribution, that is (here we use p to represent $p(d)$ for simplicity),

$$\begin{aligned} P(n|d) &= \int_0^1 P(n|p, d)\pi(p)dp \\ &= \binom{N}{n} \frac{\int_0^1 p^{n+\alpha(d)-1}(1-p)^{N-n+\beta(d)-1}dp}{B(\alpha(d), \beta(d))} \\ &= \binom{N}{n} \frac{B(n+\alpha(d), N-n+\beta(d))}{B(\alpha(d), \beta(d))}. \end{aligned} \quad (6)$$

where $B(\cdot, \cdot)$ is the Beta function.

With this result we are ready to implement a particle filtering (PF) scheme that can track tagged objects based on readings $y_t = \{< n_{ij,t}, ij >: i \in \mathcal{S}_t, j \in \{1, 2, 3\}\}$. Suppose that at time instant $t-1$ we have the random measure $\chi_{t-1} = \{x_{t-1}^{(m)}, w_{t-1}^{(m)}\}_{m=1}^M$, which approximates the posterior of x_{t-1}. Typically, we would perform a resampling of the particles $x_{t-1}^{(m)}$ and obtain M resampled particles denoted by $\bar{x}_{t-1}^{(m)}$. Given these particles, we propagate x_t according to

$$x_t^{(m)} \sim \pi(x_t|\bar{x}_{t-1}^{(m)}), \quad (7)$$

where $\pi(x_t|\bar{x}_{t-1}^{(m)})$ is the proposal distribution of $x_t^{(m)}$. The weights that are assigned to the particles are given by

$$w_t^{(m)} \propto \frac{p(y_t|x_t^{(m)})p(x_t^{(m)}|\bar{x}_{t-1}^{(m)})}{\pi(x_t|\bar{x}_{t-1}^{(m)})}, \quad (8)$$

where

$$p(y_t|x_t^{(m)}) = \prod_{i=1}^{L}\prod_{j=1}^{3}\left[\binom{N}{n_{ij,t}} f(x_t^{(m)}, n_{ij,t})\right]^{I_{ij}(x_t^{(m)})}, \quad (9)$$

where

$$f(x_t^{(m)}, n_{ij,t}) = \frac{B\left(n_{ij,t} + \alpha(x_t^{(m)}), N - n_{ij,t} + \beta(x_t^{(m)})\right)}{B(\alpha(x_t^{(m)}), \beta(x_t^{(m)}))}, \quad (10)$$

and $I_{ij}(x_t^{(m)})$ is an indicator function defined by

$$I_{ij}(x_t^{(m)}) = \begin{cases} 1, & x_{1,t}^{(m)}, x_{2,t}^{(m)} \in \mathcal{R}_{ij} \\ 0, & \text{otherwise}, \end{cases} \quad (11)$$

where $\mathcal{R}_{ij}$ is the area of sensitivity of the jth antenna of the ith reader.

In a standard PF algorithm, once the weights of the particles are computed according to (8), we normalize them and form the random measure for the time instant t, $\chi_t = \{x_t^{(m)}, w_t^{(m)}\}_{m=1}^M$. This random measure is then used to obtain the estimate of x_t, for example, by using the minimum mean square estimate

$$\widehat{x}_t = \sum_{m=1}^{M} w_t^{(m)} x_t^{(m)}. \quad (12)$$

The computation of the estimate of x_{t+1} follows the same steps as that of the estimation of x_t.

During the operation of the standard particle filter, the weights of the particles that are in a good agreement with the observations have increased values and by contrast, the particles, which are unlikely given the observations, have decreased values. When the particles are generated in parts of the space far away from the region compatible with the measurements, their weights will be very small. We propose an approach called *constrained* PF. With this method we first sum the original weights before normalization, and if the sum is below a certain threshold, we keep the particles in the region of interest (obtained from the intersection of the sensing regions of the antennas that detect the target) and remove the ones outside it. The removed particles are replaced with new ones, which are generated uniformly in the region of interest. The weights of the new particles are equal and the sum of them is the same as the sum of the ones that are replaced.

4. NUMERICAL RESULTS

We obtained the parameters of the model in (3) by using an Impinj Speedway Reader, which was connected to a single 6dBIC gain patch antenna, and we experimented with Alien Squiggle RFID tags. Both the reader and the tags are compliant with the ISO 18006C (EPC Gen 2) protocol. The tag was placed in an orientation facing the reader at various distances from the reader's antenna whose power level was set to 23.5dBm. The reader was programmed to send out queries for a period of 30s. We measured the probability of detection as a ratio of the number of times the tag was read over the total number of queries sent during the 30s period.

We modeled the observations of probability of detection with the function in (3) as shown in Fig. 2 and estimated the parameters of the model as $\widehat{a} = 0.8471$ and $\widehat{d_0} = 5.2972$. We fitted the variances of the data with a six-degree polynomial function as shown in Fig. 3 and obtained the coefficients of the polynomial $c_i, i = 0, \cdots, 6$. Note that the variance is clipped to zero when the distance is less than 1m or more than 8m.

In the first experiment, we deployed 5×5 readers with a separation distance of $L = 12$m between them in a large warehouse of size $48\text{m} \times 48\text{m}$. Our objective was to detect

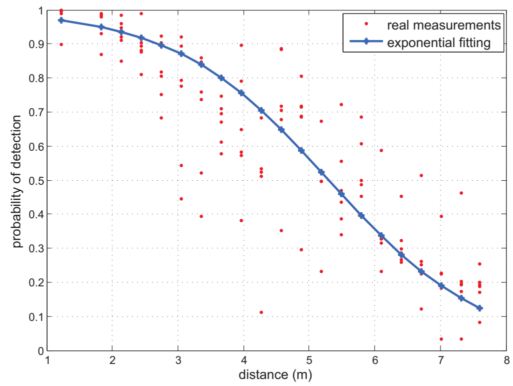

Fig. 2. The measured p(d) and the corresponding mean.

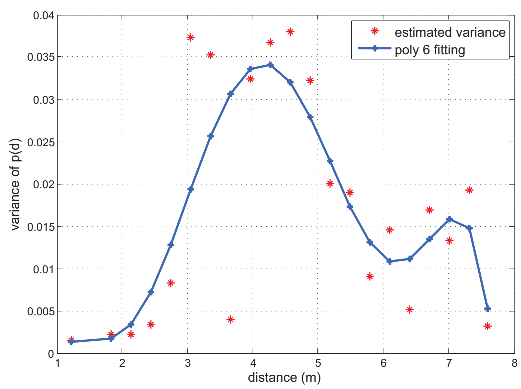

Fig. 3. The estimated variance of p(d) and the corresponding six-degree polynomial fitting.

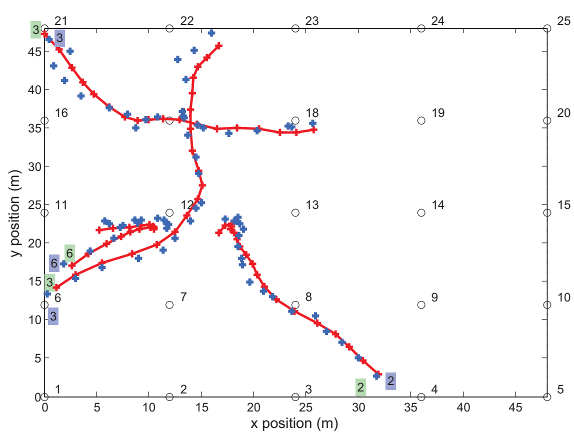

Fig. 4. A tracking example. The red line is the real trajectory and the blue crosses are the tracking results. The green (light grey) boxes indicate the time when a target appeared and the purple (dark grey) ones show the first detection time.

and track the objects with tags (targets) during a period of 20s with a sampling time $T_s = 1$s. The reader range was set to $r = 10$m. Note that there are no false alarms when tracking in RFID systems but missed detections are common.

The targets entered the region at any time. Each reader had three antennas to provide a 360° coverage, each with a 120° field of view. We assumed that the $p(d)$ at a given distance d in the field of view was the same.

Figure 4 shows the deployment of the readers and the trajectories tracked by the considered *constrained* PF algorithm as illustrated in Section 3. The tracking performance of the algorithm is shown in Fig. 5.

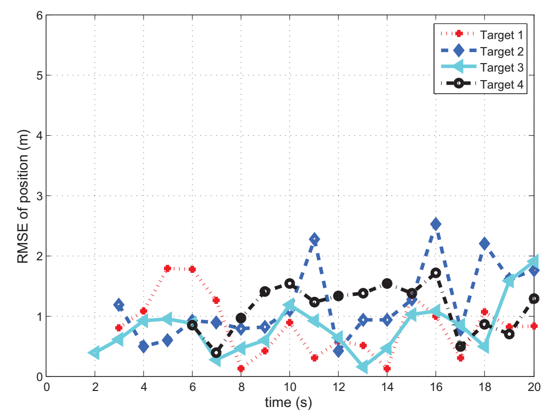

Fig. 5. The RMSE of position with constrained PF.

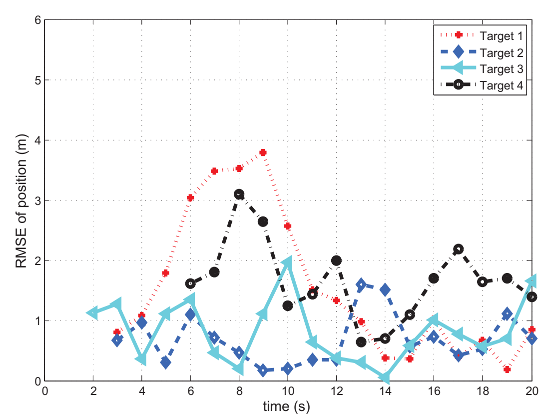

Fig. 6. The RMSE of position with standard PF.

Figure 6 displays the tracking performance with standard PF. The four curves with different colors represent the RMSEs of the four targets, respectively. We can tell which curve corresponds to which target from the stating times of the tracks. There are no missed detections in both cases. Obviously, we obtain better performance with constrained PF which, when necessary, replaces the far away particles with better ones.

In each of the next two experiments we generated 50 independent realizations. In the first experiment, we compared the tracking performance with different separation distances

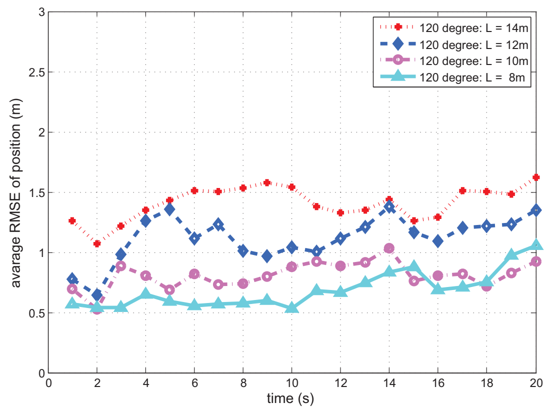

Fig. 7. The average RMSE of position with different separation distances.

L. Here $L < 10\sqrt{2}$m to provide for the full coverage. The performance is shown in Fig. 7. One can tell that the closer two readers are, the more accurate tracking results with $L \in (8, 14)$m. However, more readers will be needed to provide full coverage of the whole region with smaller L.

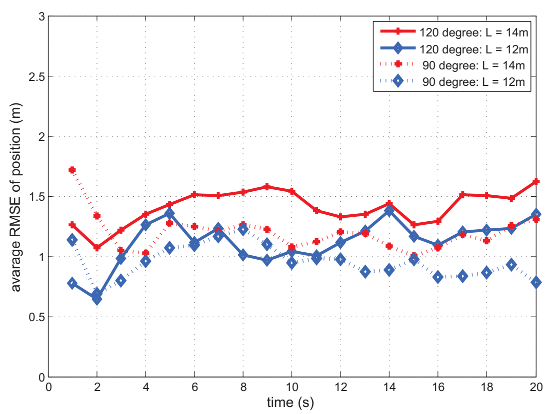

Fig. 8. Tracking performances with different ranges of the readers' field of view.

In the second of the two experiments, we studied the tracking performance with readers' field of views of 120° and 90°. We see from Fig. 8 that with the smaller field of view the PF had better tracking performance, provided that the full coverage was satisfied. This requires more antennas, and therefore is a more expensive solution.

5. CONCLUSIONS

In this paper we presented a method for tracking tagged objects in a Ultra High Frequency (UHF) Radio Frequency Identification (RFID) system. The tracking is based on aggregated binary measurements, and it is implemented by particle filtering. The aggregated measurements were modeled as random outcomes of Beta-binomial distributions. The parameters needed for the implementation of the method were obtained from real-world experiments. The performance of the method was analyzed by extensive simulations for antennas with fields of view of 120° and 90°, respectively. The tracking mean square error with antennas with field of view of 90° had a better performance.

6. ACKNOWLEDGEMENTS

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