TRACKING WITH RFID ASYNCHRONOUS MEASUREMENTS BY PARTICLE FILTERING

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ABSTRACT

This paper deals with the problem of real-time indoor tracking of tagged objects in Ultra High Frequency Radio Frequency Identification systems with asynchronous measurements. A new and more realistic model of the system is proposed, where the probability of detecting a tag by a reader is described by a function of both the distance and the angle between the tag and the reader's antenna. The model also accounts for the possibility of a tag being in a dead-zone where the tag cannot be detected. For tracking, we propose the use of the particle filtering methodology that takes into account the asynchronous nature of the measurements. The parameters for modeling the resulting system are obtained from real-world experiments and the performance of the algorithm is shown by extensive computer simulations.

Index Terms— Radio Frequency Identification (RFID), real time tracking, particle filtering, asynchronous measurements

1. INTRODUCTION

Ultra High Frequency (UHF) Radio Frequency Identification (RFID) is a rapidly growing technology that uses radio frequency electromagnetic fields and backscattering to transfer data from RFID tags [1]. In this paper, we investigate a RFID system for real-time indoor tracking of objects with attached passive tags, where the measurements are asynchronous. The problem is especially challenging due to multipath and other interferences present in indoor environments [2, 3].

Existing approaches to RFID localization and tracking vary depending on the type of sensor information used, the modeling of this information and the implemented inference method [4]. Research has shown that observation models based on received signal strength information alone are less accurate than models based on tag detection, which is primarily due to the unknown forms of superpositions of RF signals in indoor environments [5]. In [6, 7], a model based on aggregated binary measurements was studied, where the probability of reading a tag was represented as a function of the distance from the tag to the reader. The model was later extended to include the variability of this probability [8]. In this paper, a more realistic model is proposed by adding the angle from the tag to the reader into this probability and by integrating into the model the probability of a tag being in a dead-zone.

Tag responses are received by the reader following a standard protocol. A reader makes a fixed number of queries whose overall duration can vary depending on the number of tags in its proximity, the forward link symbol timing parameters, the backscatter link frequency, and the backscatter encoding scheme [9]. This entails that the overall observation model has to capture the inherent asynchronism of the measurements. We propose a tracking algorithm based on particle filtering (PF) [10, 11] that accounts for the asynchronism. Some work dealing with asynchronous measurements in traditional sensor networks can be found in [12, 13, 14]. However, to the best of our knowledge, there is no previous work on target tracking with RFID networks addressing the problem of asynchronism.

2. PROBLEM FORMULATION

Objects with attached RFID tags move in an area covered by a mesh grid of L readers whose antenna locations are known. The antennas are deployed as shown in Fig. 1 so that they provide full coverage. The readers are located in the middle of each cell of the grid and are connected to three or four antennas. We consider the situation where the readers receive the measurements in an asynchronous way.

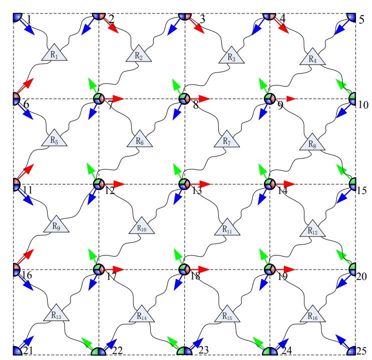

Fig. 1. Readers (triangles) are in the middle of the cells, and the antennas (sectors) are at the nodes of the grid. Curved lines denote wires connecting antennas and readers, and arrows indicate orientation of antennas.

The state of the system consists of a vector containing the information about a particular tag[1] in the area of coverage at time instant t, and it is denoted by $x_t \in \mathbb{R}^{4\times 1}$, where $x_t = [x_{1,t}\ x_{2,t}\ \dot{x}_{1,t}\ \dot{x}_{2,t}]^\top$. The first two elements of the vector represent the location of the tag in the two-dimensional Cartesian coordinate system, and the other two elements are the components of the velocity. The tagged object moves according to the model

$$x_{t_2} = A(t_1, t_2)x_{t_1} + B(t_1, t_2)v_{t_2}, \quad (1)$$

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[1] Since the localization of different tags is statistically independent due to the nature of the RFID system, we address the tracking of one particular tag.

where x_{t_i} is the state of the system at time t_i, and $v_{t_i} \in \mathbb{R}^{2\times 1}$ is a noise vector with known distribution. Let $\tau \triangleq (t_2 - t_1)$ be the time period from t_1 to t_2, and $A(t_1, t_2) \in \mathbb{R}^{4\times 4}$ and $B(t_1, t_2) \in \mathbb{R}^{4\times 2}$ be the known transition and covariance matrices, respectively, given by

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

During the time interval between two time instants, $(k-1)T_s$ and kT_s, where T_s is the intended sampling interval and $k = 1, \cdots, T$, each RFID reader sends N queries with the purpose of detecting the tags in its area of coverage. Each observation represents the number of detections out of N trials by a particular reader. In previous works, it is assumed that all the observations are obtained by the readers synchronously at the sampling instants as shown in Fig. 2 (top). These approaches ignore the time differences of each reader in receiving the measurements.

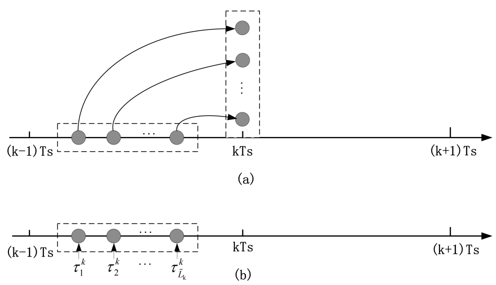


Fig. 2. Synchronous vs. asynchronous measurements.

In treating the asynchronism present in practical systems, we denote the duration of a complete round of queries and tag responses for a particular reader as τ_i^k, where i is the index of the reader within the set of readers $\mathcal{S}_{kT_s}$ that have detected the tag during the time interval $((k-1)T_s, kT_s]$. We note that the number of readers during that time interval is represented by L_k, which is the size of $\mathcal{S}_{kT_s}$. The number of received responses by reader i with its antenna j is denoted by $n_{ij,\tau_i^k} \leq N$, and $j \in \{1, 2, 3, 4\}$. For ease of explanation, we will use $i_l^*, l = 1, \cdots, L_k$ as an index indicating the ordered sequence of readers, and therefore, the number of detections will be represented by $n_{i_l^* j, \tau_{i_l^*}^k}$. Our approach accounts for asynchronous measurements where the instant $\tau_{i_l^*}^k$ is the instant at which the i_l^*th reader finalized its query/detection round, which is assumed to be known (Fig. 2 (bottom).)

The readings collected for a particular tag until time instant kT_s are gathered in the observation set $y_{1:kT_s} = \{y_{T_s}, y_{2T_s}, \cdots, y_{kT_s}\}$ where $y_{kT_s} = \{y_{i_1^*, \tau_{i_1^*}^k}, y_{i_2^*, \tau_{i_2^*}^k}, \cdots, y_{i_{L_k}^*, \tau_{i_{L_k}^*}^k}\}$ and $y_{i_l^*, \tau_{i_l^*}^k} = \{n_{i_l^* j, \tau_{i_l^*}^k} : j \in \{1, 2, 3, 4\}, i_l^* \in \{1, 2, \cdots, L_k\}\}$. The objective is to track x_t in time given $y_{1:kT_s}$. The newly proposed observation model for y_{kT_s} is discussed in the next section.

3. THE OBSERVATION MODEL

The observation model constitutes one of the major challenges when tracking with RFID systems especially in indoor environments, since the number of detections that a reader has depends on numerous factors including the distance from the antenna, the orientation of the antenna, and the multipath interference [2].

In our previous work, the probability of reading a tag was modeled as a function of the distance from the tag to the reader [8]. In this paper, a new and more realistic model of the system is proposed, where the probability of detecting a tag by a reader is described by a function of both the distance and the angle between the tag and the reader antenna.

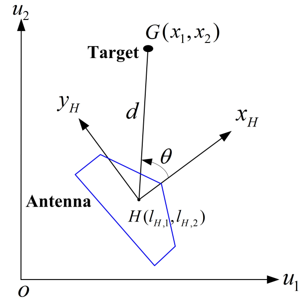


Fig. 3. Distance and angle between an antenna and a tag.

Figure 3 shows the distance, d, and the angle, θ, between a tag and an antenna located at points G and H in the global reference coordinate system $u_1 O u_2$, respectively [15]. The angle, θ, is the relative orientation between the antenna and the tag within a range of $(-\pi, \pi]$ rads, whereas d is the distance between G and H. Here the location of the antenna is assumed to be known as $(l_{H,1}, l_{H,2})$ and therefore d and θ can be readily obtained from the target state as $d = \sqrt{(x_1 - l_{H,1})^2 + (x_2 - l_{H,2})^2}$ and $\theta = \arctan((x_2 - l_{H,1})/(x_1 - l_{H,2}))$.

For a given distance d and angle θ between the tag and the antenna (here we omit the subscript t for simplicity), the probability of the tag being detected by the associated reader is a random variable, $p(d, \theta)$, following a Beta distribution $Beta(\alpha(d, \theta), \beta(d, \theta))$ with parameters $\alpha(d, \theta) > 0$ and $\beta(d, \theta) > 0$, i.e.,

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

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

$$\mathbb{E}(p(d, \theta)) \quad = \quad \frac{1}{1 + e^{(a_1 + a_2 d + a_3 |\theta|)}}, \quad (3)$$

where a_1, a_2 and a_3 is a set of model parameters that has to be estimated, and the variance follows the expression

$$\sigma^2(d, \theta) \quad = \quad c_1 + c_2 d + c_3 d^2 + c_4 |\theta| + c_5 \theta^2, \quad (4)$$

where $c_i, i = 1, \cdots, 5$ is another set of model parameters.

The mean and the variance of a Beta random variable can be obtained as functions of $\alpha(d, \theta)$ and $\beta(d, \theta)$ [16]. On the other hand, the parameters $\alpha(d, \theta)$ and $\beta(d, \theta)$ of the Beta distribution can be uniquely determined for each pair of d and θ with given mean and variance, where the mean and variance can be obtained from the experimental data.

The previous model can be further extended by adding the representation of the probability of a tag being in a dead-zone, which is defined as the probability that a tag is not detectable by an antenna even if the tag is in its field of view. Therefore, tags which are in a dead-zone will not be detected [17]. We denote the probability for a tag to be in a dead-zone as λ with $\lambda \sim Beta(\alpha_\lambda, \beta_\lambda)$. Then, the probability of detection becomes $(1 - \lambda)p(d, \theta)$.

When the object is at a distance d and an angle θ from the reader in a non dead-zone, 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 out of N trials is given by

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

Since $p(d,\theta)$ is random, the probability of the number of readings n should be obtained by averaging over all random $p(d,\theta)$ values using the Beta distribution in (2). The number of readings n is 0 in a dead-zone. It can be shown that $P(n|d,\theta)$ then follows

$$P(n|d,\theta,\lambda) = \int_0^1 P(n|p,d,\theta)(1-\lambda)\pi(p,\theta)dp + \lambda\delta(n)$$
$$= (1-\lambda)\binom{N}{n}\frac{B(n+\alpha(d,\theta), N-n+\beta(d,\theta))}{B(\alpha(d,\theta),\beta(d,\theta))} + \lambda\delta(n), \quad (6)$$

where p represents $p(d,\theta)$ for simplicity, $B(\cdot,\cdot)$ is the Beta function, and $\delta(\cdot)$ denotes the Dirac delta function. We then average over all λ and obtain

$$P(n|d,\theta) = \frac{\beta_\lambda}{\alpha_\lambda+\beta_\lambda}\binom{N}{n}\frac{B(n+\alpha(d,\theta), N-n+\beta(d,\theta))}{B(\alpha(d,\theta),\beta(d,\theta))} + \frac{\alpha_\lambda}{\alpha_\lambda+\beta_\lambda}\delta(n). \quad (7)$$

4. PROPOSED METHOD

The nonlinear nature of the observation model introduced in the previous section motivates the use of the PF methodology [18]. Suppose that at time instant t_1, a random measure of size M, $\chi_{t_1} = \{x_{t_1}^{(m)}, w_{t_1}^{(m)}\}_{m=1}^M$, is available, where $x_{t_1}^{(m)}$s are the particles of the measure, and $w_{t_1}^{(m)}$s denote the corresponding weights. Upon reception of a new observation, the particles are propagated according to

$$x_{t_2}^{(m)} \sim \pi(x_{t_2}|\bar{x}_{t_1}^{(m)}), \quad (8)$$

where $\pi(x_{t_2}|\bar{x}_{t_1}^{(m)})$ is the instrumental distribution used for generation of new particles, $x_{t_2}^{(m)}$ and $t_2 > t_1$. We note that $\bar{x}_{t_1}^{(m)}$ are the particles that came from the resampling step in the previous time instant. The weights assigned to the particles are calculated as

$$w_{t_2}^{(m)} \propto \frac{p(y_{t_2}|x_{t_2}^{(m)})p(x_{t_2}^{(m)}|\bar{x}_{t_1}^{(m)})}{\pi(x_{t_2}^{(m)}|\bar{x}_{t_1}^{(m)})}, \quad (9)$$

where the calculation of likelihood function $p(y_{t_2}|x_{t_2}^{(m)})$ will reflect the difference between the method based on the synchronism assumption in previous works and our new asynchronous scheme.

In a standard PF algorithm, once the weights of the particles are computed according to (9), they are normalized and a new random measure is formed, $\chi_t = \{x_{t_2}^{(m)}, w_{t_2}^{(m)}\}_{m=1}^M$. This random measure is then used to obtain the estimate of x_{t_2}, for example, by using the minimum mean square error estimate

$$\widehat{x}_{t_2} = \sum_{m=1}^M w_{t_2}^{(m)} x_{t_2}^{(m)}. \quad (10)$$

A final resampling step is typically performed to avoid degeneracy of the random measure.

For the "false synchronous" case, i.e., when all the measurements are wrongly assumed to arrive at kT_s, the likelihood function is calculated as

$$p(y_{kT_s}|x_{kT_s}^{(m)}) = \prod_{i=1}^{\tilde{L}_k}\prod_{j=1}^{J}\Big\{\frac{\beta_\lambda}{\alpha_\lambda+\beta_\lambda}\binom{N}{n_{ij,\tau_i^k}} f\big(x_{kT_s}^{(m)}, n_{ij,\tau_i^k}\big) + \frac{\alpha_\lambda}{\alpha_\lambda+\beta_\lambda}\delta(n_{ij,\tau_i^k})\Big\}, \quad (11)$$

where $J \in \{3,4\}$ represents the number of antennas a reader is associated to, and

$$f(x_{kT_s}^{(m)}, n_{ij,\tau_i^k}) = \frac{B\left(n_{ij,\tau_i^k} + \alpha(x_{kT_s}^{(m)}), N - n_{ij,\tau_i^k} + \beta(x_{kT_s}^{(m)})\right)}{B(\alpha(x_{kT_s}^{(m)}), \beta(x_{kT_s}^{(m)}))}. \quad (12)$$

where the $x_{kT_s}^{(m)}$ in the argument of $\alpha(\cdot)$ and $\beta(\cdot)$ can be readily converted into notation of the form $d_{kT_s}^{(m)}$ and $\theta_{kT_s}^{(m)}$ in polar coordinates with known antenna locations.

In our approach, we propagate and update the particles every time we receive a measurement. The likelihood function follows the expression

$$p(y_{\tau_{i_l^*}^k}|x_{\tau_{i_l^*}^k}^{(m)}) = \prod_{j=1}^{J}\Big\{\frac{\beta_\lambda}{\alpha_\lambda+\beta_\lambda}\binom{N}{n_{ij,\tau_{i_l^*}^k}} f\big(x_{\tau_{i_l^*}^k}^{(m)}, n_{i_l^* j,\tau_{i_l^*}^k}\big) + \frac{\alpha_\lambda}{\alpha_\lambda+\beta_\lambda}\delta(n_{ij,\tau_{i_l^*}^k})\Big\}, \quad (13)$$

and the particles are propagated according to

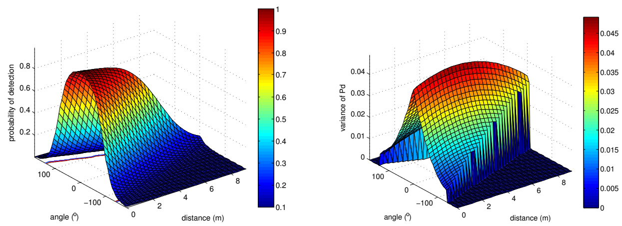
$$x_{\tau_{i_{l+1}^*}^k}^{(m)} \sim \pi(x_{\tau_{i_{l+1}^*}^k}|\bar{x}_{\tau_{i_l^*}^k}^{(m)}). \quad (14)$$

5. NUMERICAL RESULTS

We considered an RFID system composed of a grid of 4×4 readers in a warehouse of size 40 m $\times$ 40 m. We experimented with Impinj Speedway readers connected to 6 dBIC gain patch antennas, and with Alien Squiggle RFID tags [8]. Both the readers and the tags are compliant with the ISO 180006-C protocol [9]. A tag was placed in an orientation facing the reader at various distances from the reader's antennas (three or four) whose power level was set to 23.5 dBm. The reader was programmed to send out queries for a period of 30 s. We measured the probability of detection as a ratio between the number of times the tag was read and the total number of queries sent during the 30 s period. We also changed the orientation of the reader's antenna to obtain the probability of detection for different sets of (d,θ).

For each antenna, the mean of the probability of detection was modeled using (3) and it is shown in Fig. 4 (a). The parameters of the model were estimated as $\hat{a}_1 = -4.9433$, $\hat{a}_2 = 0.8370$ and $\hat{a}_3 = 0.0552$. We fitted the variances of the data with function (4) and obtained the parameters c_i. The result is shown in Fig. 4 (b). Note that the variance is clipped to zero when the distance is greater than 10 m. The experiments showed that the proposed model achieved higher modeling accuracy than the old model considered in [8].

The readers sent out queries every $T_s = 1$ s and the query period for each reader was generated using a $\mathcal{U}(0.2, 0.8)$, with



(a) (b)

Fig. 4. Fitting of the mean and the variance of the probability of detection $p(d,\ \theta)$

the values being obtained from evaluation of the ISO 180006-C protocol and the experimental setup. Note that there are no false alarms when tracking in RFID systems but missed detections are common. In all the experiments, the PF algorithm used $M = 200$ particles. The tracking performance was evaluated using the average root mean square error (RMSE) of the position of the target as a function of time over 50 independent realizations. It was calculated as $\sqrt{(\hat{x}_{1,t} - x_{1,t})^2 + (\hat{x}_{2,t} - x_{2,t})^2}$. The probability of being in a dead-zone $\lambda \sim Beta(\alpha_\lambda, \beta_\lambda)$ with $\alpha_\lambda = 0.9$ and $\beta_\lambda = 17.1$, which corresponded to a mean of the dead-zone probability of 0.05 and a variance of 0.0025.

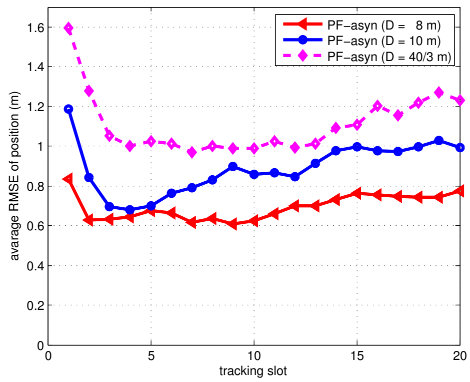


Fig. 5. Tracking performance with different separation distances.

In the first experiment, we compared the tracking performance for different grid resolutions when using the proposed method. The deployment of the antennas followed Fig.1 and the result is shown in Fig. 5. Note that the time axis in the Figure is in units of tracking slots, where in one tracking slot each reader completes a block of N rounds of queries. We can see that the performance with smaller separation distance among readers, D, achieved more accurate tracking results. However, smaller separation distance requires more readers and antennas, and thus the system is more expensive.

In the second experiment, we compared the performance of different tracking methods for two different cases for the deployment of antennas: (a) following Fig. 1; and (b) with four antennas connected to each reader. For the latter case, we needed more antennas. The separation distance was set to 10 m for both cases. We compared three methods: `PF-asyn` is the proposed PF method accounting for the asynchronous measurements, `PF-syn` is the PF method with wrongly assumed synchronism, and `CE-asyn` is a "centroid" method where the estimated position of the target is calculated as the central point of the positions of the detecting readers. The results are shown in Fig. 6. We can see that the new proposed algorithm outperforms the other two methods. Also,

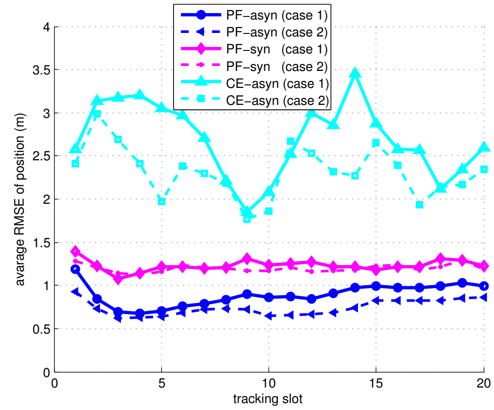


Fig. 6. Tracking performances with different algorithms and with different number of antennas. In case 1, the deployment of the antennas follows Fig. 1 and in case 2 there are four antennas connected to each reader.

as expected, the performance with more antennas was better. In practical implementations, one should use more antennas to achieve a better tracking performance.

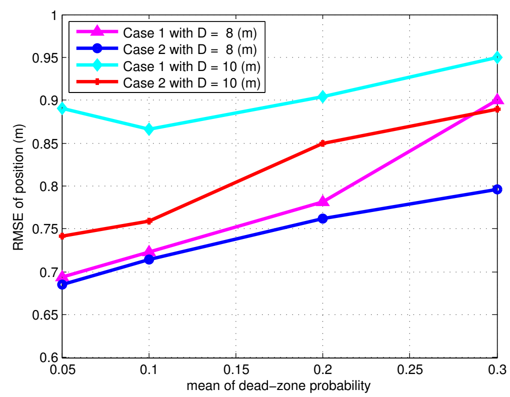


Fig. 7. Tracking performances with different mean of probability of dead-zone.

Finally, we simulated a scenario with different dead-zone probabilities. We set the variance of the dead-zone probability to 0.01 and changed the value of the mean. As seen in Fig. 7, and as expected, the performance worsened as the probability of dead-zone increased. Note that the RMSE in the figure was obtained by averaging the RMSEs over time.

6. CONCLUSIONS

In this paper the problem of tracking tagged objects using asynchronous measurements in a UHF Radio Frequency Identification (RFID) system is addressed. The proposed method is based on the Bayesian methodology and in particular on particle filtering. A more realistic parametric model for the probability of detection was introduced, where the model is a function of both the distance and the angle from the tag to the reader. This model also includes the variability of the probability of detection of a tag and the probability of a tag being in a dead-zone. The parameters needed for the implementation of the method were obtained from real-world experiments and the performance of the proposed method was analyzed by extensive simulations.

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