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TRACKING WITH ASYNCHRONOUS BINARY READINGS AND LAYOUT INFORMATION IN RFID SYSTEMS WITH SENSE-A-TAGS

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ABSTRACT

This paper addresses the problem of real-time indoor tracking of tagged objects in Ultra High Frequency Radio Frequency IDentification (RFID) systems with layout information and asynchronous readings. The method is based on binary detections and the model for the probability of detection is a function of both distance and angle between a tag and a reader and accounts for the possibility of a tag being in a dead-zone. A newly developed RFID component, called sense-a-tag, is used to improve the tracking performance, especially in areas with intersections and at portals, where the estimation of the direction of movement is important. A multi-hypothesis particle filtering method is applied for the tracking and its performance is demonstrated by computer simulations.

Index Terms— Radio Frequency IDentification (RFID), indoor tracking, particle filtering, asynchronous measurements

1. INTRODUCTION

Ultra High Frequency (UHF) Radio Frequency IDentification (RFID) is a rapidly growing technology for real-time identification and tracking that can be applied in many settings including inventory management, health care systems and the Internet of Things [1]. In this paper, we investigate the problem of real-time tracking of tagged objects in warehouse-like environments with layout information (intersections, shelves and walls). The objective is to track tagged objects moving between shelves and to estimate the direction of movement, which is especially important at intersections and portals for improved accuracy in inventory.

In our previous work [2, 3], we studied the problem of indoor UHF RFID tag tracking based on aggregated binary readings. The reader reports binary information indicating the detection of a tag and uses aggregated number of detections over a fixed number of queries. In this paper, binary detections are used for real-time tracking, where tracking is updated as soon as a detection occurs and the model is from [3]. According to that model, the probability of detection is a function of both the distance and angle from the tag to the reader, and accounts for the possibility of a tag being in a dead-zone.

Tag responses are received by the readers asynchronously. We propose the use of the particle filtering (PF) methodology [4] that takes into account the asynchronous nature of the readings. A study dealing with asynchronous readings in traditional sensor networks can be found in [5]. In the proposed approach, we also integrate available layout information, which improves the performance of the PF.

In this paper we study the use of a newly developed low-cost device called sense-a-tag (ST) [6, 7]. An ST has the same functionality as a regular tag but can also detect communication between the reader and tags in its proximity. The ST can communicate this information to the reader by backscattering. With the information received from the STs, the system can improve the accuracy of localization and can unambiguously estimate the direction of movement of a tagged object [8]. The tracking of the direction of movement of a person or object close to some monitoring area is important in a number of applications. For example, it is critical to determine if tagged goods are moving into or out of a warehouse. Methods for estimation of the direction of movement in RFID systems can be found in [9], where two antennas are used and the direction of movement is estimated by measuring the times of detection of a tagged object from the signals of the antennas. An RFID system with STs and using PF for tracking purposes was introduced in [10]. The tracking problem was investigated in a very small area with one single reader. In this paper, we extend the work from [10]. The main contribution is in a novel algorithm that operates with asynchronous readings and exploits the presence of STs in the RFID system.

2. PROBLEM FORMULATION

Consider the problem of tracking tagged objects (e.g., a warehouse worker or a forklift) that move in a warehouse. A possible deployment of a traditional reader-only system is shown in Fig. 1. Each reader R_i is connected with three

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antennas denoted by the right (red), the upper left (green), and the lower left (blue) sectors. The arrows indicate the orientation of the antennas. We assume that the layout information is known and includes intersections V_i, invalid regions, shelves and walls.

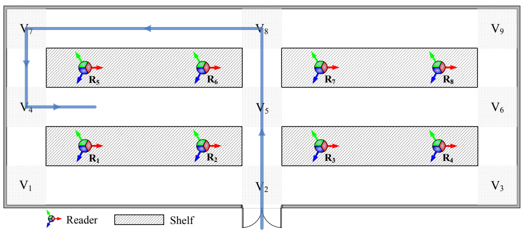


Fig. 1. The RFID system in the considered warehouse layout.

A tagged object moves along the path between two shelves, or the path between a shelf and a wall. The object can go straight or make turns at intersections. For example at a T-shaped intersection the object might turn left or right. The tracking algorithm will account for these directions of movement.

2.1. The motion model

The state of the system consists of a vector containing information about a particular tag at time instant t and is denoted by $\boldsymbol{x}_t \in \mathbb{R}^{4\times1}$, where $\boldsymbol{x}_t = [x_{1,t}\ x_{2,t}\ \dot{x}_{1,t}\ \dot{x}_{2,t}]^\top$ and $t \in \mathbb{R}^+$. The first two elements of the vector are the location of the tag in the two-dimensional Cartesian coordinate system, and the other two elements are the components of the velocity. When we focus on tracking the direction of movement of the tag, we reformulate the problem in one dimension. The tagged object moves from t_1 to t_2 according to the model

$$\boldsymbol{x}_{t_2} = \boldsymbol{A}_i(t_1,t_2)\boldsymbol{x}_{t_1} + \boldsymbol{B}_i(t_1,t_2)\boldsymbol{u}_{t_2,i}, \qquad (1)$$

where $i = 1, 2$ denotes the ith motion mode depending if the tag moves horizontally or vertically, respectively, $\boldsymbol{x}_{t_2}$ is the state of the system at time instant t_2, $\boldsymbol{u}_{t,i} \in \mathbb{R}^{2\times1}$ is a noise vector with a known distribution, and $\boldsymbol{A}_i \in \mathbb{R}^{4\times4}$ and $\boldsymbol{B}_i \in \mathbb{R}^{4\times2}$ are known matrices, respectively, given by

$$\boldsymbol{A}_1 = \begin{pmatrix} 1 & 0 & (t_2-t_1) & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}, \boldsymbol{B}_1 = \begin{pmatrix} \frac{(t_2-t_1)^2}{2} & 0 \\ 0 & 0 \\ (t_2-t_1) & 0 \\ 0 & 0 \end{pmatrix},$$

$$\boldsymbol{A}_2 = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & (t_2-t_1) \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}, \boldsymbol{B}_2 = \begin{pmatrix} 0 & 0 \\ 0 & \frac{(t_2-t_1)^2}{2} \\ 0 & 0 \\ 0 & (t_2-t_1) \end{pmatrix}.$$

2.2. The asynchronous readings

In real RFID systems, all readers start their queries at different time instants. Once a reader receives the response from a tag, it reports the detection to the data processing center. A new query is then started immediately. In the existing literature, the asynchronism of the readers is ignored and the general assumption is that all the observations are obtained synchronously at prefixed sampling instants [2, 10, 11].

Figure 2 describes the asynchronous nature of the readings of a tag of interest. Each reading represents the detection of the tag from one reader.

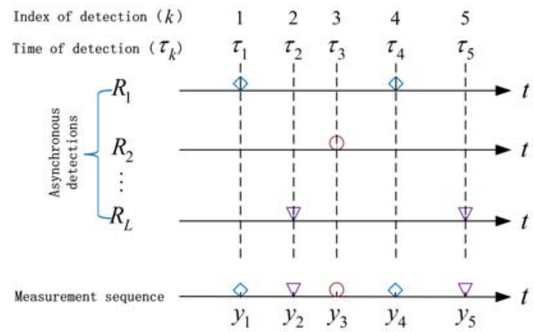


Fig. 2. Asynchronous readings (detections) in a real RFID system of a particular tag.

We denote the kth detection by $y_k = \{i_k, j_k, \tau_k\}$, where $i_k \in \{1, 2, \cdots, L\}$ is the index of the reader that detected the tag, $j_k \in \{1, 2, 3\}$ is the index of the antenna used in the detection, and $\tau_k \in \mathbb{R}^+$ is the time of the detection. We note that $\tau_1 \le \tau_2 \le \tau_3 \le \cdots$. All the readings up to time instant τ_k are collected in the observation set $\mathcal{Y}_k = \{y_1, y_2, \cdots, y_k\}$. The objective is to track $\boldsymbol{x}_t$ in time given the observations and the assumed model.

2.3. The observation model

The observation model constitutes a challenge when tracking with RFID systems especially in indoor environments, since the query and response processes depend on numerous factors including the distance from the antenna, the orientation of the antenna, and the multipath interference [11].

The probability of detecting a tag by a reader, $p(d,\theta)$, is modeled as a random variable following a Beta distribution [2, 3], which is described by a function of both the distance d and the angle θ between the tag and the reader antenna, $Beta(\alpha(d,\theta), \beta(d,\theta))$, with parameters $\alpha(d,\theta) > 0$ and $\beta(d,\theta) > 0$. The model also accounts for the possibility of a tag being in a dead-zone where the tag will not be detected even within the detecting range. We denote that probability as λ with $\lambda \sim Beta(\alpha_\lambda, \beta_\lambda)$. The observation model is given by [3]

$$
\begin{aligned}
P(n=1|d,\theta) &= \frac{\beta_\lambda}{\alpha_\lambda+\beta_\lambda}\frac{\alpha(d,\theta)}{\alpha(d,\theta)+\beta(d,\theta)} \qquad (2)\\
P(n=0|d,\theta) &= \frac{\beta_\lambda}{\alpha_\lambda+\beta_\lambda}\frac{\beta(d,\theta)}{\alpha(d,\theta)+\beta(d,\theta)}+\frac{\alpha_\lambda}{\alpha_\lambda+\beta_\lambda}.
\end{aligned}
$$

where $n=1$ and $n=0$ indicates whether a reader detected the tag or not, respectively.

The mean of the probability of tag detection is given by $\mathbb{E}(p(d,\theta)) = \alpha(d,\theta)/(\alpha(d,\theta)+\beta(d,\theta))$ [12]. Furthermore, we assume that this mean is of the form [3]

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

where a_1, a_2 and a_3 are model parameters that are estimated from experimental data. Therefore, we express the probability of detection as a function of distance and angle as

$$
P(n=1|d,\theta) = \frac{\beta_\lambda}{\alpha_\lambda+\beta_\lambda}\frac{1}{1+e^{(a_1+a_2 d+a_3|\theta|)}}. \qquad (4)
$$

3. PROPOSED METHOD

3.1. The particle filtering

The nonlinear nature of the observation model motivates the use of the PF methodology for approximation of the posterior distribution of the system state given the observations [13]. PF approximates the posterior density by using random measures composed of particles and weights associated to the particles [13]. In the considered real-time tracking problem, PF propagates and updates the particles and weights every time we receive a reading.

Suppose that at time instant τ_{k-1}, a random measure of size M, $\chi_{\tau_{k-1}} = \{\boldsymbol{x}_{\tau_{k-1}}^{(m)},\ w_{\tau_{k-1}}^{(m)}\}_{m=1}^{M}$, is available, where $\boldsymbol{x}_{\tau_{k-1}}^{(m)}$ are the particles of the measure, and $w_{\tau_{k-1}}^{(m)}$ denote the corresponding weights. Upon reception of the next observation at τ_k, the particles are propagated according to

$$
\boldsymbol{x}_{\tau_k}^{(m)} \sim \pi(\boldsymbol{x}_{\tau_k}|\boldsymbol{x}_{\tau_{k-1}}^{(m)},\ \mathcal{Y}_k), \qquad (5)
$$

where $\pi(\boldsymbol{x}_{\tau_k}|\boldsymbol{x}_{\tau_{k-1}}^{(m)},\ \mathcal{Y}_k)$ is the proposal distribution used for generation of new particles, $\boldsymbol{x}_{\tau_k}^{(m)}$, and $\mathcal{Y}_k$ is the set of all readings up to τ_k. The general expression for computing the weights of the particles is given by

$$
w_{\tau_k}^{(m)} \propto w_{\tau_{k-1}}^{(m)} \frac{p(y_k|\boldsymbol{x}_{\tau_k}^{(m)})p(\boldsymbol{x}_{\tau_k}^{(m)}|\boldsymbol{x}_{\tau_{k-1}}^{(m)})}{\pi(\boldsymbol{x}_{\tau_k}^{(m)}|\boldsymbol{x}_{\tau_{k-1}}^{(m)},\ \mathcal{Y}_k)}, \qquad (6)
$$

where $p(y_k|\boldsymbol{x}_{\tau_k}^{(m)})$ is the likelihood of $\boldsymbol{x}_{\tau_k}^{(m)}$, and $p(\boldsymbol{x}_{\tau_k}|\boldsymbol{x}_{\tau_{k-1}}^{(m)})$ is the transition distribution of the state computed at $\boldsymbol{x}_{\tau_k}^{(m)}$.

The transition distribution of the state is readily obtained from (1), the layout information, the distribution of the noise vector, and the assumption that $\boldsymbol{u}_{\tau_{k-1}}$ and $\boldsymbol{u}_{\tau_k}$ are independent. For $\pi(\boldsymbol{x}_{\tau_k}|\boldsymbol{x}_{\tau_{k-1}}^{(m)},\ \mathcal{Y}_k)$ we use $p(\boldsymbol{x}_{\tau_k}|\boldsymbol{x}_{\tau_{k-1}}^{(m)})$, and (6) simplifies to

$$
w_{\tau_k}^{(m)} \propto w_{\tau_{k-1}}^{(m)}\, p(y_k|\boldsymbol{x}_{\tau_k}^{(m)}), \qquad (7)
$$

and it can be computed as

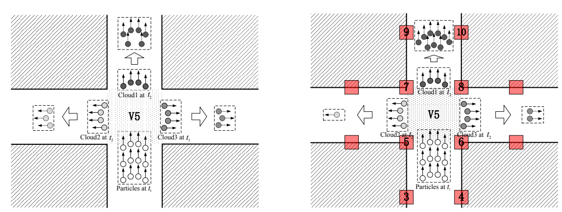
$$
w_{\tau_k}^{(m)} \propto w_{\tau_{k-1}}^{(m)}\ f(\boldsymbol{x}_{\tau_k}^{(m)}, y_k), \qquad (8)
$$

where

$$
f(\boldsymbol{x}_{\tau_k}^{(m)}, y_k) = \frac{\beta_\lambda}{\alpha_\lambda+\beta_\lambda}\frac{1}{1+e^{(a_1+a_2 d_{\tau_k}^{(m)}+a_3|\theta_{\tau_k}^{(m)}|)}}, \qquad (9)
$$

where $d_{\tau_k}^{(m)}$ and $\theta_{\tau_k}^{(m)}$ can be obtained from $\boldsymbol{x}_{\tau_k}^{(m)}$ and the location of the antenna j_k of the reader i_k that detected the tag, whereas α_λ and β_λ are estimated from experimental data.

We apply a multi-hypothesis propagation by integrating the layout information into the PF framework. Figure 3 (a) shows an example of the propagation when the system relies only on RFID readers. The particle cloud is split into three clouds with different moving directions [14]. We keep all the clouds with different hypotheses of the motion model, and update the weight for each cloud after obtaining the new observation. The resulting particle clouds have their own propagation models but the weight normalization and the resampling steps are performed over all the particles. Once more observations are obtained, the number of particles in the cloud with the true hypothesis is expected to increase, and vice versa.



(a) Reader-only system. (b) New system with STs.

Fig. 3. The multi-hypothesis particle propagation.

3.2. The sense-a-tag

In this section, we discuss a new semi-passive RFID system with ST devices [6, 8] that will improve the accuracy of tracking and will readily resolve the estimation of the direction of movement at intersections.

As pointed out, the ST is a tag-like RFID component with dual functionality. It can not only communicate with the reader like standard tags, but can also sense the communication between the reader and standard tags in its proximity. Based on the information backscattered by the STs to the reader, localization and tracking algorithms based on binary sensor principles can be developed [7, 8, 10].

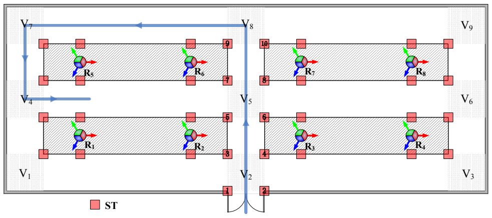


Fig. 4. The RFID system with STs.

Figure 4 shows the deployment of a novel RFID system with STs being placed in the corner of the shelves. In the new RFID system with STs, we can also obtain the readings from the STs at time instant τ_k (note that here we ignore the latency due to the reporting from the ST to a reader) and now we denote the kth detection by $y_k = \{i_k, j_k, \tau_k, \mathbf{n}_k\}$, where the new argument $\mathbf{n}_k$ is a vector of size $\tilde{L} \times 1$, with $\tilde{L}$ being the number of STs in the system. The elements of the vector $\mathbf{n}_k$ take values one or zero, depending on if the corresponding ST detected communication between the reader and the tag. We apply the model of the probability of detection of the STs from [10], which is a function of distance only and is given by $\tilde{p}(\tilde{d}) = 1/(1+e^{\tilde{\alpha}(\tilde{d}-\tilde{d}_0)})$, where $\tilde{d}$ is the distance between the ST and the tag, whereas $\tilde{\alpha}$ and $\tilde{d}_0$ are model parameters that are estimated from experimental data. The likelihood function in (8) is then multiplied by the factor

$$\prod_{i=1}^{\tilde{L}} \left\{ \tilde{p}(\tilde{d}_i^{(m)}) n_{k,i} + (1 - \tilde{p}(\tilde{d}_i^{(m)})(1 - n_{k,i}) \right\}, \qquad (10)$$

where $n_{k,i} \in \{0, 1\}$ is the ith element of $\mathbf{n}_k$, $\tilde{d}_i^{(m)}$ is obtained from the particle state $x_{\tau_k}^{(m)}$ and the known locations of the STs.

An example of the propagation of the particles is shown in Fig. 3 (b). The particle cloud quickly merges into one with the proximity information provided by the STs.

4. NUMERICAL RESULTS

The parameters of the model in (3) were obtained by using an Impinj Speedway Reader connected to a single 6 dBIC gain patch antenna and by using Alien Squiggle RFID tags. Both the reader and the tags are compliant with the ISO 180006-C (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 23.5 dBm. The reader was programmed to send out queries for a period of 30 s. We measured the probability of detection as a ratio of the number of times the tag was read over the total number of queries sent during the 30 s period.

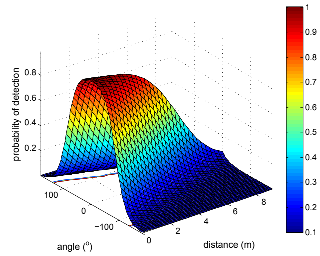
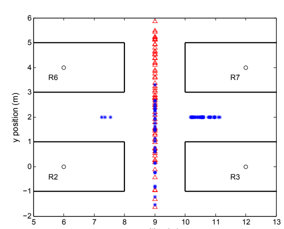


Fig. 5. Fitting of the mean of $p(d, \theta)$.

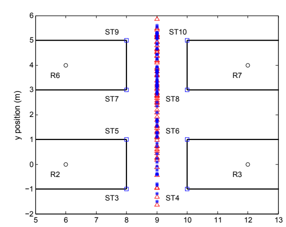
We modeled the probability of detection according to expression (3) as shown in Fig. 5 and estimated the parameters of the model as $\widehat{a}_1 = -4.9433$, $\widehat{a}_2 = 0.8370$ and $\widehat{a}_3 = 0.0552$. We applied the model from [10] for the probability of detection of an ST.

We simulated two setups. In the first setup, we deployed 8 readers in a warehouse of size 26 m $\times$ 10 m with shelves whose separation was 6 m horizontally and 4 m vertically as shown in Fig. 1. The widths of a path and a shelf were set to 2 m. The noise of the state had a covariance matrix $diag(0.01, 0.01)$ and the initial speed was 1 m/s in the moving direction. The objective was to detect and track the tagged object for a period of 15 s. In the second setup, we included four STs on the shelves' corners with a separation distance of 2 m as shown in Fig. 4.

Figure 6 shows a tracking run with the two RFID systems. The tracking near the intersections considers the multiple choices. The long detecting range, the short physical distance in the indoor setup and the asynchronism of the detections makes the estimation of direction of movement near intersections challenging. In Fig. 6 (a), the target is lost due to the wrong estimation of the direction of movement. However in the system with STs, the direction of movement is estimated correctly with the proximity information given by the STs as shown in Fig. 6 (b).



(a) The reader-only system.



(b) The system with STs.

Fig. 6. A tracking run in the two systems. The red triangles are the real states and the blue crosses are the tracking results.

Next, we generated 100 independent realizations to measure the tracking performance using the average root mean square error (RMSE) of the position of the target as a function of time over 100 independent realizations. The RMSE for one realization was calculated as $\sqrt{(\hat{x}_{1,t} - x_{1,t})^2 + (\hat{x}_{2,t} - x_{2,t})^2}$.

We compared the performance of the reader-only and the ST-based systems. The cumulative density functions (CDFs) of the RMSEs of the position with the two systems are displayed in Fig. 7. The results show that the system with STs has improved tracking performance. The STs reduce the ambiguity of the direction of movement near intersections due to their capability of detecting the tags in their close proximity. We also studied the impact of the particle size M. We can see from Fig. 7 that larger M values result in better tracking performance with the reader-only system. For the system with STs, there is no big discrepancy in the tracking performance for different M values. Thus, one can use small particle sizes to reduce the computation complexity and still achieve satisfactory performance. The advantage brought by the STs is obvious. One can use STs to improve the indoor localization or tracking performance, especially near portals and intersections.

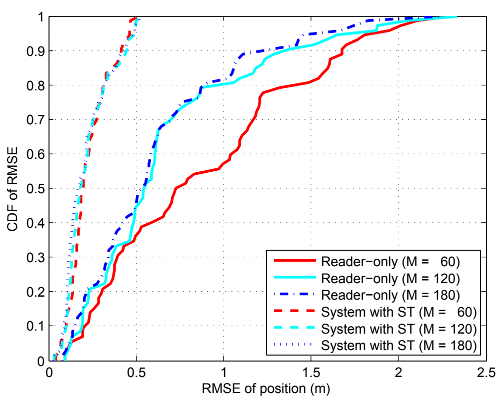


Fig. 7. CDFs of RMSEs for systems with STs and without STs (reader-only).

5. CONCLUSIONS

In this paper we addressed the problem of tracking tagged objects in indoor RFID environments using asynchronous binary readings and layout information. The tracking was implemented in an RFID system that contained sense-a-tags with known locations and that provided proximity information to the system about the queried tags. We proposed a multi-hypothesis particle filtering method for tracking so that we account for estimating the direction of movement and/or manoeuvering of the object. We demonstrated the improved accuracy of the proposed method by computer simulations.

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