REAL-TIME SELF-TRACKING IN THE INTERNET OF THINGS

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ABSTRACT

We investigate the problem of real-time self-tracking of tagged objects in a new system with low-cost "smart" tags. These tiny and battery-less devices will play a pivotal role in the infrastructure of the Internet of Things (IoT). With capabilities of low-power computation and tag-to-tag backscattered communication, no readers will be needed for running the Radio Frequency Identification (RFID) system. In order to allow for low-cost tags, self-tracking has to be performed with simple algorithms while still exhibiting high accuracy. In this paper we propose a linear observation model for which Kalman filtering (KF) is the optimal method. We also consider a nonlinear model for which we apply particle filtering (PF) of reduced complexity as the tracking method. The performance and computational complexity of the different methods are compared by computer simulations.

Index Terms— Radio Frequency Identification (RFID), Internet of Things (IoT), real-time tracking, tag-to-tag communication

1. INTRODUCTION

The Internet of Things (IoT) is expected to connect physical objects and enable intelligent interactions between them. These objects will have tiny devices that will endow them with the ability to sense signals, process information, and communicate with each other [1]. It is expected that the backbone of the IoT will be the Radio Frequency IDentification (RFID) technology and the devices with central role will be RFID tags. A significant progress has been made in developing tags that allow for computing and making decisions based on information collected by onboard sensors. Furthermore, the tags are run by low-power micro-controllers and they harvest ambient energy (e.g., light, RF) [2, 3]. The tags are expected to be cooperative in that they share information whenever necessary. The location and tracking of tags will be of critical importance in the IoT.

Present day RFID systems are composed of two types of components, RFID readers and RFID tags. The latter are of very low cost and the former are rather expensive. Clearly, the cost of the readers raises scalability issues if one envisions large infrastructure of RFID readers in the IoT [1]. On the other hand, one can readily attach tags to trillions of objects with the objective that the tags interact with each other with the ultimate goal of improving daily life [4]. In order to allow for interaction, the RFID tags of today have to be improved.

In this paper, we investigate the problem of real-time self-tracking of RFID tags that operate in a system *without* RFID readers. The tags harvest energy from a continuous wave generated by an external exciter or an ambient RF signal [5]. The tags can broadcast information to neighboring tags by backscattering. Thereby, one can argue, these tags can accomplish tag-to-tag communication [6]. Some of the tags in the system know their locations, and they backscatter this information about them periodically. Nearby moving tags read these signals and use it for self-tracking.

Tags with the ability to read other tag signals have already been introduced in [7, 8]. The use of these tags for indoor tracking in systems with RFID readers has been studied, and improved accuracy with them has been reported [9, 10]. We also note that indoor tag tracking with conventional RFID systems has extensively been studied in the wide literature, for instance in [11, 12, 13, 14].

Unlike our previous work, here we seek solutions for the self-tracking problem in a system of low-cost RFID tags where the system does not contain readers. The solution is simple enough to perform well on a tag with limited computational ability. The complexity of the self-tracking problem addressed here strongly depends on the considered observation model. We first propose a linear model that can optimally be tackled by Kalman filtering (KF). We also formulate a more precise nonlinear distance-based model for which we propose to use a particle filtering (PF) algorithm of reduced complexity [15]. We compare by computer simulations the tracking performance of three different methods - tracking by association, KF, and PF. We also analyze the computational complexity of the three methods. The main contributions of this paper are a) the formulation of the self-tracking problem in a system with RFID tags only where the tags can decode backscattered signals and b) the proposal of self-tracking algorithms with

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relatively low computational complexity while still exhibiting high accuracy.

2. PROBLEM FORMULATION

We consider the problem of self-tracking in a new RFID system with tags only. The tags backscatter information that can be read by tags that are in their proximity. The system has two types of tags: stationary tags that know their locations (also called reference tags) and mobile tags that are tasked to do self-tracking. Figure 1 shows an example with three reference tags T_1, T_2, T_3 with known locations and a self-tracking tag T_4. The tags are powered by nearby exciters that emit CWs. The goal of the mobile tag is to perform self-tracking in real time with only backscattered information that comes from the reference tags. This information comes aperiodically at random instants of time.

The main challenges are: 1) only one observation with proximity information can be used at a time due to the requirement of real-time tracking; 2) no complicated tracking algorithms can be applied due to the limited computational ability of the mobile tag; and 3) only simple protocols can be carried out due to the low-power backscattered communication.

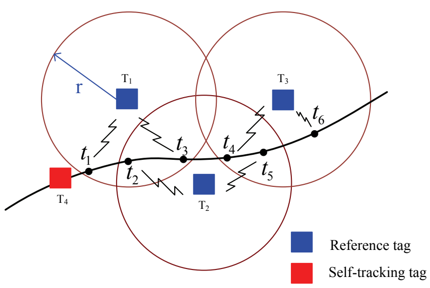

Fig. 1. A self-tracking scenario.

2.1. System description

Here we provide a more precise description of the system. As pointed out, the reference tags backscatter information about their locations. If a self-tracking tag moves close to a reference tag that backscatters so that it is in its sensing range r, it will pick up the backscattered signal, decode it, and perform an update of its location. A protocol that the reference tags may use is the all-tag-talk strategy where all the tags have equal rights to "talk" by modulating the external CW. This is done with a certain rate in a randomized Aloha-based strategy to reduce the probability of collision of the backscatterings.

2.2. The motion model

The state of the system consists of a vector containing information about the self-tracking tag at time instant t and is denoted by $\boldsymbol{x}_t \in \mathbb{R}^{2J\times 1}$, where $J \in \{1,2,3\}$ is the number of dimensions of interest, $\boldsymbol{x}_t = [x_{1,t}\ \dot{x}_{1,t}\ \cdots\ x_{J,t}\ \dot{x}_{J,t}]^\top$ where $x_{j,t}$ and $\dot{x}_{j,t}$ represent the coordinate and the velocity of the mobile tag in the jth dimension, respectively. That tag moves from t_1 to t_2 according to the model

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

where $\boldsymbol{x}_{t_2}$ is the state of the system at time instant t_2, $\boldsymbol{u}_{t_2} \in \mathbb{R}^{J\times 1}$ is a noise vector with a known distribution, and $\boldsymbol{A} \in \mathbb{R}^{2J\times 2J}$ and $\boldsymbol{B} \in \mathbb{R}^{2J\times J}$ are known matrices, respectively, given by

$$\boldsymbol{A} = \boldsymbol{I} \otimes \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \quad \text{and} \quad \boldsymbol{B} = \boldsymbol{I} \otimes \begin{bmatrix} \frac{\Delta t^2}{2} \\ \Delta t \end{bmatrix},$$

where $\otimes$ denotes the Kronecker product, $\Delta t = (t_2 - t_1)$ and $\boldsymbol{I}$ is the identity matrix with size $J \times J$.

2.3. The observation model

In the system, the reference tags start backscattering rounds asynchronously at different time instants. Without loss of generality, we assume the same rate for all the tags with a period of T_s. Figure 2 shows the backscattering time line and the asynchronous measurements for the example from Fig. 1. The ith reference tag T_i backscatters signals with information about its location. The backscattering starts at a random slot during each T_s. Here $\Delta\tau$ is the random interval after which T_1 backscatters during the first T_s. As shown in the figure, a collision occurs because T_1 and T_2 chose to backscatter at the same time slot at τ_2. At τ_1, τ_3, τ_4 and τ_5, the backscattered signals cannot reach the mobile tag because it is far away from them.

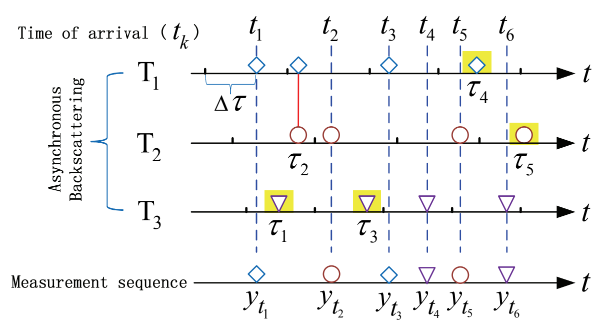

Fig. 2. Backscattering time line with asynchronous measurements. The red solid line represents collision, and the yellow shaded boxes indicate that the backscattered signal cannot reach the target.

We denote the kth signal decoded by the mobile tag by $y_{t_k} = \boldsymbol{l}_i$, where $i \in \{1,2,\cdots,L\}$ is the index of the reference tag whose backscattering is picked up at time t_k and $\boldsymbol{l}_i \in \mathbb{R}^{J\times 1}$ is the location of the lth tag in the J-dimensional Cartesian coordinate system. We note that $t_1 < t_2 < t_3 < \cdots$. The objective of the mobile tag is to perform self-tracking given the sequence of asynchronous observations.

3. TRACKING METHODS

We assume that there are L reference tags with known positions $\mathbf{l}_i$ where $i = 1, 2, \cdots, L$ and one moving tag with unknown positions and velocities, $\boldsymbol{x}_t$. The mobile tag estimates $\boldsymbol{x}_t$ as soon as it receives a backscattered signal from a reference node. Our main goal is to develop an algorithm that can perform well on the mobile tag under the constraints of limited computational ability and real-time processing. Therefore, the processing rate of the mobile tag must be greater than the arriving rate of the measurements. We studied three methods for self-tracking. They are based on i) association or nearest neighbor (NN) [15] ii) KF [16], and iii) PF [17].

The association method is the simplest, the fastest and the most adaptive to dynamic changes of the environment of all the methods. With this method we simply associate the target with the nearest reference tag [15]. The main drawback of association is that its performance completely relies on the spatial distribution of the reference tags and the sensing range of the mobile tag. When the mobile tag is in an area where it can sense more than one reference tag in a short period of time, and since it only processes one measurement at a time, the tracking will result in zigzagging.

If the mobile tag employs Bayesian inference, it estimates the posterior distribution $p(\boldsymbol{x}_{t_2}|\mathcal{Y}_{t_2})$ at time t_2 given $p(\boldsymbol{x}_{t_1}|\mathcal{Y}_{t_1})$ and the propagation distribution $p(\boldsymbol{x}_{t_2}|\boldsymbol{x}_{t_1})$, where $\mathcal{Y}_{t_k}$ denotes all the measurements collected up to time t_k. The propagation distribution is defined by the motion model in (1) and the likelihood function is defined by the observation model. According to Bayes' rule, the states of the target can be obtained by

$$f(\boldsymbol{x}_{t_2}|\mathcal{Y}_{t_2}) \propto f(\mathbf{y}_{t_2}|\boldsymbol{x}_{t_2}) \times \int f(\boldsymbol{x}_{t_2}|\boldsymbol{x}_{t_1}) f(\boldsymbol{x}_{t_1}|\mathcal{Y}_{t_1}) d\boldsymbol{x}_{t_1}. \quad (2)$$

The update from $f(\boldsymbol{x}_{t_1}|\mathcal{Y}_{t_1})$ to $f(\boldsymbol{x}_{t_2}|\mathcal{Y}_{t_2})$ can be accomplished by various types of filters. The KF method has a closed-form solution when the state and observation models are linear and the noises $\boldsymbol{u}_{t_2}$ and $\mathbf{v}_{t_2}$ are Gaussian. Because of its simplicity, we first propose a linear observation model. Suppose that at time t_2, the self-tracking tag receives a measurement $\mathbf{y}_{t_2}$, which is the location of a reference tag whose backscattering is picked up as described in Section 2.3. We model y_{t_2} according to

$$\mathbf{y}_{t_2} = \boldsymbol{H}\boldsymbol{x}_{t_2} + \mathbf{v}_{t_2}, \quad (3)$$

where $\mathbf{y}_{t_2} \in \mathbb{R}^{J\times 1}$ and $\mathbf{v}_{t_2} = [v_{1,t_2}, \cdots, v_{J,t_2}]^T$ is a random vector that accounts for the location uncertainty. The matrix $\mathbf{H}$ is defined by

$$\boldsymbol{H} = [1 \quad 0] \otimes \boldsymbol{I} \quad (4)$$

where $\boldsymbol{I}$ is the identity matrix of size $J \times J$.

The distribution of the location uncertainty $\mathbf{v}_{t_2}$ can be estimated from experimental measurements and by exploring the spatial relationships among the tags off-line and prior to tracking as discussed in [10]. In order to reduce the complexity and to apply the KF method, here we assume $\mathbf{v}_{t_2}$ to be Gaussian-distributed, i.e., $\mathcal{N}(\mathbf{0}, \mathbf{R})$, where $\mathbf{R}$ is the covariance matrix of the noise. We chose $\mathbf{R} = diag(r^2/2, r^2/2)$, where r is the sensing range of the mobile tag.

A nonlinear distance-based observation model can be also considered [9, 10, 11, 12, 13]. There, the probability of detecting a tag is modeled as a function of the distance. Since this model is nonlinear, an appropriate method for working with it is PF. With PF, one approximates the posterior density of the unknown state by using random measures composed of particles and weights associated to the particles. More specifically, the observation model is a Bernoulli distribution with the probability of detection modeled by

$$p(d) = \frac{1}{1 + e^{a_1 + a_2 d}}, \quad (5)$$

where a_1 and a_2 are the model parameters, which can be obtained from real experimental data, and d is the distance between the mobile tag and the backscattering reference tag. The details of the PF algorithm that uses this model can be found in our previous work [13, 9, 10]. Here, however, we attempt to use the method with very low number of particles so that we reduce the computational burden of the mobile tag.

4. NUMERICAL RESULTS

We simulated a setup with 10 reference tags placed on a portal and shelves in a warehouse along where the width between the shelves was 2 m. The setting is displayed in Fig. 3. The noise of the state had a covariance matrix $diag(0.01, 0.01)$ and the initial speed was $[0.1, 1]$ m/s. We set $T_s = 0.5$ s. If all the reference tags were in the range of the mobile tag, the maximum arriving rate was 20 measurements per second. Therefore, the processing time for one measurement could not exceed a threshold $\gamma = 1/20 = 0.05$ s. The threshold γ is even smaller with a higher density of the nodes. As a result, only simple algorithms with low time-complexity can be accepted for real-time tracking. The mobile tag was self-tracking in a two-dimensional space by using the received observations for a period of 12 s while it moved along the path between the shelves. Figure 3 shows a tracking run with the new tag system.

Next, we generated the time sequence of backscattering or "talk" for each tag by simulating the "all-tag-talk" protocol mentioned in Section 2. Then, we generated 100 trajectories for the three methods and for each trajectory 50 independent realizations for the PF algorithm. The tracking performance was measured by means of the root mean square error (RMSE) of the position of the mobile tag as a function

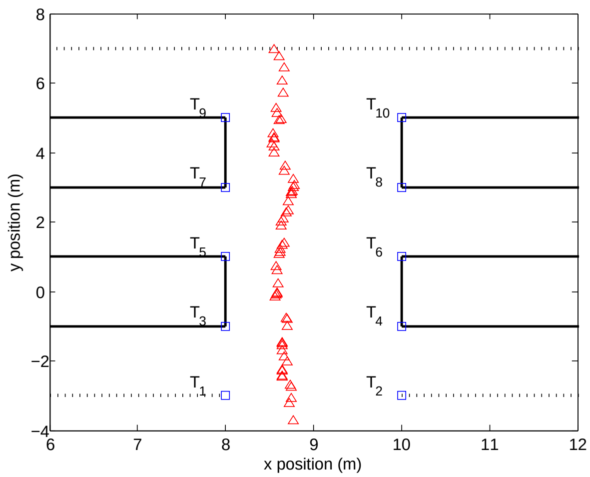

Fig. 3. A tracking realization with the new tag system.

of time. The cumulative density functions (CDFs) of the RMSEs of the position with the NN and KF methods with different sensing ranges are displayed in Fig. 4. The results in Table 1 show that the KF method performs better than the NN method with an average improvement of 0.5 m of RMSE. It also shows that the tracking performance with sensing range $r = 1.5$ m performs better than with $r = 2$ m and $r = 2.5$ m. The optimal range depends on the number of reference tags and their deployment topology.

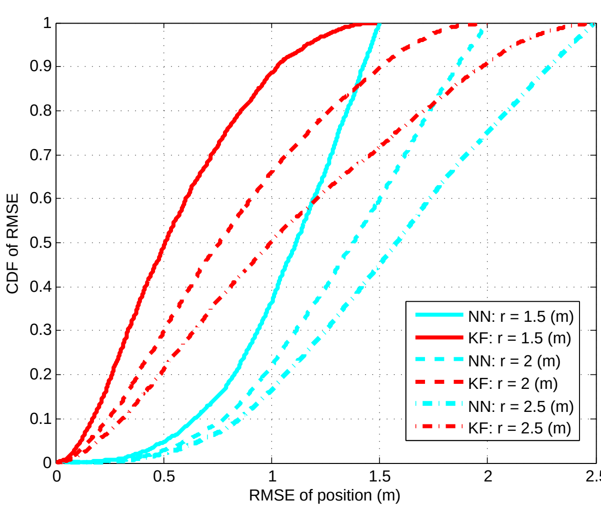

Fig. 4. CDFs of RMSEs for the KF and NN methods with different sensing ranges r.

We also compared the tracking performance of the KF and PF methods and studied the impacts of the particle size M. The results are shown in Fig. 5.

Table 2 shows the approximate computational complexity scale using the processing time of NN as a baseline. The processing time for the NN method is $0.2855\ \mu s$ using the Matlab platform with a desktop computer CPU. Clearly,

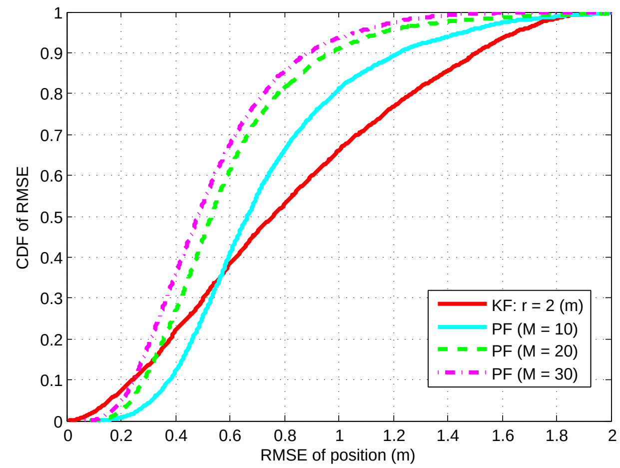

Fig. 5. CDFs of RMSEs of the KF and PF methods (with different number of particles M) for $r = 2$ m.

Table 1. The average RMSEs of different methods

r (m)	averageRMSE (m)				
	NN	KF	PF		
			M = 10	M = 20	M = 30
r = 1.5	1.0720	0.5611	0.6466	0.5484	0.5183
r = 2	1.3391	0.8203	0.7351	0.5886	0.5340
r = 2.5	1.5643	1.0782	0.8046	0.6513	0.5812

the processing time is platform- and device-dependent and therefore we only compare the ratio of the run-times of the other methods and the NN method. The results show that the KF is about 10 times slower than the NN, while the PF with $M = 10$ particles is 10 times slower than the KF. The processing time for the PF increases linearly with the size of M.

Table 2. Run time of the methods

NN	KF	PF		
		M = 10	M = 20	M = 30
1 (2.8554e-007s)	10	100	200	300

5. CONCLUSIONS

In this paper, we introduced the problem of self-tracking in a system of low-cost RFID tags where the system does not contain readers. We explored tracking algorithms of low complexity but yet with accurate performance. We introduced a simple linear observation model to allow for the use of Kalman filtering. We also investigated a more ambitious model that is nonlinear and applied particle filtering with a small number of particles. We compared the tracking performances and the computational complexities of these methods as well as of the association-based algorithm.

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