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Maneuvering Target Tracking with UKF and EKF for Indoor RFID System

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Abstract

Due to the uncertainty of the RFID measurements and limit of the placement of the readers, it's necessary to use the estimation method to obtain more accurate trajectory in RFID indoor tracking system. While the traditional recursive estimation from K to K +1 sampling point may fail, because the measurement of RFID system is irregular sampling due to the data-driven measurement mechanism. This paper develops the tracking method for indoor RFID system, including estimation dynamic model based on the estimated states and nonlinear fusion estimation algorithm for variable-irregular sampling measurements. Two estimation methods were given based on the Extended Kalman filter (EKF) and Unscented Kalman filter (UKF), respectively. The tracking performances are compared and the simulation results show that the performance of UKF can get better performance for indoor RFID tracking, especially in the low detection rate area.

Keywords: *RFID Tracking, Fusion Estimation, EKF, UKF, Irregular Sampling Interval, Indoor Target*

1. Introduction

The radio frequency identification (RFID) is one of the most widely used sensors [1, 2] among the sensors applied in indoor tracking systems. The tracking problem involves the estimation method and the models, such as the dynamic process model of the maneuvering target and the measurement model of the sensors. The estimation process of the target trajectory is as the following: we use the dynamic model to predict the trajectory at the next sampling point, then update the estimation of the real trajectory by the measurement model and the measurements from the sensors. This method is greatly effective when the target makes maneuvering movement and the measurements are uncertain or even some measurements are lost.

In the RFID system, the sensors are including the RFID readers and the tag on the target. Once the tag gets close to the readers, the distances between the tag and readers can be extracted from the received signal strength information (RSSI)[3][4]. We know the RSSI is perturbed by some noise source, for example, the backscattered signal power propagated from nearby RFID tags, so the measurement of RFID system is uncertain. And the data-driven mechanism leads to the measurements with irregular sampling interval.

In addition to the nonlinear of the RFID measurement function, the number of the system sensors is also especial in the RFID tracking system comparing with the other multi-sensor system. Because we only can get the distances from the target to the readers,

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we cannot get the accurate location and the trajectory of the target only by one or two measurements. The geometrical relationship with at least three measurements [5, 6] is used to abstain the location of the target. Some regular placement, such as the "grid" structure [5] (shown in Figure1) will make the trilateration estimation simpler and more effective. But the readers are usually unable to be placed as such regular structure. For example in the supermarket, the readers are often placed somewhere to avoid interfering with customers' shopping (shown in Figure2). Therefore in the practical indoor tracking system, the distribution density of the readers is non-uniform. When the target gets into a reader-intensive area, several readers may obtain measurement simultaneously, while no or few measurements will be obtained in a reader-sparse area.

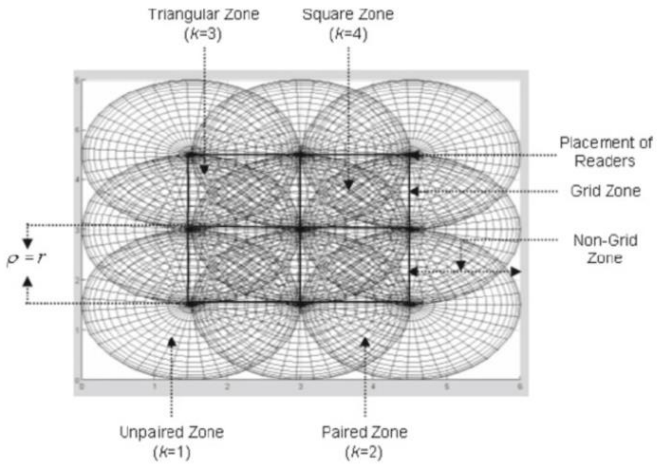

Figure 1. Layout of Square Grid RFID Reader Network In [5]

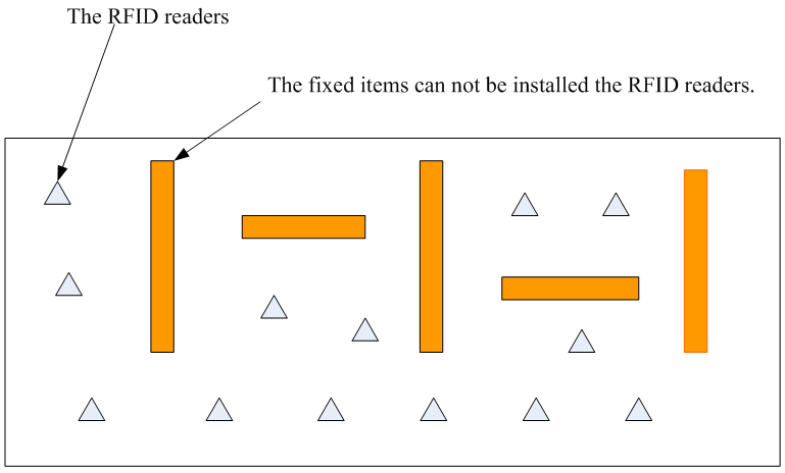

Figure 2. The Practical Indoor Tracking Area with Some RFID Readers

So we can see the measurements in the RFID tracking system, i.e., the distances between the tag and readers, are uncertain, irregular sampled, nonlinear, and multivariate, which means that the estimation issue in the RFID system is novel and challenging. Firstly, we notice that the traditional recursive estimation from K to K +1 sampling point cannot be used because of the irregular measurements in RFID system [7].

The models and the estimation method should all be reconsidered duo to the irregular sampling. [8] has developed a transform method, which transformed the irregular sampling interval estimation to the time-varying parameters of the system and used the

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recursive method from t_i to t_{i-1} to estimate the target trajectory. While in [8], the "current model" was used to describe the processing model of maneuvering target, but "current model" cannot effectively describe the dynamic model of indoor target [9].

Secondly, because of the nonlinearity of the measurement model of RFID, the Kalman filter in [8] must be replaced by a nonlinear filter, i.e., Extended Kalman filter (EKF) or Unscented Kalman filter (UKF), [10, 13]

Finally, RFID tracking involves the problem of sensor fusion with the variable number. Because of the random location of the readers, some locations may not be measured, while some locations of the target maybe have several measurements from multiple sensors at the same time.

Based on the nonlinear measurement model, this paper gives two centralized fusion estimation methods based on the Extended Kalman filter (EKF) and Unscented Kalman filter (UKF), respectively. Moreover, the performance of these two algorithms is compared and some conclusions are given.

The following parts of the paper are organized as: Section 2 builds the RFID measurement model and target dynamic model under the irregular sampling interval. Section 3 and 4 state the estimation method based on EKF and UKF, respectively. The simulations are provided in section 5. Finally, some concluding remarks are given in Section 6.

2. System Model with the Irregular Sampled Measurements

Before constructing the description model of the tracking system, we first discuss the RFID measurement model. The distance $z_n(t_i)$ between the n^{th} reader and the tag at sampling time t_i can be got by RSSI nominal value $P_n(d,\phi,t_i)$

$$z_n(t_i) = d_0 10^{\frac{P_r(d_0)-P_n(d,\phi,t_i)}{10q}} \quad (1)$$

where d_0 is the close-in reference distance, $P_r(d_0)$ is the RSSI in dBm units with the reference distance d_0 and q is the path loss exponent[14].

Let x, $\dot{\mathrm{x}}$ and $\ddot{\mathrm{x}}$ be the target location, velocity, and acceleration along the horizontal axis direction, while y, $\dot{\mathrm{y}}$ and $\ddot{\mathrm{y}}$ are the corresponding variables along the longitudinal axis direction. Then the state variable of the system at time t_i can be expressed as $x(t_i) = [\mathrm{x}(t_i) \;\; \dot{\mathrm{x}}(t_i) \;\; \ddot{\mathrm{x}}(t_i) \;\; \mathrm{y}(t_i) \;\; \dot{\mathrm{y}}(t_i) \;\; \ddot{\mathrm{y}}(t_i)]$. Let $d_n(t_i)$ be the actual distance between the n^{th} reader and the tag at sampling time t_i. We can see the actual distance $d_n(t_i)$ is the function of the state $x(t_i)$.

$$d_n(t_i) = \sqrt{(\mathrm{x}(t_i) - \mathrm{x}_n(0))^2 + (\mathrm{y}(t_i) - \mathrm{y}_n(0))^2} \quad (2)$$

where $\mathrm{x}_n(0)$ and $\mathrm{y}_n(0)$ are the horizontal and vertical coordinates of RFID readers, $\mathrm{x}(t_i)$ and $\mathrm{y}(t_i)$ are the real location of the target in the 2D tracking space.

In general, the distance $z_n(t_i)$ in (1) and the actual distance $d_n(t_i)$ are not identical, the measurement error should be considered:

$$z_n(t_i) = d_n(t_i) + v_n(t_i) \quad (3)$$

where $v_n(t_i)$ is the measurement noise of the n^{th} RFID reader at the sampling time t_i with the measurement covariance satisfying $v_n(t_i)/d_n(t_i) \sim N(0, \left(\frac{0.2303\sigma_p}{\gamma}\right)^2)$, where σ_p is the standard deviation, γ is the path loss exponent, $d_n(t_i)$ is the distance between the target and the n^{th} RFID reader and '/'means division calculation. We can see that the ratio

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of ranging error to the actual distance follows a normal distribution with a zero-mean and a standard deviation of $\frac{0.2303\sigma_p}{\gamma}$. The standard deviation of the received power σ_p can be fixed at 4 dB, which is about the average of the reported standard deviations for wireless communications. The path loss exponent γ is usually between 1.6 and 6.5 based on actual measurement [14].

Then we discuss the processing model under irregular sampling interval:

$$x(t_i) = A(t_{i-1})x(t_{i-1}) + w(t_{i-1}) \tag{4}$$

where $A(t_{i-1}) = \begin{bmatrix} A_x(t_{i-1}) & 0 \\ 0 & A_y(t_{i-1}) \end{bmatrix}$ is the state transition matrix, and $w(t_{i-1}) = \begin{bmatrix} w_x(t_{i-1}) & w_y(t_{i-1}) \end{bmatrix}^T$ represents the processing noise of the horizontal and longitudinal axis, respectively. Here we assume the noises of the two axes are independent of each other, then the covariance matrix can be defined as

$$Q(t_{i-1}) = \begin{bmatrix} Q_x(t_{i-1}) & 0 \\ 0 & Q_y(t_{i-1}) \end{bmatrix}$$

According to the adaptive statistics model in [8], the system parameters of the horizontal and longitudinal axis are as follows:

$$A_\eta(t_{i-1}) = \begin{bmatrix} 1 & th_i & \frac{\alpha_\eta th_i - 1 + e^{-\alpha_\eta th_i}}{\alpha^2} \\ 0 & 1 & \frac{1 - e^{-\alpha_\eta th_i}}{\alpha_\eta} \\ 0 & 0 & e^{-\alpha_\eta th_i} \end{bmatrix} \tag{5}$$

$$Q_\eta(t_{i-1}) = 2\alpha_\eta \delta_{\alpha\eta}^2 \begin{bmatrix} q_{11} & q_{12} & q_{13} \\ q_{12} & q_{22} & q_{23} \\ q_{13} & q_{23} & q_{33} \end{bmatrix} \tag{6}$$

$$\begin{aligned}
q_{11} &= \frac{1}{2\alpha_\eta^5}\left[1 - e^{-2\alpha_\eta th_i} + 2\alpha_\eta th_i + \frac{2\alpha_\eta^3 th_i^3}{3} - 2\alpha_\eta^2 th_i^2 - 4\alpha_\eta th_i e^{-\alpha_\eta th_i}\right] \\
q_{12} &= \frac{1}{2\alpha_\eta^4}\left[e^{-2\alpha_\eta th_i} + 1 - 2e^{-\alpha_\eta th_i} + 2\alpha_\eta T_0 e^{-\alpha_\eta th_i} - 2\alpha_\eta th_i + \alpha_\eta^2 th_i^2\right] \\
q_{13} &= \frac{1}{2\alpha_\eta^3}\left[1 - e^{-2\alpha_\eta th_i} - 2\alpha_\eta th_i e^{-\alpha_\eta th_i}\right] \\
q_{22} &= \frac{1}{2\alpha_\eta^3}\left[4e^{-\alpha_\eta th_i} - 3 - e^{-2\alpha_\eta th_i} + 2\alpha_\eta th_i\right] \\
q_{23} &= \frac{1}{2\alpha_\eta^2}\left[e^{-2\alpha_\eta th_i} + 1 - 2\alpha_\eta th_i\right] \\
q_{33} &= \frac{1}{2\alpha_\eta}\left[1 - e^{-2\alpha_\eta th_i}\right]
\end{aligned} \tag{7}$$

where $th_i = t_i - t_{i-1}$ describes the time-varying sampling interval, and $\eta = x, y$ represent the horizontal and the vertical axis, respectively. α_η is the maneuver frequency and $\delta_{\alpha\eta}^2$ is the variance of Gaussian white noise.

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Assume the estimated acceleration $\hat{a}(t_i)$ is obtained at every sampling time t_i. For a first-order stationary Markov process, we can describe the statistics relation between the autocorrelation functions with β and δ_{aw}^2 as the following

$$\begin{bmatrix} r(0) & r(1) \\ r(1) & r(0) \end{bmatrix} \begin{bmatrix} 1 \\ -\beta \end{bmatrix} = \begin{bmatrix} \delta_{aw}^2 \\ 0 \end{bmatrix}$$

where $r(0)$ and $r(1)$ are autocorrelation functions of the acceleration:

$$r_i(1) = r_{i-1}(1) + \frac{1}{i}\left[\hat{a}(t_i)\hat{a}(t_{i-1}) - r_{i-1}(1)\right] \tag{8}$$

$$r_i(0) = r_{i-1}(0) + \frac{1}{i}\left[\hat{a}(t_i)\hat{a}(t_i) - r_{i-1}(0)\right] \tag{9}$$

and the parameters β and δ_{aw}^2 are

$$\beta = \frac{r_i(1)}{r_i(0)} \tag{10}$$

$$\delta_{aw}^2 = r_i(0) - \alpha r_i(1) \tag{11}$$

Then we can use the relation equation $\delta_{aw}^2 = \delta_a^2(1-\beta^2)$ and $\beta = e^{-\alpha th_i}$ [9] to get the maneuver frequency α and the variance of Gaussian white noise δ_a^2.

3. EKF Tracking With Variable Number Of RFID Readers

The EKF linearizes the nonlinear system by Taylor series method and then applies the Kalman filter to obtain the state estimates. This method has obtained much interest because of its relative simplicity and demonstrated efficacy in handling nonlinear systems.

We construct our EKF-based tracking algorithm as follows:

1) State prediction

$$\hat{x}(t_i \mid t_{i-1}) = A(t_{i-1})\hat{x}(t_{i-1} \mid t_{i-1}) \tag{12}$$

$$P(t_i \mid t_{i-1}) = A(t_{i-1})P(t_{i-1} \mid t_{i-1})A^T(t_{i-1}) + Q(t_{i-1}) \tag{13}$$

where $P(t_i \mid t_{i-1})$ is the covariance of the state prediction.

2) State fusion estimation

$$\hat{x}(t_i \mid t_i) = \hat{x}(t_i \mid t_{i-1}) + \sum_{n=1}^{N(t_i)} K_n(t_i)\left\{z_n(t_i) - h_n\left[x_n(t_i)\right]\right\} \tag{14}$$

where $z_n(t_i)$ is the distance got by the RSSI from the n^{th} readers and $N(t_i)$ is the number of readers at time t_i, which is a variable.

$$K_n(t_i) = P(t_i \mid t_{i-1})h_{nx}^T(t_i)S_n^{-1}(t_i) \tag{15}$$

$$S_n(t_i) = h_{nx}(t_i)P(t_i \mid t_{i-1})h_{nx}^T(t_i) + R(t_i) \tag{16}$$

$$P^{-1}(t_i \mid t_i) = P^{-1}(t_i \mid t_{i-1}) + \sum_{n=1}^{N(t_i)} h_{nx}^{-1}(t_i)R_n(t_i)h_{nx}(t_i) \tag{17}$$

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$$h_n[t_i,\hat{x}(t_i\,|\,t_{i-1})]=\sqrt{(\hat{\mathrm{x}}_n(t_i\,|\,t_{i-1})-\mathrm{x}_n(0))^2+(\hat{\mathrm{y}}_n(t_i\,|\,t_{i-1})-\mathrm{y}_n(0))^2} \tag{18}$$

where the Jacobi matrix of measurement function $h_{nx}(t_i)$ is

$$h_{nx}(t_i)=\left[\nabla_x h'_n(t_i)\right]_{x=\hat{x}(t_i|t_{i-1})}$$
$$=\begin{bmatrix} \dfrac{\hat{\mathrm{y}}_n(t_i\,|\,t_{i-1})}{h_n[t_i,\hat{x}(t_i\,|\,t_{i-1})]} & 0 & 0 & \dfrac{\hat{\mathrm{x}}_n(t_i\,|\,t_{i-1})}{h_n[t_i,\hat{x}(t_i\,|\,t_{i-1})]} & 0 & 0 \end{bmatrix} \tag{19}$$

3) Parameter adaptation:

Set the estimation of acceleration $\hat{a}_\eta(t_i)$ as, $\hat{a}_x(t_i)=\hat{\ddot{\mathrm{x}}}(t_i|t_i)$, $\hat{a}_y(t_i)=\hat{\ddot{\mathrm{y}}}(t_i|t_i)$, where $\eta = x \text{ or } y$.

When $i \le K_0$, $\delta^2_{a\,i,\eta}$ and $\alpha_{i,\eta}$ are estimated by:

$$\delta^2_{a\,i,\eta}=\begin{cases} \dfrac{4-\pi}{\pi}\left[a_M-\hat{a}_\eta(t_i)\right]^2 & \text{when } \hat{a}_\eta(t_i)>0 \\ \dfrac{4-\pi}{\pi}\left[\hat{a}_\eta(t_i)-a_{-M}\right]^2 & \text{when } \hat{a}_\eta(t_i)<0 \\ \text{a small positive constant} & \text{when } \hat{a}_\eta(t_i)=0 \end{cases} \tag{20}$$

and the maneuver frequency $a_{i,h}$ is set to a positive, a_M is a positive and a_{-M} is a negative with the same absolute value of a_M.

When $i > K_0$, $\delta^2_{a\,i,\eta}$ and $\alpha_{i,\eta}$ are estimated by:

$$r_{i,\eta}(1)=r_{i-1,\eta}(1)+\frac{1}{i}\left[\hat{a}_\eta(t_i)\hat{a}_\eta(t_{i-1})-r_{i-1,\eta}(1)\right] \tag{21}$$

$$r_{i,\eta}(0)=r_{i-1,\eta}(0)+\frac{1}{i}\left[\hat{a}_\eta(t_i)\hat{a}_\eta(t_i)-r_{i-1,\eta}(0)\right] \tag{22}$$

$$\beta_{i,\eta}=\frac{r_{i,\eta}(1)}{r_{i,\eta}(0)} \tag{23}$$

$$\delta^2_{aw\,i,\eta}=r_{i,\eta}(0)-\beta_{i,\eta}r_{i,\eta}(1) \tag{24}$$

$$\delta^2_{a\,i,\eta}=\frac{\delta^2_{aw\,i,\eta}}{1-\beta^2_{i,\eta}} \tag{25}$$

$$\alpha_{i,\eta}=\frac{\ln\beta_{i,\eta}}{-th_i} \tag{26}$$

The system matrix (5)-(7) can be updated at every sampling time t_i with $\delta^2_{a\,i,\eta}$ and $\alpha_{i,\eta}$ and we can see the centralized fusion estimation (14) is with the variable number of the readers $N(t_i)$.

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4. UKF Tracking with Variable Number of RFID Readers

The unscented Kalman filter (UKF) has become a popular alternative to the extended Kalman filter (EKF) during the last decade. UKF propagates the so called sigma points by function evaluations using the unscented transformation (UT), and this is at first glance very different from the standard EKF algorithm which is based on a linearized model. The claimed advantages with UKF are that it propagates the first two moments of the posterior distribution and that it does not require gradients of the system model [10].

Suppose a set of points is constructed with a given mean and covariance. When another point with the given mean was added to the set, the mean of the set would be unaffected, but the remaining points would have to be scaled to maintain the given covariance [11]. The scaled result becomes a different sigma set, with higher moments but the same mean and covariance. As will be shown in the following, weighting this newly added point provides a parameter for controlling some aspects of the higher moments of the distribution of sigma points without affecting the mean and covariance.

Then we have the following fusion estimation algorithm based on UKF.

1) By convention, let $W^{(0)}$ be the weight on the mean point, which is indexed as the zero[th] point. In order to preserve the normality, mean, and covariance of the original points set, a sigma point selection method to the system

$$\begin{aligned} \mathrm{x}^{(0)} &= \left[\mathrm{x}_x^{(0)} \quad \mathrm{x}_w^{(0)} \quad \mathrm{x}_v^{(0)} \right]^T \\ &= \left[\hat{x}(t_{i-1} \mid t_{i-1}) \quad 0_{N_w} \quad 0_{N_v} \right]^T \end{aligned} \tag{27}$$

$$W^{(0)} = W^{(0)} \tag{28}$$

$$\begin{aligned} \mathrm{x}^{(i)} &= \left[\mathrm{x}_x^{(i)} \quad \mathrm{x}_w^{(i)} \quad \mathrm{x}_v^{(i)} \right]^T \\ &= \mathrm{x}^{(0)} + \left(\sqrt{\frac{N_x}{1-W^{(0)}} P(t_{i-1} \mid t_{i-1})} \right)_i \end{aligned} \tag{29}$$

$$W^{(i)} = \frac{1-W^{(0)}}{2N_x} \tag{30}$$

$$\begin{aligned} \mathrm{x}^{(i+N_x)} &= \left[\mathrm{x}_x^{(i+N_x)} \quad \mathrm{x}_w^{(i+N_x)} \quad \mathrm{x}_v^{(i+N_x)} \right]^T \\ &= \mathrm{x}^{(0)} - \left(\sqrt{\frac{N_x}{1-W^{(0)}} P(t_{i-1} \mid t_{i-1})} \right)_i \end{aligned} \tag{31}$$

$$W^{(i+N_x)} = \frac{1-W^{(0)}}{2N_x} \tag{32}$$

where 0_{N_w} is a column vector with the same dimension as the processing noise $w(t_{i-1})$, while 0_{N_v} is a column vector with the same dimension as the measurement noise $v(t_{i-1})$, N_x is the dimension of the system state and $\left(\sqrt{\frac{N_x}{1-W^{(0)}} P(t_{i-1} \mid t_{i-1})} \right)_i$ is the i^{th} column of the principal square root of the matrix.

2) The transformed set is given by instantiating each point through the processing model

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$$\hat{\mathrm{x}}^{(i)} = A(t_{i-1})\mathrm{x}_x^{(i)} + \mathrm{x}_w^{(i)},\ i = 0,1,\cdots 2N_x \tag{33}$$

3) The predicted mean is computed as

$$\hat{\mu} = \sum_{i=0}^{2N_x} \hat{\mathrm{x}}^{(i)} W^{(i)} \tag{34}$$

4) The predicted covariance is computed as

$$P(t_i \mid t_{i-1}) = \sum_{i=0}^{2N_x} W^{(i)} \left\{\hat{\mathrm{x}}^{(i)} - \hat{\mu}\right\}\left\{\hat{\mathrm{x}}^{(i)} - \hat{\mu}\right\}^T + Q(t_{i-1}) \tag{35}$$

5) Instantiate each of the prediction points through the measurement model

$$\hat{z}_n^{(i)} = h_n[t_i, \hat{\mathrm{x}}^{(i)}] + \mathrm{x}_v^{(i)} \tag{36}$$

6) The predicted observation is calculated by

$$\hat{z}_n = \sum_{i=0}^{2N_x} \hat{z}_n^{(i)} W^{(i)} \tag{37}$$

7) The innovation covariance is

$$S_n(t_i) = \sum_{i=0}^{2N_x} W^{(i)} \left\{\hat{z}_n^{(i)} - \hat{z}_n\right\}\left\{\hat{z}_n^{(i)} - \hat{z}_n\right\}^T + R_n(t_i) \tag{38}$$

8) The cross covariance matrix is determined by

$$P_{xz,n}(t_i) = \sum_{i=0}^{2N_x} W^{(i)} \left\{\hat{\mathrm{x}}^{(i)} - \hat{\mu}\right\}\left\{\hat{z}_n^{(i)} - \hat{z}_n\right\}^T \tag{39}$$

9) Finally, the update can be performed using the fusion estimation

$$\hat{x}(t_i \mid t_i) = \hat{x}(t_i \mid t_{i-1}) + \sum_{n=1}^{N(t_i)} K_n(t_i)\{z_n(t_i) - \hat{z}_n]\} \tag{40}$$

$$K_n(t_i) = P_{xz,n}(t_i) S_n^{-1}(t_i) \tag{41}$$

The estimation covariance is

$$P(t_i \mid t_i) = P(t_i \mid t_{i-1}) - \sum_{n=1}^{N(t_i)} K_n(t_i) S_n(t_i) K_n^T(t_i) \tag{42}$$

9) Parameter adaptation: The same as the step 3) in Section 4.

As the above algorithm shows, the step 1)-8) are the basic UKF method, in which we use the processing model in (33) and the measurement model in (36) with the sigma point of (29). But the step 9) is totally different from UKF [12], where the measurements from all the readers are fused at time t_i. The filter gain (41), the state estimaion update (40) and the estimation covariance (42) all apply the centralized fusion estimation.

5. Simulations

A 2D simulation platform tracking system with RFID readers is developed to simulate the measurement mechanism, such as the measurement noise and the uncertainty of RFID readers discussed on the Section 2. The relation of loss measurement is assumed to be detection rate inversely proportional to the distance to the RFID reader.

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The initial state estimate x_0 and the covariance P_0 are assumed to be $x_0 = [\mathrm{x}(0) \quad 0 \quad 0 \quad \mathrm{y}(0) \quad 0 \quad 0]^T$ and $P_0 = diag(10,10,10,10,10,10)$. The initial value of the maneuver frequency α_η is set to be $1/20$ and $\alpha_M = 30$, $\alpha_{-M} = -30$. The initial weight of the mean point $W_x^{(0)} = \frac{\kappa}{N_x + \kappa}$, and the scale parameter $\kappa = -3$ and $N_x = 6$.

We placed 19 RFID readers (coordinate points are shown in Table 1) on the simulation platform and the measurement spaces with high detection rate of every reader are shown with circles (from inside to outside in contour map) in Figure 3. In the white area the distance information of the target can only be obtained with low detection rate. The reference trajectory of the target is shown with "black" star in the Figure3.

From Figure3, we note that there are two low detection rate areas, which are circled by the red line. Table 2 gives part of the trajectory information in Figure 3 from 11.1s to 12.1s (in low detection area) and '\' means no measurements are obtained.

We can see from Table 2 the sampling time is irregular, because we get no measurement data from 11.5s to 11.7s and from 11.8s to 12.0s. Moreover, only one measurement data got at most times because of the low detection rate area. We know the measurement got by RFID is the distance, so it is impossible to get the accurate target location with one measurement by the geometric relation [5,6]. While in this paper, we use the dynamic model of target to estimate the trajectory when only few measurements can be got.

Table 1. The Coordinate Point of RFID Readers

No.	1	2	3	4	5	6	7	8	9	10
Horizontal	22.46	13.94	25.92	43.66	48.27	9.56	11.41	52.41	80.76	68.77
Vertical	28.80	60.96	83.47	77.63	50.44	37.87	9.79	7.74	16.22	54.53
No.	11	12	13	14	15	16	17	18	19	
Horizontal	65.092	74.77	87.90	92.28	91.82	61.17	34.678	5.64	95.05	
Vertical	78.51	94.59	83.77	59.50	39.03	27.63	60.67	95.17	7.456	

Table 2. Measurements Get by RFID Readers System

sampling time / readers	11.1	11.2	11.3	11.4	11.5	11.7	11.8	12.0	12.1
1	\	\	\	\	\	\	\	\	\
2	\	\	\	\	\	\	\	\	\
3	\	\	\	\	\	\	\	\	27.629
4	\	20.502	\	\	\	\	18.050	20.269	\
5	\	\	\	\	\	\	\	\	\
6	\	\	\	\	\	\	\	\	\
7	\	\	\	\	\	\	\	\	\
8	\	\	\	\	\	\	\	\	\
9	\	\	\	\	\	\	\	\	\
10	\	\	\	\	\	\	\	\	\
11	17.524	\	\	21.693	\	\	\	\	23.469
12	\	20.297	25.370	\	23.228	\	\	\	27.779
13	\	\	\	\	\	\	\	\	\
14	\	\	\	\	\	\	\	\	\
15	\	\	\	\	\	\	\	\	\
16	\	\	\	\	\	\	\	\	\
17	\	\	\	\	\	37.689	\	\	\
18	\	\	\	\	\	\	\	\	\
19	\	\	\	\	\	\	\	\	\

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The EKF and UKF-based methods are used to estimate the trajectory in Figure 3. We get the estimation of trajectory with estimation covariance 43.7320 in the horizontal axis and 30.1378 in the vertical axis by UKF, shown in Figure 4. The estimation trajectories and errors of horizontal and longitudinal axis are shown in Figure 5 and Figure 6, respectively.

We can see the estimation obtained by variable number of readers is smooth without abrupt change, even when the number of readers has undergone great changes. Moreover in the low detection rate area, the approximately movement direction of the target can be estimated, and once enough measurements are obtained, the estimation error reduces rapidly.

Figure 7 - Figure 9 give the estimation results of the EKF-based method and the estimation covariance is 49.2714 in the horizontal axis and 38.5249 in the vertical axis. Comparing with UKF, we notice that the total estimation covariance of EKF is larger, while the estimation does not get the especial worse significantly at low detection rate area.

The reason is that the nonlinear measurement model has been linearized in EKF estimation method, so the distance measurement mode didn't affect the estimation. But because of the measurement model errors caused by linearized mechanism, the estimation performance decreased totally. Therefore the estimation performance of the EKF is worse than UKF in the RFID indoor tracking system.

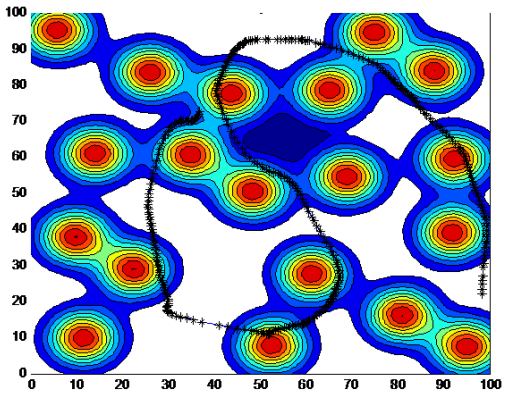

Figure 3. The Measurement Space of RFID Readers and the Reference Trajectory

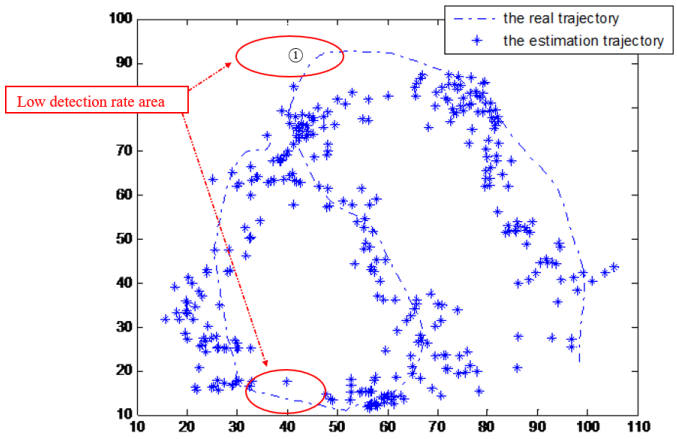

Figure 4. The Real Trajectory and the Estimation Trajectory by UKF

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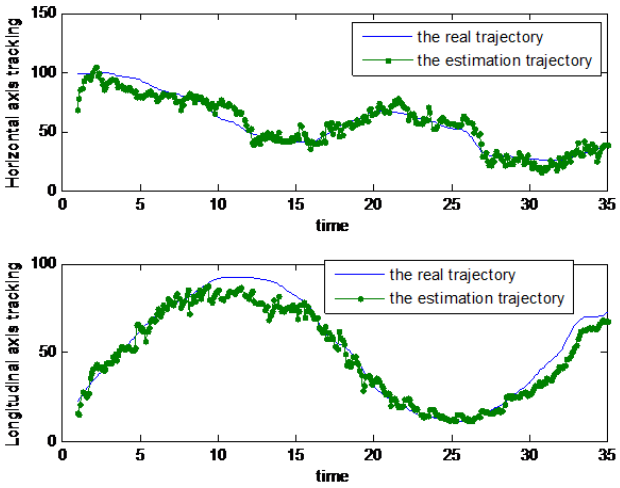

Figure 5. The Estimations of Horizontal and Longitudinal Axis by UKF

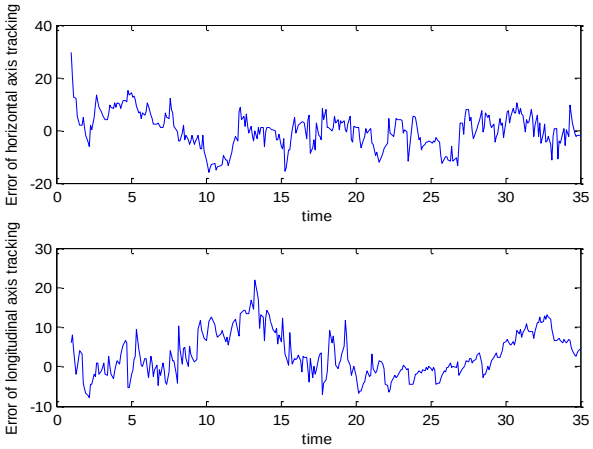

Figure 6. The Error of Tracking by UKF

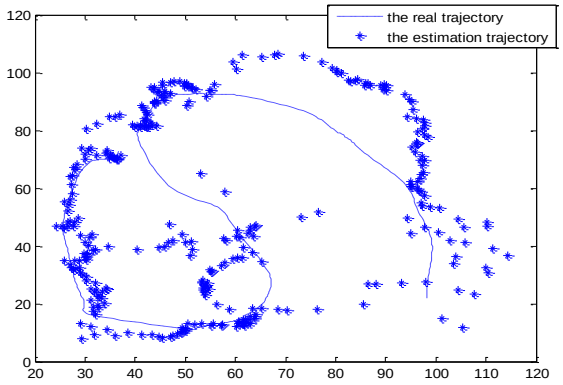

Figure 7. The Real Trajectory and the Estimation Trajectory by EKF

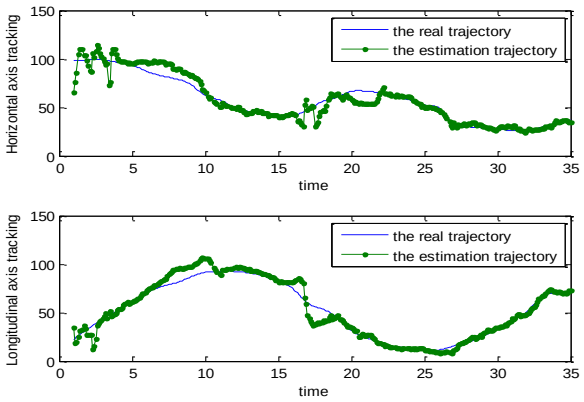

Figure 8. The Estimations of Horizontal and Longitudinal Axis by EKF

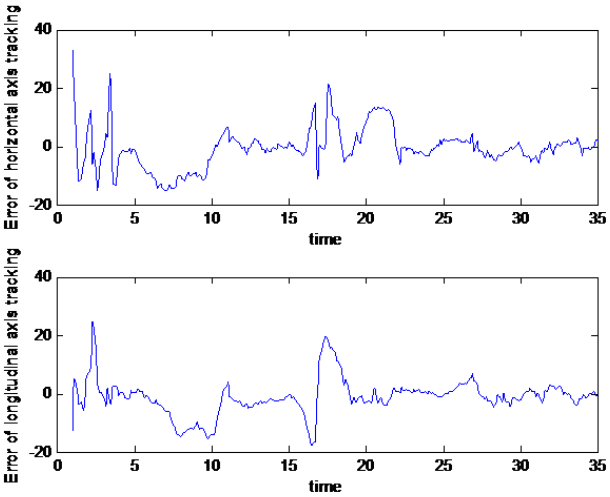

Figure 9. The Error of Tracking by EKF

6. Conclusions

It is necessary to consider the maneuvering target in the RFID tracking system. When the tag is within the RFID measurement range, the distance between the tag and readers can be extracted from RSSI. Because of the characteristics of the measurement process in the indoor RFID tracking system, the distances obtained by RFID are multivariate, irregular sampled, uncertain and nonlinear.

This paper has analyzed the features of RFID measurement and given a RFID measurement model, then proposed the EKF and UKF-based fusion estimation algorithms. The simulation results show that the UKF-based method developed here can provide better estimation performance and it will still work well even when the target steps into the low detection rate area.

However, the developed algorithm is only with serial processing mode, which means the modeling and estimating processing is processed serially. Our future work on developing the parallel algorithm will attempt to improve this, which is able to calculate the dynamics parameters and estimated trajectories of the target simultaneously in parallel.

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References

[1] S. Srinivasan and H. Ranganathan, "RFID sensor network-based automation system for monitoring and tracking of sandalwood trees", International Journal of Computational Science and Engineering, vol. 8, no. 2, **(2013)**, pp. 154-161.
[2] S. Park and H. Lee, "Self-recognition of vehicle position using UHF passive RFID tags", IEEE Transactions on Industrial Electronics, vol. 60, no. 1, **(2013)**, pp. 226-234.
[3] A. Bekkali and M. Mitsuji "RFID indoor tracking system based on inter-tags distance measurements", Lecture Notes in Electrical Engineering, Wireless Technology: Applications, Management, and Security, vol. 44, no. 4, **(2009)**, pp. 41-62.
[4] S.S. Saab and Z.S. Nakad, "A standalone RFID indoor positioning system using passive tags," IEEE Transactions on Industrial ElectronicS, vol. 58, no. 5, **(2011)**, pp. 1691-1670.
[5] R.A. Wasif, G.T. Kim and D. Kaharudin, "Tracking via square grid of RFID reader positioning and diffusion algorithm", Wireless Personal Communications. vol. 61, no. 1, **(2011)**, pp.227-250.
[6] J. Wang, L. Zongwei and E.C. Wong, "RFID-enabled tracking in flexible assembly line", International Journal of Advanced Manufacturing Technology, vol. 46, no. 1, **(2010)**, pp. 351-360.
[7] H.H. Zhang, M.V. Basin and M. Skliar, "Ito-Volterra optimal state estimation with continuous, multirate, randomly sampled, and delayed measurements", IEEE Transactions on Automatic Control, vol. 52, no. 3, **(2007)**, pp. 401-416.
[8] X.B. Jin, J.J. Du and J. Bao, "Target tracking of linear-time-invariant system under irregular sampling", International Journal of Advanced Robotic Systems, vol. 9, no. 9, (**2012**), pp. 1-12.
[9] X.B. Jin, J.J. Du and J. Bao, "Maneuvering target tracking by adaptive statistics model", Journal of China Universities of Posts and Telecommunications, vol. 20, no.1, **(2013)**, pp. 108-114.
[10] F. Gustafsson and G. Hendeby, "Some Relations Between Extended and Unscented Kalman Filters", IEEE Transactions on Signal Processing, vol. 60, no. 2, **(2012)**, pp. 545-555.
[11] J. Li, "An unscented Kalman smoother for volatility extraction: Evidence from stock prices and options", Computational Statistics and Data Analysis, vol. 58, no. 1, **(2013)**, pp.15-26.
[12] S.J. Vol and J.K. Uhlmann, "Unscented filtering and nonlinear estimation", Proc. IEEE. vol. 92, no. 3, **(2004)**, pp.401-422.
[13] M. Karimi, M. Bozorg and A.R. Khayatian, "A comparison of DVL/INS fusion by UKF and EKF to localize an autonomous underwater vehicle", First RSI/ISM International Conference on Robotics and Mechatronics (ICRoM), **(2013)**, pp. 62-67.
[14] J. Zhou and J. Shi, "A comprehensive multi-factor analysis on RFID localization capability", Advanced Engineering Informatics, vol. 25, no. 1, **(2011)**, pp. 32-40.

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