Performance Analysis of Nonlinear Filters in Indoor Human Localization Based on Wireless Sensor Networks

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Abstract

Indoor localization systems based on wireless sensor networks have been used for tracking the locations of human, robots, and equipment in diverse field of industry. To reduce bad effects of noises in indoor environments, many localization systems adopt filters. By using filters, we can suppress measurement noises and obtain accurate localization results. In recent years, localization systems require the ability of real-time processing as well as the noise suppression ability. Thus, fast computation speed is required for filters. In this paper, we investigate the performances of the three nonlinear filters, such as the extended Kalman filter, unscented Kalman filter, and particle filter, in a human localization problem. We present simulation results and performance analysis of three nonlinear filters in terms of localization accuracy and computation speed.

***Keywords**: Indoor localization, human localization, wireless sensor network, nonlinear filters.*

1. Introduction

Real-time locating systems (RTLS) are a type of localization systems that can track the location of objects in real-time [1]. The RTLS have been used for positioning human, robots, and equipment in indoor environments, and they have attracted the attention of engineers and users in many fields of industry including logistics, robotics, and wireless communications [2]. In recent years, the RTLS have been used for tracking the location of human in factories, hospitals, and construction sites [3, 4].

RTLS technology is based on wireless sensor networks, which consist of tags attached to moving objects and other tags positioned at fixed reference points. To compute the position of moving tags, the RTLS use various types of measurements, such as time-of-arrival (TOA) [5], time-difference-of-arrival (TDOA) [6], and angle-of-arrival (AOA) [7]. Wireless signals are often corrupted by noises, which degrades the positioning accuracy. Thus, the RTLS utilize filters to improve the positioning accuracy.

The Kalman filter (KF) [8] is the most renowned filter that estimates unknown variables by using noisy measurements. Since the system models are given by linear state-space models in many cases, nonlinear KFs, such as the extended Kalman filter (EKF) [9] and the unscented Kalman filter (UKF) [10], are more often used than the KF. In recent years, the particle filter (PF) [11] has been popularly used for localization systems. The PF can solve global localization problems in which initial positions of objects are not given [12]. The KFs can solve only local localization (i.e., tracking) problems in which initial positions are given. However, the PF has the disadvantage that the real-time processing is difficult due to the large computational burden [13].

In human localization problems, information on the motion of a moving person is uncertain, which means that the speed and course of a person can be changed in a random manner. Thus, the random-walk motion model is commonly used for human localization problems [1–4, 14]. The random walk motion model is a linear model. In contrast, the measurement model in the human localization is given by nonlinear model. In localization problems given by highly nonlinear models, the PF usually exhibits better performance than the nonlinear KFs [12–14]. However, the human localization problem includes linear motion model, and its nonlinearity is low. At this point, we can wonder that which filter performs best in the human localization problem with unknown initial positions. This paper answers to this question.

2. Indoor human localization scheme

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In this section, we explain indoor human localization scheme. To this end, we assume a human localization problem, which can be described as follows:

- A person walks in an indoor environment.
- The indoor space is square shape measuring $20m \times 20m$.
- Four receivers are installed at fixed positions, $(0,0), (0,20), (20,0)$, and $(20,20)$.
- A transmitter is attached to the person.
- The receivers and the transmitter organize a WSN, which produces TDOA measurements.
- The localization processor produces estimated positions of the person by using filters and the TDOA measurements.

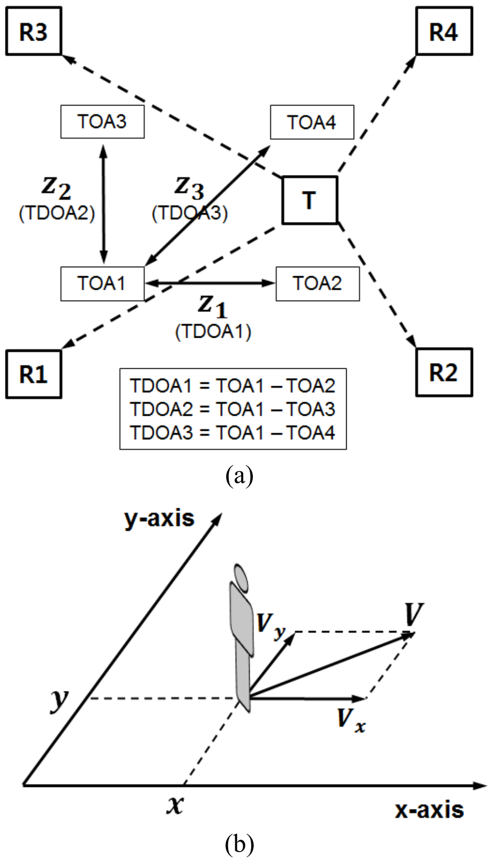


Figure 1. Human localization scheme: (a) TDOA measurements and (b) 2D geometry of human motion

Figure 1(a) illustrates the WSN and the TDOA measurements. In this figure, 'R1', 'R2', 'R3', and 'R4' indicate the four receivers. 'T' is the transmitter attached to the person. The TOA is the traveling time of a wireless signal between the transmitter and a receiver. From the four receivers, we can obtain four TDOA measurements, which are denoted by 'TOA1', 'TOA2', 'TOA3', and 'TOA4'. The TDOA measurement is the difference between the TOA measurements. From the four TOA measurements, we can obtain three TDOA measurements. Figure 1(b) illustrates 2D geometry of human motion. The motion of a person is represented by using four variables: 2D coordinates, (x, y) and speeds along the x and y axes, (V_x, V_y).

In order to use filters, a state-space model that describes the motion and the measurement of a system is required. The TDOA measurement can be represented in a state-space form as follows [6]:

$$\mathbf{z}_k = \begin{bmatrix} z_{1,k} \\ z_{2,k} \\ z_{3,k} \end{bmatrix} = \frac{1}{c} \begin{bmatrix} d_{1,k} - d_{2,k} \\ d_{1,k} - d_{3,k} \\ d_{1,k} - d_{3,k} \end{bmatrix} + \mathbf{v}_k, \qquad (1)$$
$$d_{i,k} = \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2}, \ (i = 1,2,3,4),$$

where $\mathbf{z}_k$ denotes the measurement vector at time k, $z_{1,k}$, $z_{2,k}$, and $z_{3,k}$ are the TDOA measurements, c is the speed of light, $d_{i,k}$ denote the distances between the transmitter and i-th receivers, and $\mathbf{v}_k$ is the measurement noise vector. In addition, (x_k, y_k) is the coordinate of the transmitter at time k, and (x_i, y_i) are the positions of four receivers. We assume that the measurement noise, $\mathbf{v}_k$, is a zero-mean white Gaussian noise with the covariance, $\mathbf{R}_k$.
Human motion can be described by using random walk model, which is represented as follows [1,14]:

$$\mathbf{x}_k = \begin{bmatrix} x_k \\ y_k \\ V_{x,k} \\ V_{y,k} \end{bmatrix} = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_{k-1} \\ y_{k-1} \\ V_{x,k-1} \\ V_{y,k-1} \end{bmatrix} + \mathbf{w}_k, \qquad (2)$$

where $\mathbf{x}_k$ denotes the state vector at time k, T is the sampling time, and $\mathbf{w}_k$ is the process noise vector. The process noise is assumed to be a zero-mean white Gaussian noise with the covariance, $\mathbf{Q}_k$.

Given the state-space models (1) and (2), we can estimate positions of the person by using nonlinear filters. In this paper, we consider three nonlinear filters including the EKF, UKF, and PF. These three filters are well-known, and their algorithms and equations can be easily found in many literatures. Thus, in this paper, we do not present the algorithms of three nonlinear filters.

3. Simulation results

In this section, we examine the EKF, UKF, and PF in the indoor human localization problem. We assume the global localization problem. Because the initial position of the person is unknown, we set the initial state estimate for the EKF and the UKF as follows. The first and second states, the x-y positions, are initially set as $(10m, 10m)$, which is the center position of the square-shaped indoor space. The third and fourth states, the velocities along the x-y axes, are initially set as $(0.11m/s, 0.11m/s)$ considering walking speed of human. The PF can deal with the global localization problem by generating random particles to be uniformly distributed in the state space. The number of particles is set as $N = 500$. The measurement noise covariance is taken as $\mathbf{R}_k = 0.5\mathbf{I}_3$, where $\mathbf{I}_3$ is the 3×3 indentity matrix. The process noise covariance, $\mathbf{Q}_k$, is uncertain when using the random walk motion model. Thus, we try three different values of $\mathbf{Q}_k$, such as $\mathbf{I}_4$, $0.1^2\mathbf{I}_4$, and $0.01^2\mathbf{I}_4$, where $\mathbf{I}_4$ is the 4×4 identity matrix. Using the parameter setting above, we apply the three nonlinear filters (i.e., the EKF, UKF, and PF) to the human localization.

Firstly, we tried taking the process noise covariance as $\mathbf{Q}_k = \mathbf{I}_4$. Figure 2 shows the simulation results of human localization when $\mathbf{Q}_k = \mathbf{I}_4$. We see that all the three nonlinear filters work well without failures, and their localization errors are similar. In this simulation, the ALEs of the EKF, UKF, and PF are 0.3291, 0.3330, and 0.3395, respectively.

Next, we tried decreasing the process noise covariance. We set $\mathbf{Q}_k = 0.1^2\mathbf{I}_4$. Figure 3 shows the localization results when $\mathbf{Q}_k = 0.1^2\mathbf{I}_4$. In this case, the three nonlinear filters exhibit better performances than those in the case of $\mathbf{Q}_k = \mathbf{I}_4$. In this simulation, the ALE of the EKF, UKF, and PF are 0.2781, 0.2854, and 0.2747, respectively. By decreasing $\mathbf{Q}_k$, we achieved the improved localization accuracy. This is because the uncertainty in the motion model is reduced by decreasing $\mathbf{Q}_k$. In the random walk motion model, the process noise covariance means amount of movement. The value of $\mathbf{Q}_k$ fits to the amount of real movement, which means the random walk motion model accurately represent the real motion. The simulation results indicate that the random-walk motion model using $\mathbf{Q}_k = 0.1^2\mathbf{I}_4$ represents the real motion of the person more accurately compared with that using $\mathbf{Q}_k = \mathbf{I}_4$. Decreasing $\mathbf{Q}_k$ results in improvements of localization accuracy in terms of the ALE, but it degrades the tracking (or convergence) speed of filters in the early period. We can observe that the localization errors of the three filters are relatively large in Figure 3 compared with those in Figure 2.

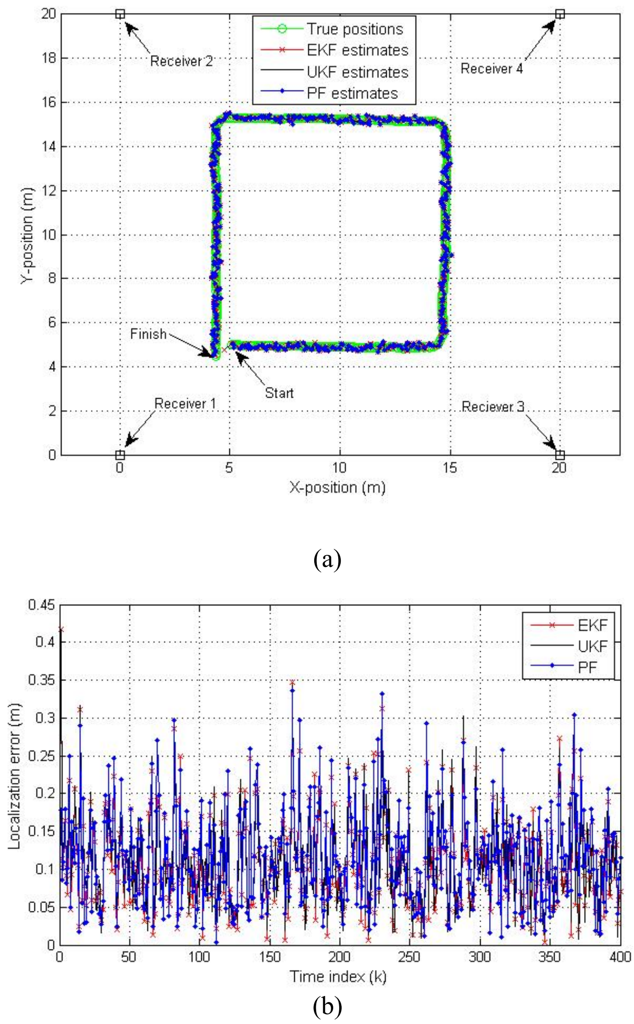
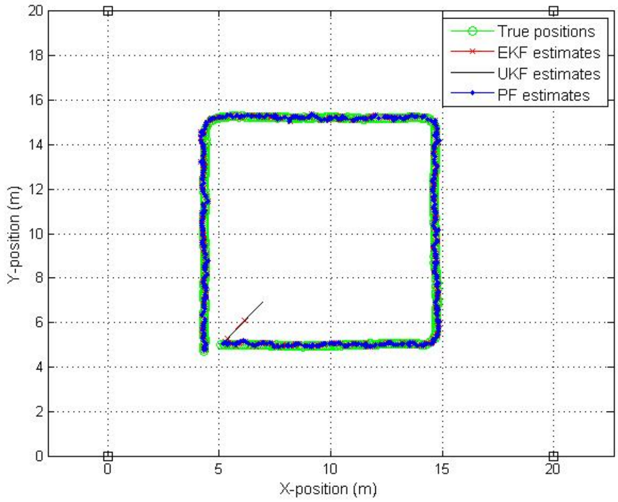
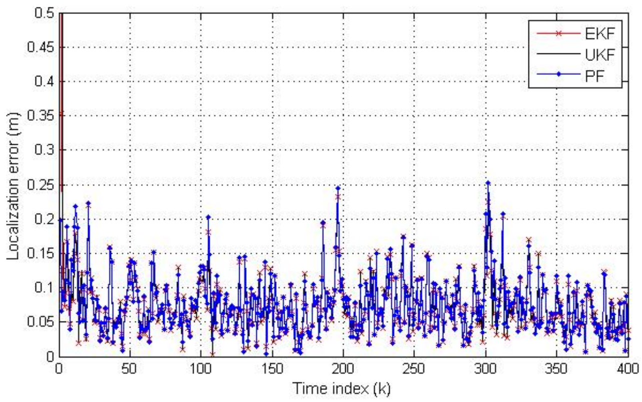


Figure 2. Localization results when $\mathbf{Q}_k = \mathbf{I}_4$: (a) estimated positions by nonlinear filters, and (b) localization errors

Lastly, we further decreased the process noise covariance. We set $\mathbf{Q}_k = 0.01^2\mathbf{I}_4$. Figure 4 shows the localization results when $\mathbf{Q}_k = 0.01^2\mathbf{I}_4$. In this figure, we see that all three filters exhibit poor performances compared with the cases of $\mathbf{Q}_k = 0.1^2\mathbf{I}_4$ and $\mathbf{Q}_k = \mathbf{I}_4$. In particular, the PF completely fail to track the positions of the person, and it diverges. The nonlinear KFs (i.e., the EKF and the UKF) exhibit poor performances when the person changes the course at the time points, $k = 100, 200, 300$. This is because the value of was too small. A small means that the amount of movement is small. However, the person moved dramatically at the corners. Thus, the random walk model using did not fit to the real motion. In addition, the small caused sample impoverishment of the PF. Thus, the PF diverged.



(a)



(b)

Figure 3. Localization results when $\mathbf{Q}_k = 0.1^2\mathbf{I}_4$: (a) estimated positions by nonlinear filters, and (b) localization errors

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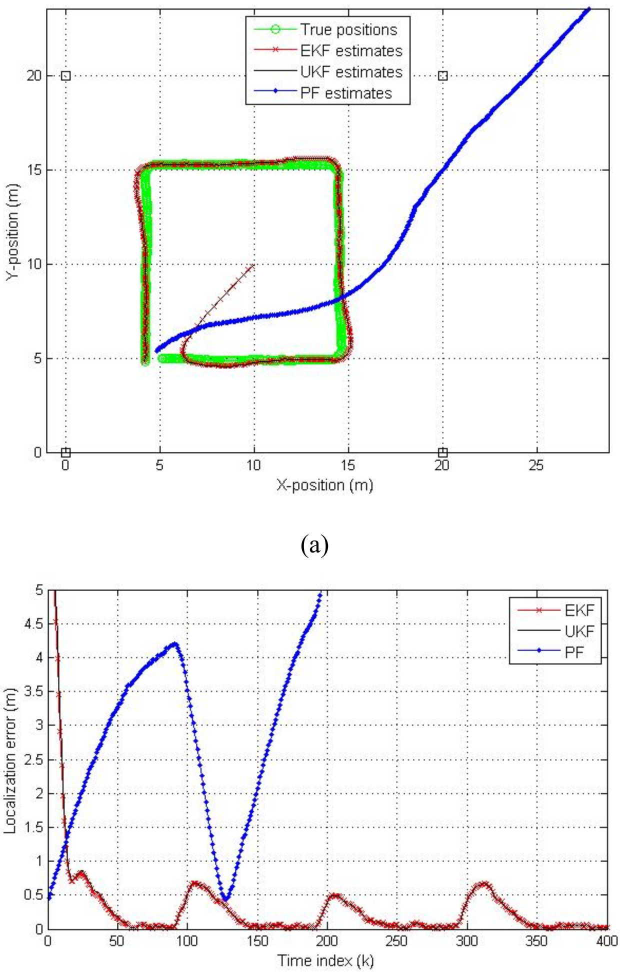

(a)

(b)

Figure 4. Localization results when $\mathbf{Q}_k = 0.01^2\mathbf{I}_4$: (a) estimated positions by nonlinear filters, and (b) localization errors

4. Conclusion

In this paper, we investigated the performances of the EKF, UKF, and PF in the human localization based on WSNs. In the human localization problem represented by a linear random-walk motion model and nonlinear measurement model, the EKF, UKF, and PF exhibited similar performances in terms of localization accuracy. However, the EKF's operation time was much smaller than the UKF and the PF. In addition, the EKF showed superior reliability compared with the PF. In recent years, the RTLS requires real-time processing. Thus, fast computation speed of the EKF can be a strong advantage. Therefore, we can conclude that the EKF is the best filter among the three filters in the human localization problem.

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