Journal of Industrial Information Technology and Application Vol.2 No.4
ISSN(Online) : 2586-0852

Performance Analysis of the Ranging-based Localization Methods and CKF-based Performance Enhancement

Seong Yun Cho*
School of Robotics Engineering, Kyungil University, Gyeongsan, Korea

Abstract. In this paper, the performance of the wireless localization methods using the ranging measurements is analyzed. The ranging measurements in indoor environments may include non-Gaussian errors caused by the NLOS (Non-Line-of-Sight) error or calibration error. The ranging errors may be always positive because it is caused by the additional propagation path or the additional circuit path for signals. The localization performance depends on the measurement accuracy and localization methods. When the ranging measurements contain the non-Gaussian errors, in this paper, the localization performance is analyzed according to the localization methods including the model-free methods such as ILS (Iterative Least Squares), DS (direct Solution), and DSRM (Difference of Squared Ranging Measurements) methods, and model-based Kalman filtering such as CKF (Cubature Kalman Filter). The analysis results show that the DSRM method has better performance than the other model-free methods when the ranging measurements have positive non-Gaussian errors. Also, it shows that the CKF-based filtering has better performance than the model-free methods.

Keywords; model-free localization; model-based Kalman filtering; DSRM; CKF

1. Introduction

When the location of pedestrians, robots, objects, pets, etc is estimated in indoor/outdoor environments, several wireless localization methods have been used widely. In the wireless localization methods, ranging-based, angle-of-arrival-based, and received signal strength-based methods are included. Among these methods, the ranging-based method has been most used due to its performance. To obtain the accurate ranging measurements in indoor environments, impulse radio-ultra wideband (IR-UWB), chirp spread spectrum, ultrasonic wave, etc can be used.

---

* Corresponding author: sycho@kiu.kr
Received: 2017.10.13; Accepted: 2017.11.21; Published: 2018.12.30

After the localization system is implemented uisng a particular wireless infra mentioned above, calibration has to be carried out. If the calibration is done properly, the ranging measurement can be denoted as following ranging equation.

$$\tilde{r}_j = \sqrt{(x_j - x_M)^2 + (y_j - y_M)^2} + w_j \quad (1)$$

where $\tilde{r}_j$ is the ranging measurement between an anchor node (AN) j and a mobile node (MN), w_j is the white Gaussian noise, $[x_j \quad y_j]^T$ and $[x_M \quad y_M]^T$ are the locations of the AN j and MN, respectively.

The localization problem is to estimate $[x_M \quad y_M]^T$ using the several ranging measurements. If it is difficult to calibrate the localization system, however, the ranging error may occur due to the additional circult path between the antenna and RF chip. In spite of the proper calibration, also, the ranging errors occur due to the unpredictable NLOS error and multipath signals depending on the surrounding environments. Therefore, the actual ranging measurement eqation can be denoted as [1]

$$\tilde{r}_j = \sqrt{(x_j - x_M)^2 + (y_j - y_M)^2} + b_j + w_j \quad (2)$$

where b_j is the non-Gaussian error that is always positive due to the additional circuit path or the additional signal propagation path.

The ranging errors cause localization errors and the error characteristics also depend on the localization methods. In this paper, the characteristics of the localization errors are analyzed based on that of the localization methods that can be categorized into two groups: model-free methods and model-based Kalman filtering. The model-free methods can also be divided into iterative method such as ILS method and closed-from solutions such as DS and DSRM methods [2, 3]. There are several types of Kalman filters for the wireless localization: extended Kalman filter, unscented Kalman filter, CKF [4, 5], etc. In this paper, CKF is used for comparision with the model-free localization methods. The Performance of the localization methods is analyzed based on the simulation results. The results show that the positive measurement errors cause additional localization errors. The errors in the DSRM method are somewhat diminished due to the mechanism of the localization equation. And the CKF can estimate the location of the MN more accurately than other model-free methods even in the case that measurements have non-Gaussian errors.

2. Wireless Localization Methods

The wireless localization methods dealt in this paper include ILS, DS, and DSRM methods and CKF-based filtering. The information of the ILS, DS, and DSRM methods can be obtained from [3].

The measurement equation (1) is nonlinear. So, nonlinear Kalman filters such as EKF, UKF, CKF, etc can be used in the wireless localization. For the system model of the Kalman filter, CV (Constant Velocity) model or CA (Constant Acceleration) model can be selected in the light of the dynamics of the MN. In this paper, the localization filter is designed using the CKF with CV (Constant Velocity) model.

CKF is the cubature rule-based approximate Bayesian filter, and the performance of the 3[rd] degree CKF is similar to that of UKF. If the CV model is defined in the 2-D coordinate frame, $2N$ cubature points (ξ_i, $i = 1, 2, \cdots, 2N$, N is the system dimension, that is 4) are generated. The cubature points are time-propagated as follows [4]:

$$\begin{aligned}
\hat{\xi}^-_{i,k+1}(1) &= \hat{\xi}_{i,k}(3) \cdot dt \\
\hat{\xi}^-_{i,k+1}(2) &= \hat{\xi}_{i,k}(4) \cdot dt \\
\hat{\xi}^-_{i,k+1}(3) &= \hat{\xi}_{i,k}(3) \\
\hat{\xi}^-_{i,k+1}(4) &= \hat{\xi}_{i,k}(4)
\end{aligned} \tag{3}$$

where $i = 1, 2, \cdots, 2N$, dt is the time interval of the measurement acquisition, and the indexes 1, 2, 3, and 4 denote location and velocity of x and y axes, respectively.

The time-propagated state vector and covariance matrix are calculated as follows:

$$\begin{aligned}
\hat{x}^-_k &= \sum_{i=1}^{2N} \frac{1}{2N} \hat{\xi}^-_{i,k} \\
P^-_k &= \sum_{i=1}^{2N} \frac{1}{2N} (\hat{\xi}^-_{i,k} - \hat{x}^-_k)(\hat{\xi}^-_{i,k} - \hat{x}^-_k)^T + Q
\end{aligned} \tag{4}$$

where Q is the covariance of the process noise.

Then, measurement-update is performed as

$$\begin{aligned}
\hat{x}_k &= \hat{x}^-_k + K_k(\tilde{y}_k - \hat{z}^-_k) \\
P_k &= P^-_k - K_k P^T_{xz}
\end{aligned} \tag{5}$$

where $\hat{z}_k^- = \sum_{i=1}^{2N} \frac{1}{2N} [\hat{r}_{1,i,k}^- \quad \cdots \quad \hat{r}_{n,i,k}^-]^T$, $\hat{r}_{j,i,k}^- = \sqrt{(x_j - \hat{\xi}_{i,k}^-(1))^2 + (y_j - \hat{\xi}_{i,k}^-(2))^2}$, and other parameters including the Kalman gain K_k can be obtained in [4].

New cubature points are generated as

$$\hat{\xi}_{ik} = S_k \sqrt{N}[1]_i + \hat{x}_k \tag{6}$$

where S_k can be calculated using the Cholesky factorization as $P_k = S_k S_k^T$.

The Kalman filtering estimates the state variables using the system equations as well as the measurements. That is, the model-based localization filtering can yield more accurate locations solutions than the model-free localization methods such as ILS, DS, and DSRM methods. So, the solution of the Kalman filtering can have good features of a low-pass filter. Also, the effect of the non-Gaussian measurement errors can be diminished.

3. Simulation Analysis

To analyze the performance of the several model-free and model-based localization methods, some simulations are performed. In these simulations, it is assumed that the wireless infra used for localization is the IR-UWB, so the noise of the ranging measurement is set to $N(0,\ 0.3^2)$. In addition, the non-Gaussian error denoted in (2) is defined as $|N(0,\ 1.5^2)|$. The size of the test area is set to $20m$ x $15m$ and four ANs are installed in the area.

Fig. 1 shows the comparative results of the localization methods. In this figure, four red circles in the corners of the test area denote the ANs. Based on the error statistics, 1000 ranging measurements are generated each in the 24 fixed locations. The location of the MN is calculated using the individual localization method and, then, the location error is calculated.

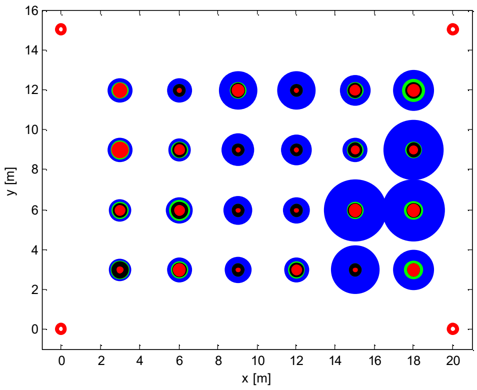

Fig 1. Comparative results of the localization methods

TABLE I. SUMMARY OF SIMULATION (1000 SAMPLES)

Localization Error [m]	ILS	DS	DSRM	CKF
Mean Value	1.248	2.559	1.071	0.723
Standard Deviation	0.794	1.035	0.609	0.274

In this figure, the sizes of the circles denote the comparative mean values of the location errors. The green-, blue-, black-, and red-colored circles denote the ILS, DS, DSRM methods, and CKF, respectively. The location errors are summarized in Table 1.

4. Conclusion

In this paper, several wireless localization methods using the ranging measurements are considered when the measurements include non-Gaussian errors as well as Gaussian noise. The measurement errors are considered as always positive. The localization methods analyzed in this paper are ILS, DS, and DSRM methods for model-free methods, and CKF for model-based Kalman filtering. First, the characteristics of each method are analyzed based on the expansion of the localization equations. Then, some simulations are carried out to verify the performance of the localization methods under the measurement error occurrence. The simulation results show that the relative location errors of the DSRM method compared with the DS, and ILS methods are 41.8%, and 85.8%, respectively. Also, the relative location errors of the CKF compared with the DS, ILS, and DSRM methods are 28.2%, 57.9%, and 67.5%, respectively.

Consequently, it can be concluded that the DSRM method can yield comparatively more accurate location solution among the model-free localization methods when the ranging measurements contain non-Gaussian errors with positive numbers. In addition, the CKF-based filtering can enhance the localization performance compared with the model-free methods.

Acknowledgment

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (NRF-2015R1D1A1A01059606).

References

[1] S. Y. Cho, "Adaptive wireless localization filter containing NLOS error mitigation function," Journal of Positioning, Navigation, and Timing, vol. 5, pp. 1–9, March 2016.

[2] I. Biton, M. Koifman, and I. Y. Bar-Itzhack, "Improved direct solution of the global positioning system equation," Journal of Guidance, Control, and Dynamics, vol. 21, pp. 45-49, 2016.

[3] S. Y. Cho, and B. D. Kim, "Linear closed-form solution for wireless localisation with ultra-wideband/chirp spread spectrum signals based on difference of squared range measurements," IET Wireless Sensor Systems, vol. 3, pp. 255-265, 2013.

[4] I. Arasaratnam, and S. Haykin, "Cubature Kalman filters," IEEE trans. Automatic Control, vol. 54, pp. 1254-1269, 2009.

[5] B. Jia, M. Xin, and Y. Cheng, "High-degree cubature Kalman filter," Automatica, vol. 49, pp. 510-518, 2013.