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Enhancing Localization of Mobile Robots in Distributed Sensor Environments for Reliable Proximity Service Applications

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ABSTRACT Mobile robots can effectively coordinate information among sensor nodes in a distributed physical proximity. Accurately locating the mobile robots in such a distributed scenario is an essential requirement, such that the mobile robots can be instructed to coordinate with the appropriate sensor nodes. Packet loss is one of the prevailing issues on such wireless sensor network-based mobile robot localization applications. The packet loss might result from node failure, data transmission delay, and communication channel instability, which could significantly affect the transmission quality of the wireless signals. Such issues affect the localization accuracy of the mobile robot applications to an overwhelming margin, causing localization failures. To this end, this paper proposes an improved Unscented Kalman Filter-based localization algorithm to reduce the impacts of packet loss in the localization process. Rather than ignoring the missing measurements caused by packet loss, the proposed algorithm exploits the calculated measurement errors to estimate and compensate for the missing measurements. Some simulation experiments are conducted by subjecting the proposed algorithm with various packet loss rates, to evaluate its localization accuracy. The simulations demonstrate that the average localization error of the robot is 0.39 m when the packet loss rate is less than 90%, and the average running time of each iteration is 0.295 ms. The achieved results show that the proposed algorithm exhibits significant tolerance to packet loss while locating mobile robots in real-time, to achieve reliable localization accuracy and outperforms the existing UKF algorithm.

INDEX TERMS Mobile robot localization, unscented Kalman filter, wireless sensor networks, packet loss, measurements compensation.

I. INTRODUCTION

Research on mobile robots and their applications have gained considerable attention in recent years [1]–[4]. Recent developments in wireless sensor networks have led to an increased deployment of proximity sensors in mobile robots, which finds a wide range of sensing applications. Mobile robots can effectively coordinate for collecting, processing and transmitting information among sensors distributed in physical proximity. The mobile robot localization problem in physical proximity is one of the general issue demanding a concrete solution, as it plays an essential role in driving the autonomous behaviors of the mobile robots [5]–[7]. The localization plays an essential role in the autonomous behavior of mobile robots because when a robot navigates along a given route map, it must accurately identify its location, to be successful in completing a set of given tasks [8]. According to the localization environment, the mobile robot localization problem can be divided into two categories: outdoor localization and indoor localization. The outdoor localization usually utilizes the Global Positioning System (GPS) to track the mobile robot. However, GPS cannot

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be applied to indoor localization due to the influence of obstacles. Therefore, the indoor localization usually utilizes a wireless sensor network-based localization system [9]–[13], where the system can exploit various wireless measurements such as, TOA (time of arrival), TDOA (time difference of arrival), AOA (Angle of Arrival) and RSS (received signal strength) [14]–[17], for navigation. Such wireless measurements include information regarding the distance between the sensor and the mobile tag, which usually comprise measurement noise. Finally, the localization system calculates the target location according to the distance information obtained by various participating sensors. To improve the localization accuracy and to reduce the effect of noise, state estimators are commonly used in the localization system. In the context of mobile robot localization problem, the measurement model is commonly represented by a nonlinear equation. Therefore, nonlinear state estimators such as extended Kalman filter (EKF), particle filter (PF) and Unscented Kalman Filter (UKF) have been commonly used in the existing state-of-the-art [18]–[20].

Among the estimators as mentioned above, UKF tends to be more attractive as it characterizes relatively lower computation overheads with higher estimation accuracy [21]. At present, UKF based algorithms have replaced the traditionally used EKF algorithms for nonlinear state estimation, and the former is being widely deployed in the contexts of navigation, signal processing, target tracking and so on. UKF works by approximating the posterior probability density function of the nonlinear system state using the unscented transform (UT) [22]. Therefore, UFK algorithm has the following two advantages to that of EKF [23]–[25]. Firstly, the UKF algorithm avoids the need for calculating the Jacobian matrix, thereby reducing the computational intensity. Secondly, the UKF algorithm can achieve better accuracy of estimation when dealing with a high degree of nonlinear systems. Also, the UKF algorithm adopts a deterministic sampling strategy to approximate the nonlinear distribution instead of randomly sampling the particles. Thus, the number of sampled particle points (commonly called Sigma points) is usually very small. Although the estimation accuracy of the UKF algorithm is usually lower than the particle filter, the UKF algorithm avoids the particle impoverishment [26], [27]. For indoor localization problem, UKF algorithm not only ensures accuracy and stability of the localization algorithm but also meets the real-time requirements of mobile robot localization. Hence the UKF algorithm is one of the most suitable state estimation methods for mobile robot localization problem.

Although the UKF algorithm can effectively resolve the issues of measurement noise and the nonlinear measurement equation in mobile robot localization applications, problems incurred during the wireless signal transmission due to obstacles, equipment failure, signal interference and packet loss, cannot be undermined [28]–[31]. Such transmission issues can significantly impact the reliability of measurements obtained during the localization process of mobile robots. In particular, the impacts of packet loss on the localization system is one of the most critical issues to be noted [32]–[36]. During the process of localization, packet loss can be caused by several factors including the failure of the sensor node, delay in the information transmission and the instability of the communication channel. The worse impact can occur when packets containing vital distance information are lost, which may then significantly affect the localization accuracy to fail the entire localization process. Therefore, developing a localization algorithm that can resist and reduce the impacts of packet loss becomes imperative.

A wide range of research works has addressed the issue of packet loss in the context of wireless transmission applications to date. Justus and Sekar [32] developed latency-aware packet scheduling schemes for wireless sensor networks to avoid the energy costs incurred by unnecessary latency resulting from the retransmission of lost packets. Cirstea *et al.* [33] developed a scheme to identify the best communication path in order to avoid the energy cost incurred by packet loss in wireless sensor networks. This research work only focuses on reducing the energy consumption of wireless sensor networks comprising a large number of sensors. Moreover, this work did not consider improving the localization accuracy and avoiding localization failures. Hence, such optimization strategies are not well suitable for mobile robot localization.

Li *et al.* [34] proposed a novel RHE based scheme for addressing Bernoulli-type packet loss to achieve the consensus of accurate state estimation. Phung *et al.* [35] developed a state estimator based on an extended Kalman filter to solve the problem of localization by reducing the impacts of packet loss and random delay. Despite existing methods address reducing the impacts of packet loss on the accuracy of state estimation, their increased computational intensity does not meet the real-time requirements of robot localization applications. Ahmad and Namerikawa [36] proposed an EKF based algorithm by exploiting the intermittent measurements, which can effectively ignore the measurement updates during packet loss. However, for an indoor localization system with multiple sensors, ignoring the measurement updates will increase the boundary of uncertainty in the estimation accuracy, particularly when there is repeated packet loss.

To this end, this paper proposes a novel localization algorithm to eliminate the effects of packet loss in mobile robot localization applications, by developing an improved state estimator called measurements compensation-based Unscented Kalman Filter (MC-UKF). The core methodology behind the proposed approach is to determine an ‘‘approximate compensation error’’ that describes the correlation of measurements from the previous moment, based on which estimating the present measurement. This method means that the compensation error is used to update the compensation measurements in order to enable the UKF algorithm to achieve a better localization accuracy during packet loss. In order to evaluate the performance of the proposed algorithm, some simulations are performed in MATLAB. The achieved results show that the proposed algorithm conclusively exhibits highly stable performance and characterizes good localization accuracies for various packet loss rates in mobile robot localization applications.

The remainder of this paper is organized as follows. Section II defines the system model and problem formulation. Section III details the proposed MC-UKF algorithm. Section IV discusses the experiments and the obtained results, and Section V concludes this paper along with outlining our future research plans.

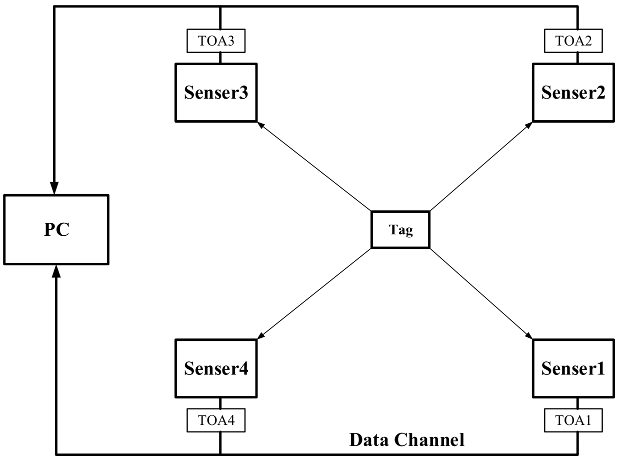

FIGURE 1. Localization system based on the wireless sensor network.

II. SYSTEM MODEL AND PROBLEM FORMULATION

In this paper, a time-of-arrival based indoor mobile robot localization system is modeled, built with four sensors, a tag, a wireless data transmission channel, and an upper monitor (i.e., PC), as shown in Fig.1. The tag is a signal transmitter that sends wireless signals composed of the signal transmission time and the identification information. The tag is attached to a mobile robot. The sensors are installed at fixed locations to receive wireless signals sent from the tag. Each sensor computes TOA measurements utilizing the local clock, which reflects the signal transmission time between the tag and the sensor.

After obtaining three TOA measurements, the localization of the mobile robot is achieved by the triangulation method [36]. As shown in Fig. 1, this paper considers the case of a mobile robot localization system with four sensors, where the sensors are positioned at fixed points at the following coordinates $(x_a^{(1)}, y_a^{(1)})$, $(x_a^{(2)}, y_a^{(2)})$, $(x_a^{(3)}, y_a^{(3)})$ and $(x_a^{(4)}, y_a^{(4)})$. The TOA measurements $z_{1,k}, z_{2,k}, z_{3,k}$ and $z_{4,k}$ are transmitted to the upper monitor using the wireless network. The upper monitor handles the measurements and calculates the localization of the mobile robot.

The motion model of the mobile robot can be described as a constant velocity (CV) model, constant turn (CT) model, constant acceleration (CA) model. In Fig.2, the CV model is used to describe the motion of the mobile robot [38], [39]. The state-space model of the mobile robot localization system can be written as:

$$x_k = F_k x_{k-1} + G_k \omega_k \tag{1}$$

$$z_k = h_k(x_k) + \upsilon_k \tag{2}$$

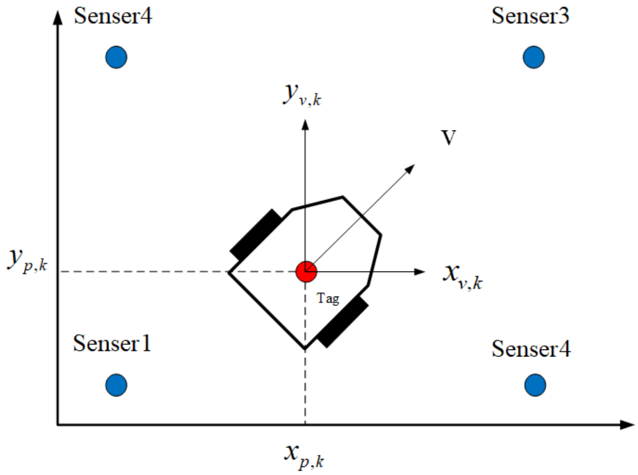

FIGURE 2. The motion model of the mobile robot.

where x_k is the state vector of the system.

$$x_k = \begin{bmatrix} x_{p,k} & y_{p,k} & x_{v,k} & y_{v,k} \end{bmatrix}^T \tag{3}$$

where $x_{p,k}$ and $y_{p,k}$ are the localization coordinates of the target at time k, $x_{v,k}$ and $y_{v,k}$ are the velocities of the mobile robot in the x-axis and y-axis, respectively, F_k is the state transition matrix of the system, F_k and G_k can then be written as

$$F_k = \begin{bmatrix} 1 & 0 & t_k & 0 \\ 0 & 1 & 0 & t_k \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad G_k = \begin{bmatrix} \frac{t_k^2}{2} & 0 \\ t_k & 0 \\ 0 & \frac{t_k^2}{2} \\ 0 & t_k \end{bmatrix} \tag{4}$$

where t_k is the sampling interval, ω_k is the system process noise, which is Gaussian white noise with mean equal to 0 and covariance matrix Q_k. ω_x and ω_y represent the noise acceleration of the target in the x-direction and the y-direction at time k respectively.

$z_k = [\, d_{1,k} \; d_{2,k} \; d_{3,k} \; d_{4,k} \,]^T$ is the distance between the mobile robot and the sensors respectively, where $d_{j,k} = cz_{j,k}$. The c is the signal transmission speed that is approximately equal to the speed of light. $h_k\,(x_k)$ is the systematic measurement matrix, which can be written as:

$$h_k(x_k) = [\, h_{1,k} \;\; h_{2,k} \;\; h_{3,k} \;\; h_{4,k} \,]^T \tag{5}$$

$$h_{j,k} = \sqrt{\left(x_{p,k} - x_a^{(j)}\right)^2 + \left(y_{p,k} - y_a^{(j)}\right)^2} \tag{6}$$

The υ_k is the measurement noise, which is written as.

$$\upsilon_k = \begin{bmatrix} \upsilon_{1,k} & \upsilon_{2,k} & \upsilon_{3,k} & \upsilon_{4,k} \end{bmatrix}^T \tag{7}$$

where $\upsilon_{j,k}$ is the respective measurement noise, which is Gaussian noise with mean equal to 0 and variance R_k and it is not related to the process noise ω_k.

Failure of a sensor node may result in data transmission delay or communication channel instability, and both lead the indoor localization system to experience packet loss. Packet loss causes one or more sensors to lose the measurements, which results in lower localization accuracy, and adversely affects the real-time localization efficiency, and may even cause a localization failure. Therefore, it is necessary to compensate for the missing measurements to ensure that the real-time operation of the localization algorithm is stable. When considering the packet loss, the measurement equation of the state-space model can be represented as follows.

$$z_k = \Xi_k h_k(x_k) + (I - \Xi_k) h_{k-1}(x_{k-1}) + \upsilon_k \tag{8}$$

$$\Xi_k = \begin{bmatrix} \xi_{1,k} & 0 & 0 & 0 \\ 0 & \xi_{2,k} & 0 & 0 \\ 0 & 0 & \xi_{3,k} & 0 \\ 0 & 0 & 0 & \xi_{4,k} \end{bmatrix} \tag{9}$$

where the Ξ_k indicates whether a given sensor receives the measurement data or not at time k. A value of $\xi_{j,k} = 1$ depicts that the i^{th} sensor did not lose the packets at time k. A value of $\xi_{j,k} = 0$ depicts that the i^{th} sensor is losing packets at time k. The packet loss rate at the i^{th} sensor can be represented as:

$$\Pr\left\{\alpha_{j,k} = 0\right\} = p_i \tag{10}$$

$$\Pr\left\{\alpha_{j,k} = 1\right\} = 1 - p_i \tag{11}$$

III. MEASUREMENTS COMPENSATION-BASED UNSCENTED KALMAN FILTER

A measurements compensation-based Unscented Kalman Filter (MC-UKF) algorithm is proposed in this section, which aims at eliminating the impacts of packet loss in a mobile robot localization process. The working process of the algorithm is detailed as follows.

A. UNSCENTED KALMAN FILTER INITIALIZATION

The initial state x_0 of the mobile robot and the initial error covariance matrix P_0 are set.

B. TIME UPDATE

Calculate the sigma points.

The primary sampling strategies of the sigma point include simple sampling, symmetrical sampling, and scaled symmetric sampling. In order to ensure a positive semi-definiteness of covariance and to solve the non-local effect problem of sampling, this paper adopts a scaled symmetric sampling strategy [40].

$$\begin{cases} \hat{x}_{k-1}^{(0)} = \hat{x}_{k-1|k-1} & \\ \hat{x}_{k-1}^{(i)} = \hat{x}_{k-1|k-1} + \tilde{x}^{(i)} & i = 1, \mathrm{L}, 2n \\ \tilde{x}^{(i)} = (\sqrt{(n+\lambda)P_{k-1|k-1}})_i & i = 1, \mathrm{L}, n \\ \tilde{x}^{(m+i)} = -(\sqrt{(n+\lambda)P_{k-1|k-1}})_i & i = 1, \mathrm{L}, n \end{cases} \tag{12}$$

Calculate the scale factor.

$$\lambda = \alpha^2 (n + \kappa) - n \tag{13}$$

Calculate the weighting factor of the sigma point.

$$\begin{cases} W_x^{(0)} = \dfrac{\lambda}{n+\lambda} \\ W_p^{(0)} = \dfrac{\lambda}{n+\lambda} + (1 + \alpha^2 - \beta) \\ W_x^{(i)} = W_p^{(i)} = \dfrac{1}{2(n+\kappa)} \quad i = 1, 2, L, 2n \end{cases} \tag{14}$$

where n is the system state dimension, $(\sqrt{(n+\lambda)P_{k-1|k-1}})_i$ is the i^{th} row of $(\sqrt{(n+\lambda)P_{k-1|k-1}})$, λ is the scale factor. In equation (13), κ is the scaling factor, it is a constant set to 0 or 3-n, which can be used to reduce the errors in the mean and covariance approximations. α is the distance from the sigma point to the prior state estimation $\hat{x}_{k|k-1}$, which is usually in the range of $10^{-4} \leq \alpha \leq 1$. Equation (14) is the calculation of the sigma point weight. $W_x^{(i)}$ is the weighted coefficient of the mean value of $\hat{x}_{k-1}^{(i)}$, $W_p^{(i)}$ is the weighted coefficient of the variance of $\hat{x}_{k-1}^{(i)}$. β is used to fuse the prior information of random variables. For Gaussian distributions, the value of β is usually set to 2.

Sigma points are spread through the process equations.

$$\hat{x}_k^{(i)} = F_k \hat{x}_{k-1}^{(i)} + G_k \omega_k \tag{15}$$

Calculate the priori state estimates.

$$\hat{x}_{k|k-1} = \sum_{i=0}^{2n} W_x^{(i)} \hat{x}_k^{(i)} \tag{16}$$

Calculate the covariance of the priori estimation error.

$$P_{k|k-1} = \sum_{i=0}^{2n} W_p^{(i)} (\hat{x}_k^{(i)} - \hat{x}_{k|k-1})(\hat{x}_k^{(i)} - \hat{x}_{k|k-1})^T + Q_{k-1} \tag{17}$$

C. MEASUREMENT COMPENSATION AND MEASUREMENT UPDATE

Sigma points are spread through the system of equations.

$$\hat{z}_k^{(i)} = h(\hat{x}_k^{(i)}) \tag{18}$$

Calculate the predictive value of the measurement.

$$\hat{z}_k = \sum_{i=0}^{2n} W_x^{(i)} \hat{z}_k^{(i)} \tag{19}$$

Calculate the covariance of the predicted measurement.

$$P_{z,k} = \sum_{i=0}^{2n} W_p^{(i)} (\hat{z}_k^{(i)} - \hat{z}_k)(\hat{z}_k^{(i)} - \hat{z}_k)^T + R_k \tag{20}$$

Calculate the covariance between $\hat{x}_{k|k-1}$ and $\hat{z}_k$.

$$P_{xz,k} = \sum_{i=0}^{2n} W_p^{(i)} (\hat{x}_k^{(i)} - \hat{x}_{k|k-1})(\hat{z}_k^{(i)} - \hat{z}_k)^T + R_k \tag{21}$$

Calculate the gain of the Kalman filter.

$$K_k = P_{xz,k} P_{z,k}^{-1} \tag{22}$$

In general, the sampling period of a real-time localization system is usually set between 0.1 s and 1 s. Usually, a marginal difference may exist between the measurements of adjacent moments. Therefore, in consideration of the trade-off between computation intensity and estimation accuracy, what a data packet is lost at time k, the measurement data at time $k-1$ is used to compensate the missing measurement data at time k. Let Δ_k denotes the error in the measurement equation after the measurement compensation during a data packet loss, which can be calculated as follows:

$$\Delta_k = (I - \Xi_k)(h_k(x_k) - h_{k-1}(x_{k-1})) \tag{23}$$

Since the measurement equation proposed in this paper is time-varying, it can be observed from the expression of error Δ_k that the size of the error Δ_k is related only to the system state at time k and $k-1$. For localization of mobile robot in real-time, both the variation of system state and the error Δ_k are usually insignificant under normal circumstances. However, during a consistent packet loss, the error Δ_k of the measurement equation will increase continuously, which will then affect the accuracy of the compensation measurement data. On the other hand, the packet loss compensation will adversely affect the localization algorithm. Therefore, it is necessary to calculate the error Δ_k of the measurement equation after the measurement compensation process. Let x_{k-1} is equal to the posteriori state estimate $\hat{x}_{k-1|k-1}$ at time $k-1$, and the x_k is equal to the estimated value $\hat{x}_{k|k}$ at time k. The value of $\hat{x}_{k-1|k-1}$ is usually known, but not the $\hat{x}_{k|k}$ value, which cannot also be computed. Therefore, it is only possible to compute an approximated value of $\hat{x}_{k|k}$. This paper considers using the one-step prediction of $\hat{x}_{k-1|k-1}$ to approximate the value of $\hat{x}_{k|k}$, then the approximate compensation error is calculated as follows.

$$\Delta_k = (I - \Xi_k)(h_k(F_k\hat{x}_{k-1|k-1} + G_k\omega_k) - h_{k-1}(\hat{x}_{k-1|k-1})) \tag{24}$$

The system state and the corresponding estimated error covariance are calculated based on the corrected packet loss measurement data.

$$z_{c,k} = \Xi_k z_k + (I - \Xi_k)z_{k-1} + \Delta_k \tag{25}$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} - K_k(z_{c,k} - \hat{z}_k) \tag{26}$$

$$P_{k|k} = P_{k|k-1} - K_k P_{z,k} K_k^T \tag{27}$$

The flowchart illustrating the entire process of the localization algorithm is shown in Fig.3.

IV. SIMULATION RESULTS AND ANALYSIS

In this section, some simulation experiments have been conducted to demonstrate the efficiencies of the proposed measurements compensation-based Unscented Kalman Filter (MC-UKF) while localizing the positions of a mobile robot. The experiments use various packet loss rates to evaluate the performance of the proposed localization system.

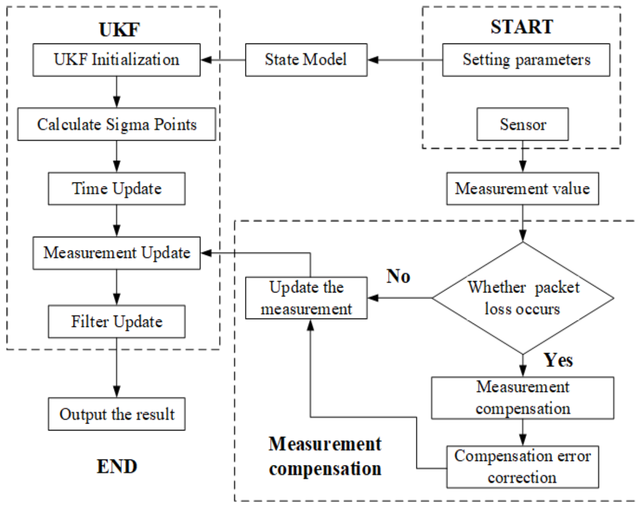

FIGURE 3. Flowchart of the proposed localization algorithm.

The first step of the simulation is to set the parameters of the localization system as well as the mobile robot. The coordinates of the four localization sensors $(x_{a,j}, y_{a,j})$ are fixed at (0, 0), (20, 0), (20, 20) and (0, 20), and the motion trajectory of the mobile robot is then set. The mobile robot first moves along a circle centered at (5.00, 10.00) of the 5-meter radius. Then the mobile robot moves along a circle with a circle centered at (15.00, 10.00) of the 5-meter radius. When the mobile robot moves along the first circle, its angular velocity is $-\pi/25$ rad/s. When the mobile robot moves along the second circle, its angular velocity is $\pi/25$ rad/s. The mobile robot starts from the point (10, 10) with a velocity of $v = 0.62$ m/s. The process noise covariance matrix is set to $Q_k = diag\,(0.1, 0.1, 0.1, 0.1)$. The measurement noise covariance matrix is set to $R_k = diag\,(0.1, 0.1, 0.1, 0.1)$. The sampling interval is set to $t_k = 0.5$s. The number of time steps is set to 200. The initial state of the localization algorithm and the initial state error covariance matrix are set as $x_0 = (10.00, 10.00, 0, -0.31)$ and $P_0 = diag\,(0.1, 0.1, 0.1, 0.1)$ respectively.

The localization results based on the proposed measurements compensation-based Unscented Kalman Filter are depicted in Fig. 4, Fig.5 and Fig. 6 respectively for the probability of packet loss (p_i) of 30%, 50% and 70% for each sensor. The black line represents the actual position of the mobile robot, and the red line represents the estimated position of the mobile robot. Fig.7, Fig. 8 and Fig.9 show the moment at which packet loss occurred, where a value of 1 indicates the occurrence of packet loss and a value of 0 indicates no packet loss.

The simulation results show that the proposed localization algorithm can effectively resolve the problem of packet loss in mobile robot localization systems and can achieve reliable accuracy of localization regardless of the packet loss rates, which means that the proposed algorithm is suitable for real-time practical applications.

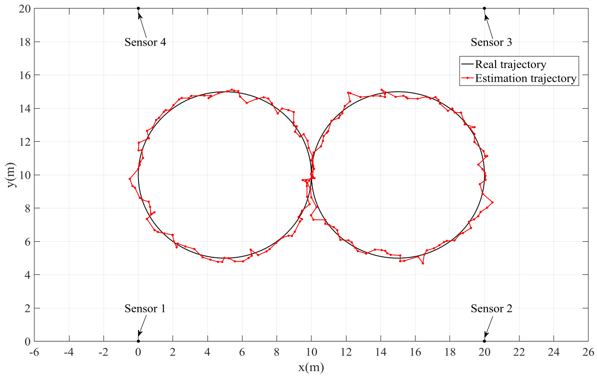

FIGURE 4. Localization result of the mobile robot with 30% packet loss rate.

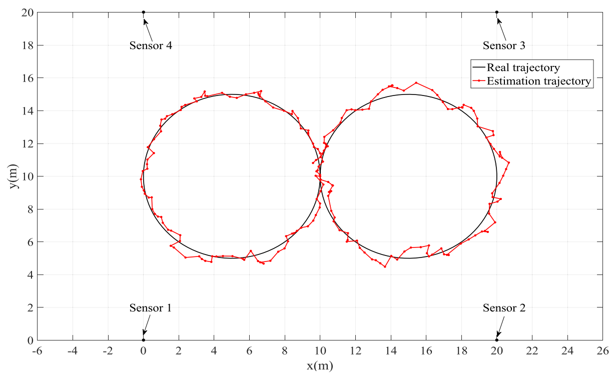

FIGURE 5. Localization result of the mobile robot with 50% packet loss rate.

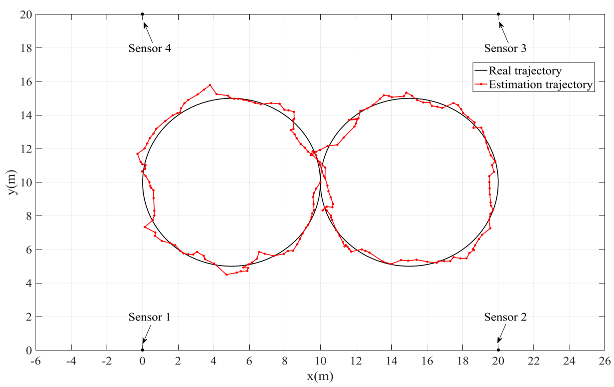

FIGURE 6. Localization result of the mobile robot with 70% packet loss rate.

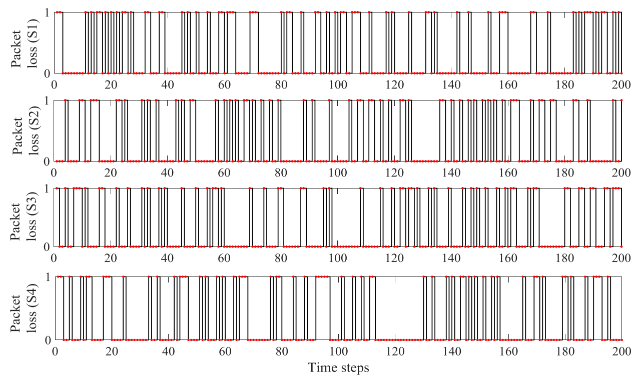

FIGURE 7. The moment of packet loss occurs with 30% packet loss rate.

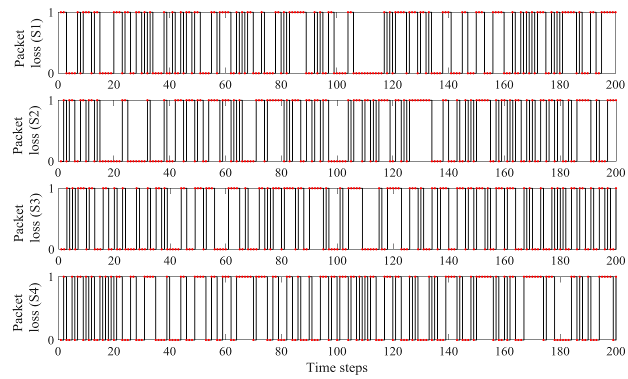

FIGURE 8. The moment of packet loss occurs with 50% packet loss rate.

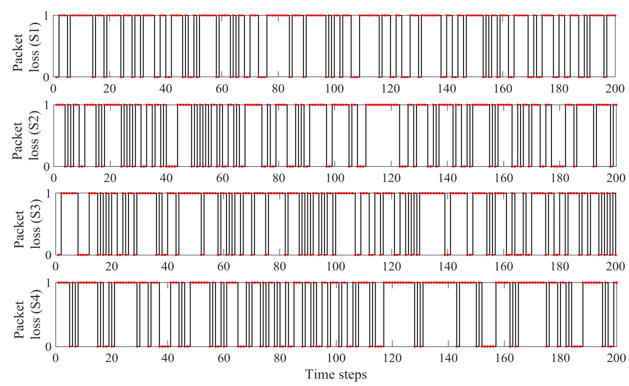

FIGURE 9. The moment of packet loss occurs with 70% packet loss rate.

Fig. 10, Fig. 11 and Fig. 12 presents a comparison of the average localization error between the proposed MC-UKF and UKF algorithms respectively for a packet loss rate of 30%, 50% and 70%. It is clear that the UKF algorithm suffers significant performance constraints during packet loss. A similar improved EKF algorithm considering packet loss is presented in [29]. This paper presents an improved localization based on extending the original UKF algorithm. During packet loss, the posteriori estimate of UKF ignores the measurement innovation, and it is calculated as follows:

$$\hat{x}_{k|k} = P_{k|k-1} - (\prod_{j=1}^{4} \xi_{j,k}) K_k (z_k - \hat{z}_k) \tag{28}$$

The calculation method of localization error can then be calculated as follows:

$$e_k = \frac{1}{N} \sum_{n=1}^{N} \sqrt{\left(x_{p,k}^{(n)} - x_k\right)^2 + \left(y_{p,k}^{(n)} - y_k\right)^2} \tag{29}$$

where N is the number of simulations. $x_{p,k}^{(n)}$ and $y_{p,k}^{(n)}$ are the estimated coordinates of the mobile robot in the

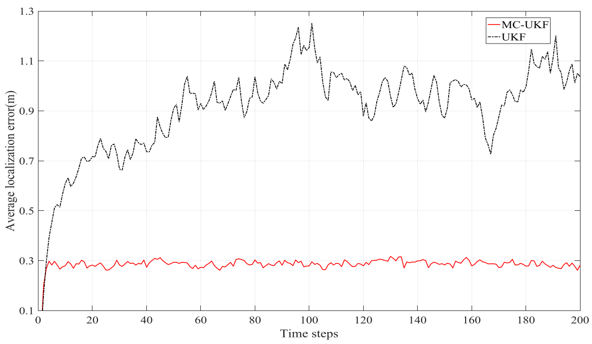

FIGURE 10. **The average localization error of MC-UKF and UKF with 30% packet loss rate.**

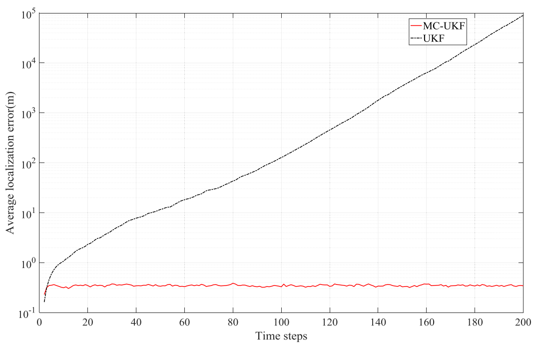

FIGURE 11. **The average localization error of MC-UKF and UKF with 50% packet loss rate.**

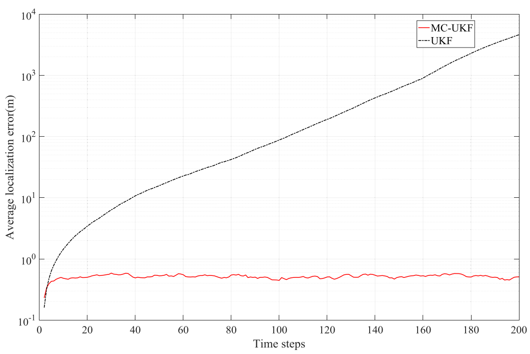

FIGURE 12. **The average localization error of MC-UKF and UKF with 70% packet loss rate.**

n^{th} simulation. According to the simulation results shown in Fig.10, Fig.11, and Fig.12, the proposed algorithm can effectively resolve the problem of mobile robot localization during various packet loss rates, and it characterizes a better localization accuracy than the UKF approach especially during higher packet loss rates.

The absolute localization errors of MC-UKF are shown in Fig.13, the packet loss rates p_i and the absolute localization errors E are shown in the x-axis and y-axis respectively. E is defined as:

$$E = \frac{1}{n} \sum_{k=1}^{200} \sqrt{\left(x_{p,k} - x_k\right)^2 + \left(y_{p,k} - y_k\right)^2} \tag{30}$$

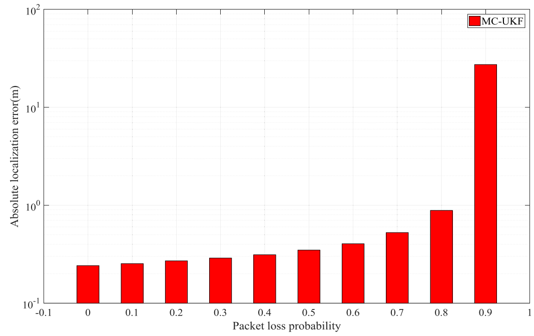

FIGURE 13. **The absolute localization error of MC-UKF under different packet loss rate.**

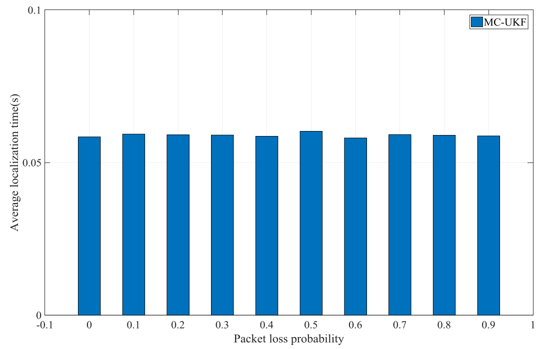

FIGURE 14. **The average localization time of MC-UKF with different packet loss rate.**

The simulation results are summarized as follows: when the packet loss rate is less than 90%, the MC-UKF has a relatively stable localization accuracy. However, with an increase in the packet loss rate, the localization accuracy of MC-UKF is generally decreased. This downward trend is most pronounced when the packet loss rate is over 90%.

Therefore, the performance of the MC-UKF is not stable during a remarkably higher packet loss rate. Fig. 14 shows the average location time of MC-UKF under different packet loss rates. The simulation results demonstrate that MC-UKF can satisfy the real-time requirements of mobile robot localization systems.

V. CONCLUSION

In this paper, a new localization algorithm named measurements compensation-based Unscented Kalman Filter (MC-UKF) for the localization of mobile robot is proposed. Unlike other algorithms, the proposed algorithm compensates the measurements by calculating the compensation error, with which the indoor localization systems can estimate the positions of the robots with reliable accuracy under high packet loss rates, despite missing some measurements. The achieved simulation results show that the proposed algorithm exhibits good performance regarding localization accuracy, stability, and speed. Based on the simulation results, it can be observed that the proposed algorithm characterizes good localization accuracy even when the packet loss rate is 80%. Regarding computational complexity, the proposed compensation algorithm fully satisfies the real-time requirements of robot localization systems. However, when the packet loss rate is higher than 90%, the accuracy of the algorithm is significantly reduced. Thus, improving the localization accuracy when the packet loss rate is better than 90% is one of our future research plans. Moreover, there many interfering factors leading to the uncertainty of system performance[41]–[43], such as transmission delay, channel degradation, signal quantization[44] and etc., which will be the main focuses in our future research.

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