Pedestrian Positioning Technology Combining IMU and Wireless Signals Based on MC-CKF

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Abstract: In the paper, the pedestrian position is estimated by integrating the inertial measurement unit (IMU) and the wireless signal using the Cubature Kalman filter (CKF) based on the maximum correntropy criterion (MCC). Wireless signals may include short-range wireless communications such as ultra-wideband (UWB) signal and mobile communication signals such as LTE/5G. UWB can measure distances with an error of less than 30 cm in a line-of-sight (LoS) environment, but in an environment with LoS, it provides range measurements with a wide range of non-Gaussian uncertainty errors. In this case, ia an IMU/UWB system is configured with a conventional minimum mean square error (MMSE)-based filter, significant errors will occur. To address this issue, this paper designed an MCC-based CKF and applied it to pedestrian positioning technology. Simulation analysis results demonstrated that the proposed filter is robust to UWB uncertainty and enables reliable IMUUWB integration.

1 INTRODUCTION

A system integrating an inertial measurement unit (IMU) and wireless signals is being considered for indoor pedestrian navigation. An IMU can be integrated using LTE/5G-based wireless positioning solutions or ultra-wideband (UWB)-based ranging measurements. This paper first describes an integration filter using UWB. UWB enables accurate range measurements and position estimates in line-of-sight (LoS) environments, but it is difficult to provide accurate position information in non-line-of-sight (NLoS) environments such as indoors because range measurements include various uncertainty errors (Banani et al., 2013, Cho, 2019). In order to integrate IMU and UWB, nonlinear filters such as the extended Kalman filter (EKF) (Brown and Hwang, 2012) and the Cubature Kalman filter (CKF) (Arasaratnam and Haykin, 2009) can be used to take into account the nonlinear characteristics of inertial navigation and ranging measurement. However, these minimum mean square error (MMSE)-based filters do not adequately respond to UWB uncertainties, potentially leading to large errors. In this paper, we introduce a maximum correntropy criterion (MCC)–based CKF (MC-CKF) considering this issue.

MCC-based filters are designed based on a kernel function that maximizes the similarity between the estimates and the measurement and reflects the error characteristics of the measurement. The sum of the kernel function values, including the residuals calcualted in the measurement update process, is used as the cost function. And state variables are then estiamted to maximize this cost function. If uncertainty errors occur in the UWB measurement, the MCC-based filter adjusts the P and R matrices to minimize the impact of measurement uncertainty errors (Chen et al., 2017, Li et al., 2022).

The purpose of this paper is to apply MCC to CKF so that it can be used in nonlinear systems. The designed MC-CKF is applied to a tightly coupled IMU/UWB system for indoor pedestrian navigation. The performance of the MC-CKF-based IMU/UWB integrated navigation system is verified through simulation. The simulation results confirmed the following: When UWB measurements contain non-Gaussian uncertainty errors (Cho, 2019), MC-CKF significantly adjusts the R matrix corresponding to

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the error measurements to provide stable position estimates. This is the contribution of this paper to the field of indoor pedestrian navigation.

2 IMU/UWB INTEGRATION BASED ON MC-CKF

For integration of an IMU-based inertial navigation system (INS) with UWB, the state variables are first set as follows:

$$x = \left[Pos^L \quad Vel^L \quad Euler \quad \nabla \quad \varepsilon \right]^T \tag{1}$$

where Pos^L and Vel^L are the position and velocity in the local level coordinate system, $Euler$ is the attitude expressed in Euler angles, and ∇ and ε are the accelerometer bias and gyro bias, respectively.

In CKF, these state variables are converted into cubature points. The number of cubature points is 2*N*, and since the system dimension *N* is 15, there are 30 cubature points.

In CKF, cubature points are time-propagated using the following INS equations (Farrell and Marth, 1999):

$$Pos_k^L = Pos_{k-1}^L + Vel_{k-1}^L \cdot dt \tag{2}$$

$$\begin{aligned} Vel_k^L = Vel_{k-1}^L + \Big\{ & C_{b,k-1}^L (f_{k-1}^b - \hat{\nabla}_{k-1}) - \\ & (2\omega_{ie,k-1}^L + \omega_{eL,k-1}^L) \times Vel_{k-1}^L + g_{k-1}^L \Big\} \cdot dt \end{aligned} \tag{3}$$

$$\begin{aligned} Q_k = Q_{k-1} + \frac{1}{2} \Big\{ & Q_{k-1} * \Big(\omega_{ib,k-1}^b - \hat{\varepsilon}_{k-1} \\ & - C_{L,k-1}^b (\omega_{ie,k-1}^L + \omega_{eL,k-1}^L) \Big) \Big\} \cdot dt \end{aligned} \tag{4}$$

where f^b and ω_{ib}^b are the accelerometer output and gyro output, respectively, $\hat{\nabla}$ and $\hat{\varepsilon}$ are the estimated accelerometer bias and gyro bias, respectively, and dt is the INS update interval. Q is a quaternion, ω_{ie}^L is the Earth's angular velocity vector, and ω_{eL}^L is the rotational angular velocity vector in the local level coordinate system caused by the velocity.

When the ranging measurements are obtained via UWB, the measurement-update is processed in the CKF. The ranging measurement equation is as follows (Cho, 2019):

$$r_{j,k} = \sqrt{(AN_j^x - Pos_k^x)^2 + (AN_j^y - Pos_k^y)^2} + w_{j,k} \tag{5}$$

where $[AN_j^x \quad AN_j^y]^T$ is the position of anchor node j, Pos^j is the *j*-axis position of the pedestrian in the local level coordinate system, and $w(j)$ is the noise contained in channel *j*. And $j \in \{1, 2, \cdots, M\}$.

In general, *w* in (5) can be modelled as Gaussian noise in LoS environments. However, in indoor environments, *w* can appear as a non-Gaussian heavy-tailed impulse error. Considering this, the kernel function of MC-CKF can be set as follows (Chen et al., 2017):

$$G(e) = \exp(-e^2 / 2\sigma^2) \tag{6}$$

where σ is the kernel bandwidth.

Applying a fixed-point iteration algorithm during the measurement-update process can improve the convergence performance of the filter. The P and R matrices are adjusted as follows:

$$\bar{P}_{k(i)}^- = B_P (C_{k(i)}^x)^{-1} B_P^T \tag{7}$$

$$\bar{R}_{k(i)} = B_R (C_{k(i)}^y)^{-1} B_R^T \tag{8}$$

where i is the iteration order, $B_P B_P^T = P_k^-$ and $B_R B_R^T = R$. P_k^- must be computed before the measurement-update using the time-propagated cubature points. $C_{k(a)}^x$ and $C_{k(a)}^y$ are computed as follows:

$$C_{k(i)}^x = \begin{bmatrix} G\left(e_{k(i)}^x(1)\right) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & G\left(e_{k(i)}^x(N)\right) \end{bmatrix} \tag{9}$$

$$C_{k(i)}^y = \begin{bmatrix} G\left(e_{k(i)}^y(1)\right) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & G\left(e_{k(i)}^y(M)\right) \end{bmatrix} \tag{10}$$

where

$$e_{k(i)}^x = B_P^{-1} (\hat{x}_k^- - \hat{x}_{k(i-1)}^-) \tag{11}$$

$$e_{k(i)}^y = B_R^{-1} (\tilde{y}_k - \hat{y}_{k(i)}^-) \tag{12}$$

After the fixed-point iteration algorithm completes, the state variables and error covariance matrix are updated as follows:

$$\hat{x}_k = \hat{x}_k^- + P_{xy,k(i)} P_{yy,k(i)}^{-1} (\tilde{y}_k - \hat{y}_{k(i)}^-) \tag{13}$$

$$P_k = \bar{P}_{k(i)}^- - P_{xy,k(i)} P_{yy,k(i)}^{-T} P_{xy,k(i)}^T \tag{14}$$

Where

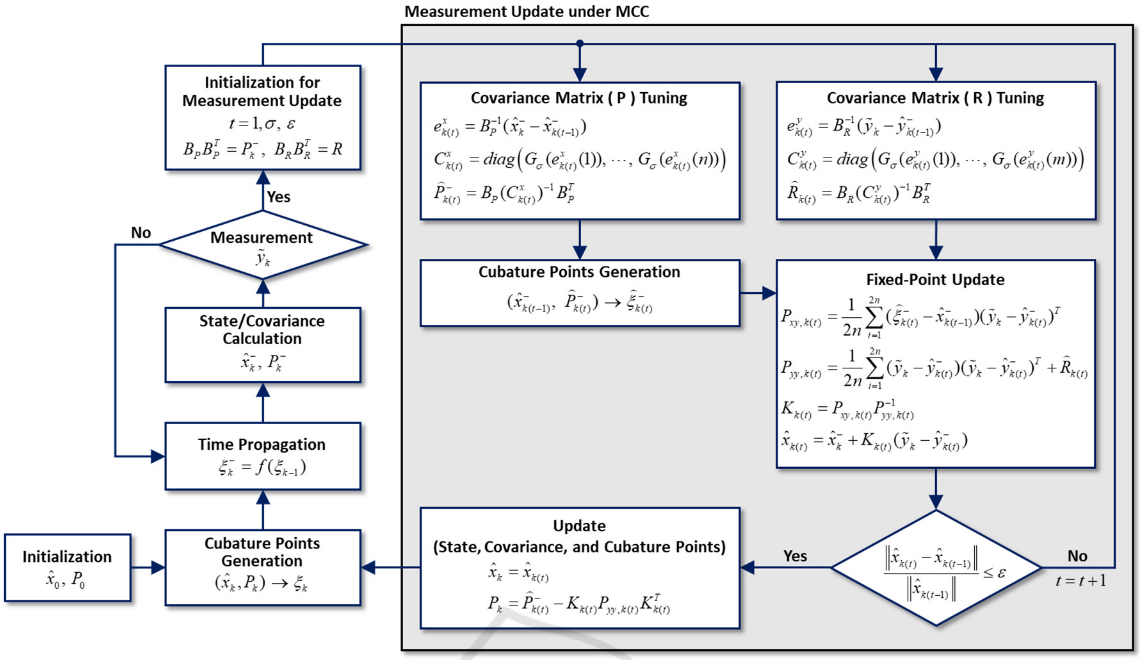


Figure 1: Flowchart of MC-CKF.

$$P_{xy,k(i)} = \frac{1}{n}\sum_{i=1}^{n}(\hat{\chi}^{-}_{k(i)} - \hat{x}^{-}_{k(i-1)})(\tilde{y}_k - \hat{y}^{-}_{k(i)})^T \tag{15}$$

$$P_{yy,k(i)} = \frac{1}{n}\sum_{i=1}^{n}(\tilde{y}_k - \hat{y}^{-}_{k(i)})(\tilde{y}_k - \hat{y}^{-}_{k(i)})^T + \bar{R}_{k(i)} \tag{16}$$

where n is the number of the Cubature points.

The proposed filter can be summarized as shown in Figure 1.

3 SIMULATION ANALYSIS

A simulation was conducted to analyse the performance of an MC-CKF-based IMU/UWB integrated pedestrian navigation system in an indoor space. The pedestrian's walking trajectory was set as shown in Figure 2, with four anchor nodes.

The simulation assumes two scenarios: the first is a LoS environment where only noise exists in the measurements, and the second is an NLoS environment where the measurements include biases, impulse errors, and ramp errors (Cho, 2019).

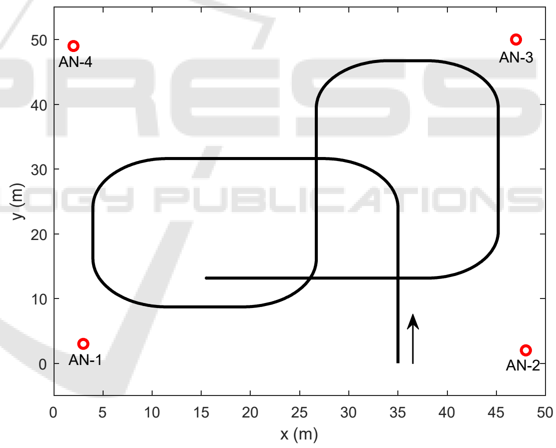
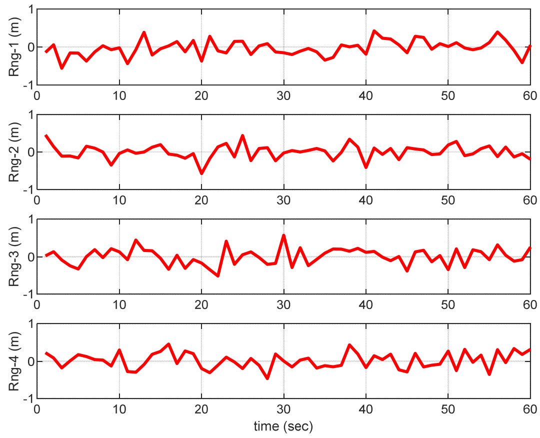


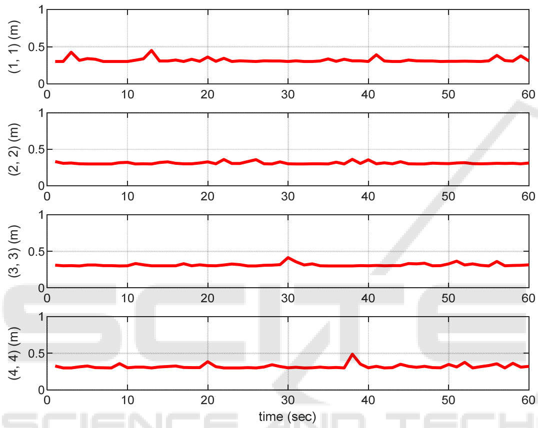
Figure 2: Simulation trajectory.

Figure 3 shows the results performed in a LoS environment, and Figure 4 shows the results performed in an NLoS environment.

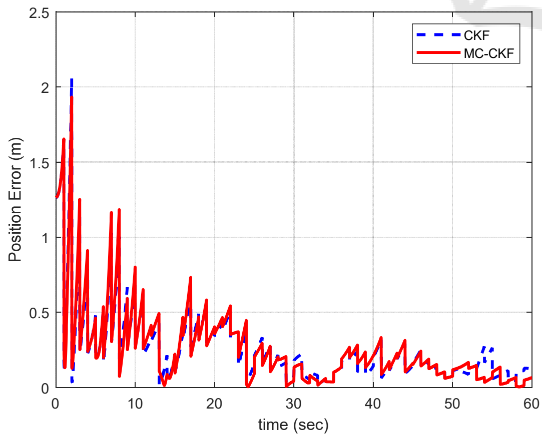
In the first simulation, only noise exists in the four range measurements, so little adjustment of R matrix is made. Additionally, the positioning results of CKF and MC-CKF are almost the same, and the heading estimation performance is slightly improved in MC-CKF.



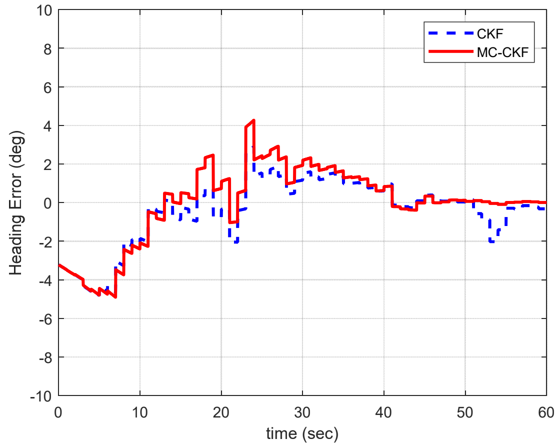
(a) measurement error



(b) square root of adjusted R matrix



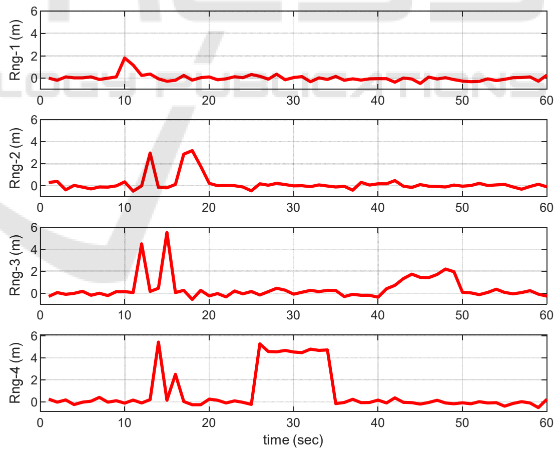
(c) position error



(d) heading error

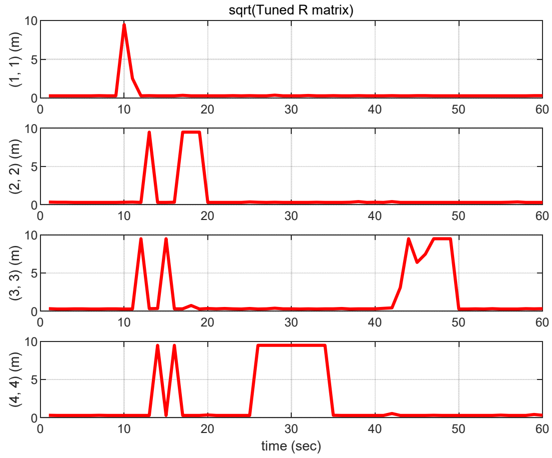
Figure 3: Simulation result in the LoS environment.

In the second simulation, the four range measurements include not only noise but also impulse, bias, and ramp errors. Consequently, the adjusted R matrix of MC-CKF accurately reflects the error characteristics of each measurement. As a result, while CKF incurs large position and heading errors due to the measurement errors, MC-CKF estimates position and heading information with the same accuracy as in a LoS environment.

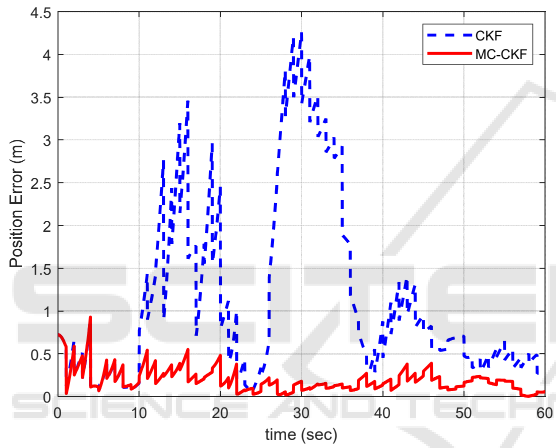


(a) measurement error

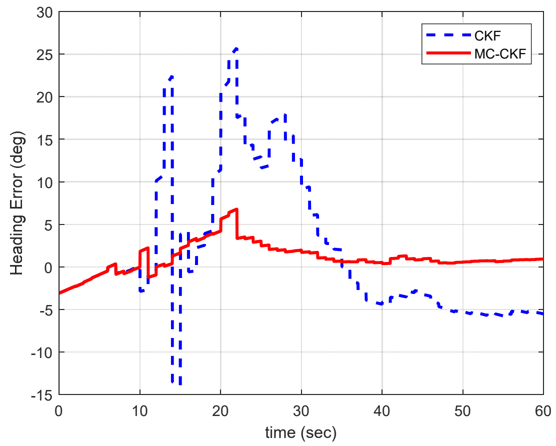
Figure 4: Simulation result in the NLoS environment.



(b) square root of adjusted R matrix



(c) position error



(d) heading error

Figure 4: Simulation result in the NLoS environment (cont.).

4 CONCLUSIONS

This paper discusses a navigation technology that integrates an IMU and wireless signals for indoor pedestrian positioning. UWB uses wireless signals to measure range information. While range measurements in LoS environments are only subject to noise, NLoS environments include bias, impulse, and ramp errors. In these environments, filters such as EKF and CKF generate significant positioning errors. To address this issue, we propose MC-CKF. This filter recognizes measurement errors and adjusts the R matrix for each channel. Simulation results demonstrate that the same positioning accuracy is maintained in NLoS environments as in LoS environments.

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