Distributed Quaternion Kalman Filter for Human Tracking Using IMU and UWB Measurement

Jing Cao[1], Yunguang Wang[2], Wanjie Ren[3], Mingran Li[1], and Shuhui Bi[1](✉)

[1] School of Electrical Engineering, University of Jinan, Jinan 250022, China
cse_bish@ujn.edu.cn
[2] State Grid Intelligent Technology Company Limited, Jinan 250000, China
[3] Shandong Institute of Non-Metallic Materials, Jinan 250000, Shandong, China

Abstract. For improving the accuracy of the indoor navigation system, a Kalman filter (KF) will be proposed to filter the quaternion and to obtain the acceleration. Then, the human body is tracked based on the distributed quaternion extended Kalman filter (DQEKF) by combing with inertial navigation system (INS)/ultra-wide band (UWB) technology. In the proposed algorithm, the used local data filter is composed by four sub-filters, the position information is used as the state vector, which is more effective in dealing with the noise. In the following, the outputs of the local filters are the inputs to the main filters for fusion and provide the best estimate. Finally, experimental results show that the proposed scheme can reduce the positioning error effectively.

Keywords: Quaternion · Inertial measurement unit · Ultra wide band · Indoor human localization

1 Introduction

With the development of science and technology, people's demand of accurate location information becomes more and more intense. For example, in a large store, customers can use positioning technology to find the location where they need to buy items and get the best route more easily [1]. Parents can use positioning information to locate their children in real time. Positioning technology is the basis of providing for various location services [6]. However, with the existing positioning technology, it is difficult to achieve the expected results of indoor positioning, and indoor metal components, electrical signals, obstacles, etc., will interfere with the positioning signal, resulting in inaccurate indoor positioning. For the positioning technology in the indoor environment, how to use the limited sensor information obtained to eliminate the influence of the complex indoor navigation environment on the obtained pedestrian position information has become a hot topic of research.

S.-H. Wang and Y.-D. Zhang (Eds.): ICMTEL 2022, LNICST 446, pp. 667–674, 2022.
https://doi.org/10.1007/978-3-031-18123-8_52

The Kalman filter (KF) was proposed in the last century and has made a remarkable contribution to the connection between cybernetics and information theory. Unlike traditional frequency-domain filtering, Kalman filtering is a time-domain state predictor. Since there will be some errors due to internal noise and external interference when collecting data, Filters can correct the data, and this process can also be seen as a filtering process. In recent years, KF has developed rapidly. When dealing with some nonlinear systems, the extended Kalman filter (EKF) comes into play, which is a KF that linearizes expectation and variance [5].

This paper studies a method that can effectively improve the positioning accuracy. First, KF filters the quaternion to calculate acceleration [3]. Then, distributed quaternion EKF (DQEKF) filtering is performed on the position and velocity position of the pedestrian. Then the output of the local filter is input to the main filter for fusion to eliminate the influence of the complicated indoor navigation environment on the obtained pedestrian position information and ensure the continuous stability of the pedestrian navigation information [4].

The remainder of this paper is arranged as follows. Section 2 discusses the pedestrian positioning scheme based on quaternion. The performance of the proposed algorithm is verified through simulation results in Sect. 3, and Sect. 4 summarizes this article.

2 Fusion Model

In this section, the indoor pedestrian integrated navigation scheme based on quaternion distributed filter will be designed in details. Figure 1 shows the block diagram of the distributed filter. For distributed filters, it includes four sub-filters and a main filter. In the structure, the sub-filter is used to estimate the system parameters. Among them, d_1, d_2, d_3, d_4 are the distance information collected by ultra-wide band (UWB). The output of the sub-filter is used as the input of the main filter to perform data fusion to obtain more accurate pedestrian position [2]. When the signal is collected, it will be affected by the interference of external signals and the internal noise of the device, and hence error and randomness happens in the received signal. In order to obtain the desired signal, the signal needs to be filtered to eliminate the disturbance.

This procedure includes two steps: KF is used to filter the quaternion, and DQEKF is designed to filter the position information of pedestrians.

2.1 Quaternion Filtering

A quaternion is used as state vector and the state equation is:

$$\mathbf{Q}_k^q = \mathbf{F}_{k-1}^q \mathbf{Q}_{k-1}^q + \mathbf{M}_{k-1}^q, \tag{1}$$

where $\mathbf{Q}_k^q = \begin{bmatrix} \mathrm{Q}_1 & \mathrm{Q}_2 & \mathrm{Q}_3 & \mathrm{Q}_4 \end{bmatrix}^T$, $\mathbf{M}_k^q$ is the noise of $\mathbf{Q}_k^q$ at time k.

The state matrix is:

$$\mathbf{F}_k^q = \left[\mathbf{I}_{4\times4} + \frac{\Delta t}{2} \mathbf{\Omega} \left(\mathbf{c}_k - \mathbf{v}_k \right) \right], \tag{2}$$

where $\mathbf{c}_k$ represents the current gyroscope measurement, and $\mathbf{v}_k$ is the average value of the gyroscope measurement in an attitude phase.The definition of $\boldsymbol{\Omega}(\mathbf{n})$ is as follows:

$$\boldsymbol{\Omega}(\mathbf{n}) = \begin{bmatrix} 0 & -\mathbf{n}^T \\ \mathbf{n} & -[\mathbf{n}\times] \end{bmatrix}, \forall \mathbf{n} = \begin{bmatrix} n_1 \; n_2 \; n_3 \end{bmatrix}^T \in R^3, \tag{3}$$

$$[\mathbf{n}\times] = \begin{bmatrix} 0 & -n_3 & n_2 \\ n_3 & 0 & -n_1 \\ -n_2 & n_1 & 0 \end{bmatrix}. \tag{4}$$

The observation matrix is:

$$\mathbf{H}_k = \begin{bmatrix} 0 & -\left(\mathbf{g}_k - [\mathbf{A}(\mathbf{Q}_k^q)]^{-1}\mathbf{g}_k\right)^T \\ \mathbf{g}_k - [\mathbf{A}(\mathbf{Q}_k^q)]^{-1}\mathbf{g}_k & \left(\mathbf{g}_k - [\mathbf{A}(\mathbf{Q}_k^q)]^{-1}\mathbf{g}_k\right)\times \end{bmatrix}, \tag{5}$$

In the formula, $\mathbf{g}_k = [0 \; 0 \; G]$, G is the gravitational acceleration at the corresponding location. $\mathbf{A}(\mathbf{Q}_k^q)$ is the direction cosine matrix:

$$\mathbf{A}(\mathbf{Q}_k^q) = \left(r^2 - \mathbf{e}^T\mathbf{e}\right)\mathbf{I}_{3\times 3} + 2\mathbf{e}\mathbf{e}^T - 2r[\mathbf{e}\times], \tag{6}$$

where r and $\boldsymbol{e}$ are the scalar part and vector part of the quaternion $\boldsymbol{Q}_k^q$ respectively, $\boldsymbol{I}_{3\times 3}$ is the identity matrix.

Based on this model, the next step is to design a KF filter. $\boldsymbol{a}_k^b$ represents the acceleration in the carrier coordinate system, converted to the geographic coordinate system using the filtered quaternion:

$$\boldsymbol{a}_k^n = \boldsymbol{A}(\boldsymbol{Q}_k^q)\,\boldsymbol{a}_k^b. \tag{7}$$

2.2 Position Filtering

The DQEKF is used to filter the position and estimate the position. The state vector consists of position and velocity. The state equation is:

$$\mathbf{S}_k^l = \underbrace{\begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}}_{\mathbf{A_{k-1}^l}} \mathbf{S}_{k-1}^l + \underbrace{\begin{bmatrix} \frac{\Delta t^2}{2} \\ \frac{\Delta t^2}{2} \\ \Delta t \\ \Delta t \end{bmatrix}}_{\mathbf{C_{k-1}^l}} \mathbf{a}_{k-1}^{l,n} + \mathbf{w}_k^l, \tag{8}$$

where $\mathbf{S}_k^l = [x_k, y_k, v_{x,k}, v_{y,k}]^T$ is the state vector of the l_{th} local filter at the time index k. At time k, $[x_k, y_k]$ represents the current pedestrian position, $[v_{x,k}, v_{y,k}]$ represents the current pedestrian speed vector, $\mathbf{a}_k$ represents the acceleration vector , the $\mathbf{w}_k^l \sim \mathcal{N}\left(0, \mathbf{B}^l\right)$ is the noise of the $\mathbf{S}_k^l$.

The observation equation is:

$$\mathrm{d}_{i,k}^l = \sqrt{((x_k) - (x_i))^2 + ((y_k) - (y_i))^2} = h\left(\mathbf{S}_k^l\right) + \nu_k^l, i = 1, 2, ... \tag{9}$$

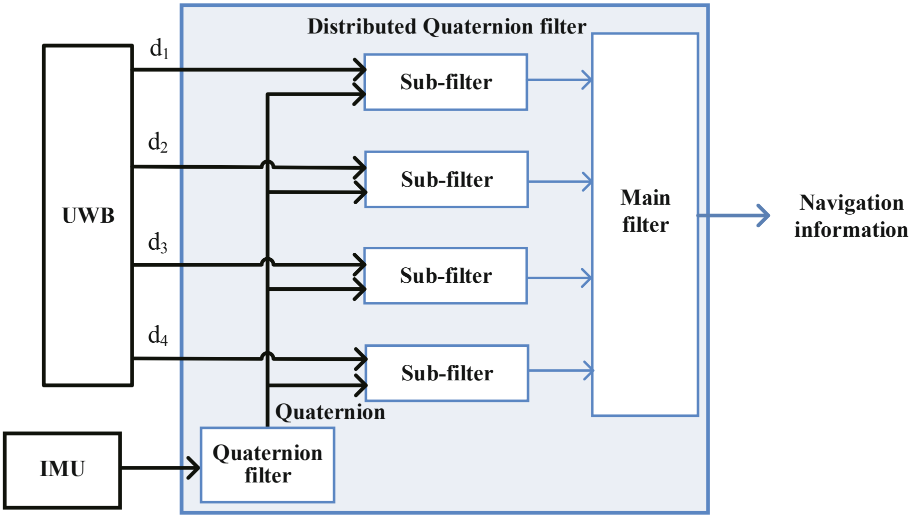

Fig. 1. Structure diagram of distributed filter.

Among them, (x_i, y_i) is the coordinate of the i-th reference node (RN), (x_k, y_k) are the location information of the target pedestrian in the east and north directions, $\nu_k^l \sim \mathcal{N}\left(0, \mathbf{R}^l\right)$ is the measurement noise.

Firstly, with the initial value $\mathbf{S}_0^l$ and $\mathbf{P}_0^l$, the $\mathbf{S}_{k+1}^l$ and $\mathbf{P}_{k+1}^l$ can be predicted at the time index k via Eqs. (10) and (11).

$$\mathbf{S}_k^l = \mathbf{A}_{k-1}^l \mathbf{S}_{k-1}^l + \mathbf{C}_{k-1}^l \mathbf{a}_{k-1}^{l,n} + \mathbf{w}_k^l, \tag{10}$$

$$\mathbf{P}_k^l = \mathbf{A}_{k-1}^l \mathbf{P}_{k-1}^l \left(\mathbf{A}_{k-1}^l\right)^T + \mathbf{B}_{k-1}^l, \tag{11}$$

where $\mathbf{P}_k^l$ represents the covariance matrix of $\mathbf{S}_k^l$. Then, the $\mathbf{S}_k^l$ and $\mathbf{P}_k^l$ can be updated at the time index k via Eqs. 12, 13 and 14.

$$\mathbf{K}_k^l = \mathbf{P}_k^l \left(\mathbf{H}_k^l\right)^T [\mathbf{R}_k^l + \mathbf{H}_k^l \mathbf{P}_k^l \left(\mathbf{H}_k^l\right)^T]^{-1}, \tag{12}$$

$$\mathbf{S}_k^l = \mathbf{S}_k^l + \mathbf{K}_k^l [\mathrm{d}_{i,k}^l - h(\mathbf{S}_k^l)], \tag{13}$$

$$\mathbf{P}_k^l = [\mathbf{I} - \mathbf{K}_k^l \mathbf{H}_k^l] \mathbf{P}_k^l, \tag{14}$$

where $\mathbf{H}_k^l = \frac{\partial \mathbf{h}(\mathbf{s}_k^l)}{\partial \mathbf{s}_k^l}$.

With the local EKF's output $\mathbf{S}_k^l$ and $\mathbf{P}_k^l$, the main filter works to provide the optimal output by fusing $\mathbf{S}_k^l$ and $\mathbf{P}_k^l$ by Eqs. (15) and (16).

$$\mathbf{S}_k = \mathbf{P}_k \left(\left(\mathbf{P}_k^1\right)^{-1} \mathbf{S}_k^1 + \left(\mathbf{P}_k^2\right)^{-1} \mathbf{S}_k^2 + \left(\mathbf{P}_k^3\right)^{-1} \mathbf{S}_k^3 + \left(\mathbf{P}_k^4\right)^{-1} \mathbf{S}_k^4 \right), \tag{15}$$

$$\mathbf{P}_k = \left(\left(\mathbf{P}_k^1\right)^{-1} + \left(\mathbf{P}_k^2\right)^{-1} + \left(\mathbf{P}_k^3\right)^{-1} + \left(\mathbf{P}_k^4\right)^{-1} \right)^{-1}. \tag{16}$$

3 Experimental Testing

In this section, the performance of the above mentioned dual filters is verified through tests.

3.1 Experimental Environment

The indoor environment selected for this experiment is the lobby on the first floor of the Machinery Building of the West Campus University of Jinan, as shown in the Fig. 2. In which, four UWB reference nodes (UWB RNS) are used to make the measured data more accurate, so that the height of the UWB blind node (UWB BN) is consistent with the height of RNS. The UWB BN on the shoulder is used to receive RNS signals to measure the distance between them, and then process them to obtain the UWB trajectory. The target pedestrian is shown in Fig. 3, the data measured by the UWB and the encoder on the wheel are processed as a reference trajectory, the inertial measurement unit (IMU) on the foot is used to measure the quaternion data, and the computer is used to collect and process data.

Fig. 2. Test environment.

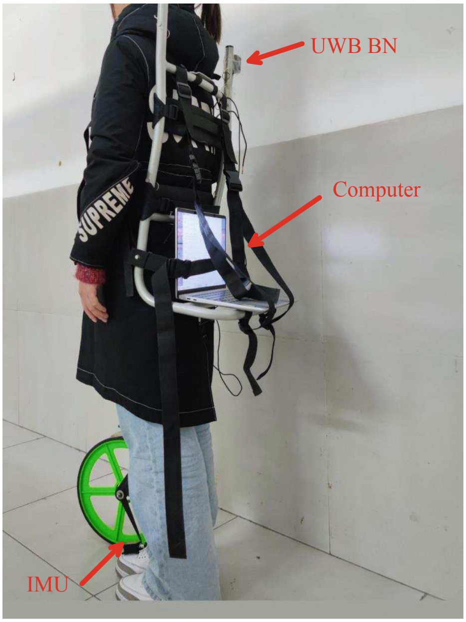

Fig. 3. Experimental equipment and target personnel.

3.2 Performance Analysis of the Proposed Algorithm

In this chapter, to verify the effectiveness of the proposed algorithm, it is compared with UWB and distributed EKF (DEKF) trajectories. The reference path and trajectory estimated by UWB, DEKF and DQEKF are shown in the Fig. 4, which shows that DQEKF can provide accurate path. In addition, the purple circle in the Fig. 4 represents the position of the UWB RNS, the triangle represents the starting position, and the square represents the end point. Figure 5 is given to depict the cumulative distribution function (CDF), and the Fig. 5 shows that the DQEKF has good estimation performance. To be more convincing, Table 1 lists the root mean square error (RMSE) of the estimated positions for UWB, DEKF, and DQEKF. It can be seen from Table 1 that the RMSE is larger than that of UWB due to the large error in the intermediate position of the DEKF experiment. The RMSE estimated by DQEKF is the smallest at 0.358 m and 0.297 m in the east and north positions, respectively.

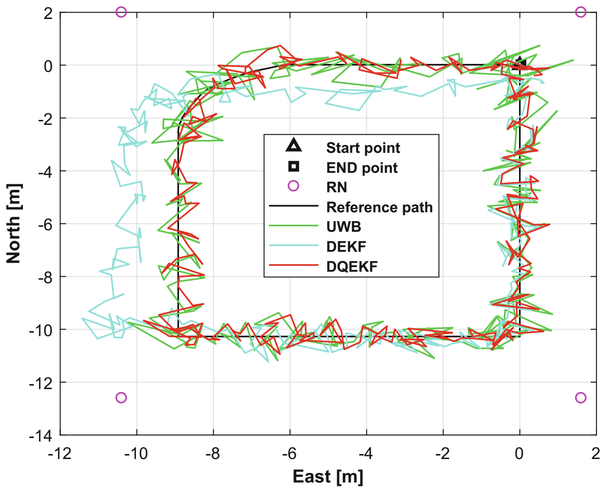

Fig. 4. The estimated path is provided by DQEKF, DEKF and UWB.

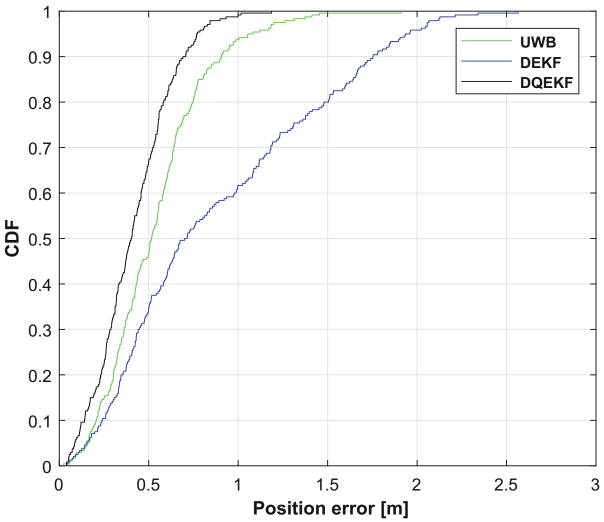

Fig. 5. The CDFs of the DQEKF, DEKF, and UWB.

Table 1. The RMSE (m) generated by UWB, DEKF and DQEKF

Filter	RMSE	
	East	North
UWB	0.474	0.385
DEKF	0.930	0.5058
DQEKF	0.358	0.297

4 Conclusion

This article studies how to perform distributed filtering on quaternion and location information. The acceleration is calculated from the filtered quaternion, and then the pedestrian's position and velocity information is used as the state vector, and the distributed EKF is used for filtering. In this algorithm, four EKFs are used as local data fusion filters, and the output of the local filters is used as the input of the main filter. The fusion obtains the optimal estimation, thereby obtaining more accurate pedestrian position information. The experiment test results show that comparing with the traditional model, the presented design model can effectively reduce the error.

Acknowledgements. This paper is supported by the Natural Science Foundation of Shandong Province (ZR2021MF074 and ZR2020KF027), the National Key R&D Program of China (2018AAA0101703), and Shandong Key R&D Program (2019JZZY021005).

References

1. Dardari, D., Closas, P., Djuric, P.M.: Indoor tracking: theory, methods, and technologies. IEEE Trans. Veh. Technol. **64**(4), 1263–1278 (2015)
2. Wang, Y., Li, X.: An improved robust EKF algorithm based on sigma points for UWB and foot-mounted IMU fusion positioning. J. Spat. Sci. **66**(2), 329–350 (2021)
3. Wen, K., Yu, K., Li, Y., Zhang, S., Zhang, W.: A new quaternion Kalman filter based foot-mounted IMU and UWB tightly-coupled method for indoor pedestrian navigation. IEEE Trans. Veh. Technol. **69**(4), 4340–4352 (2020)
4. Xu, Y., Chen, X.: Online cubature Kalman filter Rauch-Tung-Striebel smoothing for indoor inertial navigation system/ultrawideband integrated pedestrian navigation. Proc. Inst. Mech. Eng. **232**(4), 390–398 (2018)
5. Yang, J., et al.: A height constrained adaptive Kalman filtering based on climbing motion model for GNSS positioning. IEEE Sens. J. **17**(21), 7105–7113 (2017)
6. Zhang, Z., Meng, X.: Use of an inertial/magnetic sensor module for pedestrian tracking during normal walking. IEEE Trans. Instrum. Meas. **64**(3), 776–783 (2015)