C-T-U fusion indoor localization method based on TOF

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Abstract. In indoor localization systems, improving the accuracy of indoor localization can be achieved by optimizing existing localization algorithms. This paper first utilizes Ultra-Wideband (UWB) technology and an improved Time-of-Flight (TOF) algorithm to obtain high-precision distance information, thereby enhancing ranging accuracy. Subsequently, the Chan algorithm is employed to obtain the initial three-dimensional coordinates, which are then optimized using both the Taylor series expansion and an improved Unscented Kalman Filter (UKF) algorithm, resulting in two optimized coordinates. Finally, the two optimized coordinates are integrated through weighted fusion to obtain the final localization result. Experimental results demonstrate that the proposed algorithm improves indoor localization accuracy by over 60%, significantly enhancing the precision of indoor localization.

1 Introduction

Currently, indoor localization technologies mainly include WIFI, ZigBee, and Ultra-Wideband (UWB). UWB, with its high temporal resolution and strong anti-interference capability, has become one of the preferred technologies for indoor localization. UWB determines the distance between devices by measuring the propagation time of radio signals, with the Time-of-Flight (TOF) algorithm being a commonly used ranging method[1]. However, the traditional TOF algorithm suffers from clock synchronization errors, which limit its ranging accuracy. To improve localization accuracy, researchers have proposed various optimization methods. For example, Lu Yin[2] et al. optimized the Chan algorithm by introducing non-line-of-sight error values; Chen Dawei[3] et al. combined simulated annealing and Taylor algorithms to enhance localization accuracy; Yang Ziyang[4] et al. proposed an optimization algorithm based on Chan-UKF; Xu Shuping[5] et al. improved the Chan-Taylor collaborative algorithm by introducing weight factors; and Hong Xinlei[6] et al. optimized the particle swarm optimization algorithm using a fireworks algorithm, although with a larger computational load.

In summary, this paper proposes a C-T-U fusion indoor localization method based on TOF. Experiments have shown that this method significantly improves localization accuracy in indoor environments.

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2 Improved TOF ranging algorithm

To address the issue of clock synchronization inconsistency in TOF localization technology, which leads to significant ranging errors, an improved TOF algorithm, namely the Asymmetric TOF algorithm, is proposed. This algorithm increases the ranging accuracy and reliability by adding two independent and reverse signal transmission and reception steps during the ranging process, thereby reducing the dependence on clock synchronization. The working principle of the Asymmetric TOF algorithm is illustrated in Figure 1.

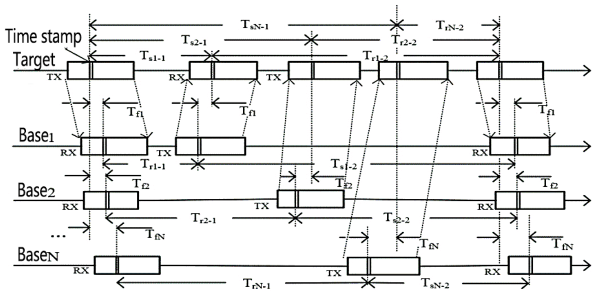

Fig. 1. Working principle diagram of asymmetric TOF.

The specific measurement process is as follows: taking the mobile tag and base station 1 as an example, the tag sends an electrical signal to the base station 1, and the base station 1 sends a response signal after receiving the response delay T_{r1-1}, and the tag receives and records the time T_{f1}, and obtains the time T_{s1-1} of the tag from sending the signal to receiving the response signal;The tag sends the response signal to base station 1 again after the response delay T_{r1-2}, and base station 1 receives and records the time $\mathrm{T_{f1}}$, and obtains the time T_{s1-2} from when base station 1 receives the response signal from the tag for the first time to when it receives the response signal from the tag again.According to the description of the above ranging process, the asymmetric TOF expression of N base stations is shown in formula (1).

$$\mathrm{T}_{fN}=\frac{T_{sN-1}\times T_{sN-2}-T_{rN-1}\times T_{rN-2}}{T_{sN-1}+T_{sN-2}+T_{rN-1}+T_{rN-2}} \qquad (1)$$

$$d=\mathrm{c}*T_{fN}$$

In the formula, d is the TOF ranging value between the tag and the base station;c is the speed of light, $3*10^8$m/s.

3 Improved UKF algorithm

The classical UKF algorithm requires two Unscented Transformations (UT), resulting in a large computational load[7]. To address this issue, this paper proposes a method that performs only one UT transformation. This method omits the first UT transformation step for obtaining the Sigma point set, thereby improving localization accuracy and computational efficiency.

(1) Initialization

Define the state vector $X_{k-1|k-1}$ and covariance matrix $P_{k-1|k-1}$, representing the estimated position state and covariance at time $k-1$, respectively. The process noise covariance matrix is also defined Q_{k-1}.

(2) Prediction Step

The following are the formulas for state prediction, covariance prediction, sigma point prediction, and predicted observation values, respectively.

$$X_{k|k-1} = FX_{k-1|k-1}$$
$$P_{K|K-1} = FP_{K-1|K-1}F^{T} + Q_{K-1}$$
$$X_{K-1|K-1}^{(i)} = \begin{cases} X_{K-1|K-1} & i=0 \\ X_{K-1|K-1} + \left(\sqrt{(n+\lambda)P_{K-1|K-1}}\right)_{i} & i=1,...,n \\ X_{K-1|K-1} - \left(\sqrt{(n+\lambda)P_{K-1|K-1}}\right)_{i-n} & i=n+1,...2n \end{cases} \tag{2}$$
$$Z_{k|k-1}^{(i)} = h(X_{k|k-1}^{(i)})$$

Here, F is the state transition matrix, n is the dimension of the state vector, $\lambda = \alpha^{2}(n+k) - n$ is the predicted state, α is typically set to 0.01, and k determines the distance between the Sigma points and the mean. h is the observation matrix.

(3) Update Step

The following are the formulas for updating the Kalman gain, state update, and covariance update, respectively.

$$K_{k} = P_{X_{k}Z_{k}}P_{Z_{k}Z_{k}}^{-1}$$
$$X_{k|k} = X_{k|k-1} + K_{k}\left(Z_{k} - Z_{k|k-1}\right) \tag{3}$$
$$P_{k|k} = P_{k|k-1} - K_{k}P_{ZkZk}K_{k}^{T}$$

Compared with the classical UKF algorithm, this algorithm omits the first UT transform and directly uses state prediction and observation prediction to perform Kalman filter calculation, which reduces the amount of calculation and improves the positioning accuracy and adaptability of the algorithm in complex environments.

4 Weighted fusion algorithm

To integrate the estimates from the Chan-Taylor algorithm and the Chan-UKF algorithm, this paper employs a weighted average method. The weights are assigned based on the sum of squared residuals of the two algorithms to obtain a more accurate localization result. The sum of squared residuals for the Chan-Taylor algorithm and the Chan-UKF algorithm is given by Equations (4).

$$R_{es1} = \sum_{i=2}^{N}[R_{i,1} - (\sqrt{(x_a - x_i)^2 + (y_a - y_i)^2 + (z_a - z_i)^2} - \sqrt{(x_a - x_1)^2 + (y_a - y_1)^2 + (z_a - z_1)^2})]^2 \tag{4}$$
$$R_{es2} = \sum_{i=2}^{N}[R_{i,1} - (\sqrt{(x_b - x_i)^2 + (y_b - y_i)^2 + (z_b - z_i)^2} - \sqrt{(x_b - x_1)^2 + (y_b - y_1)^2 + (z_b - z_1)^2})]^2$$

where $R_{i,1}$ is the measured distance, (x_a,y_a,z_a) represents the estimated coordinates by the Chan-Taylor algorithm, (x_b,y_b,z_b) represents the estimated coordinates by the Chan-UKF algorithm, and (x_i,y_i,z_i) represents the coordinate of the ith base station.

From this, weights w_1 and w_2 can be obtained, and they are normalized to w_1' and w_2'.

$$w_1 = \frac{1}{\alpha + Res_1} \qquad w_2 = \frac{1}{\alpha + Res_2}$$
$$w_1' = \frac{Res_1}{Res_1 + Res_2} \quad w_2' = \frac{Res_2}{Res_1 + Res_2} \tag{5}$$

In order to prevent the weight from being infinite, a weight adjustment factor is introduced with a value of 0.01.

From this, the final positioning coordinate $(x_{final}, y_{final}, z_{final})$ can be obtained.

$$x_{final} = w_1' x_a + w_2' x_b$$
$$y_{final} = w_1' y_a + w_2' y_b \tag{6}$$
$$z_{final} = w_1' z_a + w_2' z_b$$

5 Experiments and simulation analysis

5.1 Simulation experiments of the improved TOF algorithm

The experimental venue is a 10m × 10m × 5m teaching building hall with concrete walls and no large obstructions. Four base stations are set up at coordinates (0,0,0), (10,0,0), (0,10,0), and (10,10,5). The tag node is fixed at a position with a signal clock offset $e_t = \pm 20\,ppm$, and the error follows a Gaussian distribution (mean = 0, standard deviation = 0.1 ns). Figures 2 and 3 show the ranging errors of the TOF algorithm and the Asymmetric TOF algorithm with varying clock offsets e_t and delays T_r.

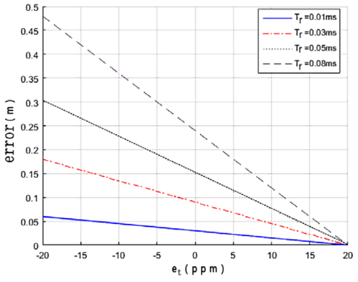

Fig. 2. TOF ranging error

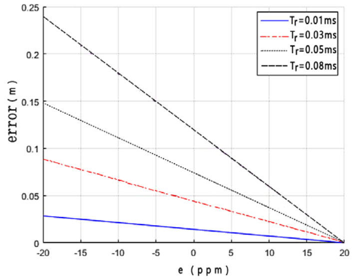

Fig. 3 Asymmetric TOF ranging error

The experimental results indicate that the ranging error of the Asymmetric TOF algorithm is significantly lower than that of the traditional TOF algorithm. For example, at a clock offset of -20 ppm and a delay of 0.08 ms, the TOF error is 0.48 m, while the Asymmetric TOF error is 0.24 m, validating the high-precision advantage of the Asymmetric TOF algorithm.

5.2 Simulation experiments of the improved UKF-based fusion algorithm

This experiment uses MATLAB simulation to compare the Chan-Taylor algorithm[8], the Chan-UKF algorithm[9] and the improved Chan-Taylor-UKF fusion algorithm.The experimental environment is the same as in section 4.1, the label moves from (5, 5, 0) to (10, 10, 2.5) at a uniform speed, as shown in Figure 4.After 1000 experimental tests, the root mean square error (RMSE) of each fusion algorithm is obtained.As shown in Table 1.

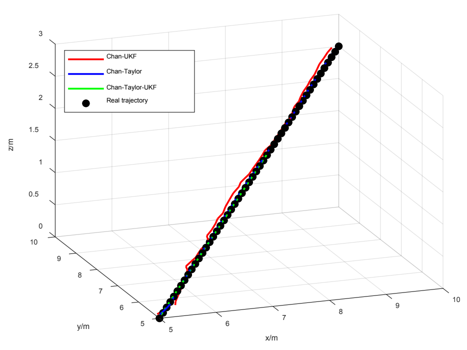

Fig. 4. Positioning trajectory diagram

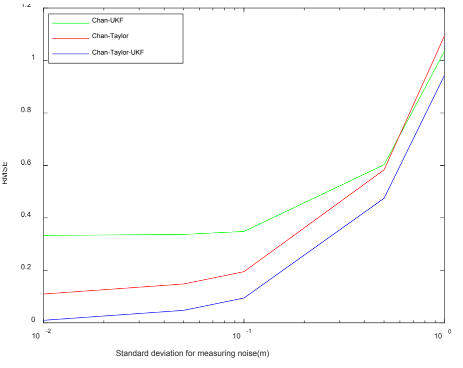

Fig. 5. Positioning error comparison diagram

Table 1. RMSE of three algorithms

Algorithm	RMSE/m
Chan-Taylor	1.41
Chan-UKF	1.02
Chan-Taylor-UKF	0.37

It can be seen from Table 1 that the improved Chan-Taylor-UKF fusion algorithm in this paper significantly reduces the positioning accuracy in a complex indoor environment, and the positioning accuracy increases by about 64%~70%, showing a better positioning effect.

At the same time, under different measurement noise standard deviations (10^{-2},10^{0}), the Chan-UKF fusion algorithm, the Chan-Taylor fusion algorithm and the improved Chan-Taylor-UKF fusion algorithm are compared and analyzed, as shown in Figure 5.

It can be seen from Figure 5 that under different measurement noise standard deviations, the improved Chan-Taylor-UKF fusion algorithm has the smallest positioning error change and is always better than the other two algorithms, verifying its superior performance in a dynamic environment.

6 Conclusions

The C-T-U fusion indoor localization method based on TOF proposed in this paper significantly improves indoor localization accuracy by enhancing the TOF ranging algorithm and the UKF localization algorithm and integrating them with the Chan and Taylor algorithms. It performs exceptionally well in dynamic environments and can provide high-precision solutions for complex indoor localization.

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