Proceedings of the 2015 International Conference on
Advanced Mechatronic Systems, Beijing, China, August, 22-24, 2015

The indoor real-time 3D localization algorithm using UWB

Xuehong Li
School of Automation
University of Science and Technology Beijing
Beijing, China
lixuehong1220@163.com

Shuhua Yang *
School of Automation
University of Science and Technology Beijing
Beijing, China
yangshuhua@ustb.edu.cn

***Abstract*—The actual location application always demands rapid initial positioning, high real time performance and high accuracy. In order to meet the demands above, this paper mainly focus on the UWB indoor real-time 3D TDOA localization algorithms based on the kalman filter. Firstly, the LKF, EKF and UKF algorithms are applied to 3D localization, and the model parameters are given. And then, this paper proposes a collaborative algorithm which is the Chan algorithm provides the initial value and the LKF, EKF, UKF real time positioning algorithms do the subsequent operations, and proposes a method to switch the algorithms dynamically. Finally, the result of the simulation shows the indoor real-time 3D dynamic positioning algorithms achieve a good performance in both speed and precision.**

Keywords—UWB; real time positioning; 3D location; kalman filtering

I. INTRODUCTION

With the emergence and development of the global satellite positioning technology, people pay attention to the location-based service (LBS) more and more, and gradually rely on navigation and positioning. The 80% of the activities are held indoors, so demands for indoor positioning is growing. Places such as the exhibition hall, warehouse, supermarket and workshop complex indoor environment often need to determine the precise location of the equipment, items, and staff, in order to realize intelligent, reliable, efficient and systematic scheduling management [1].

According to the principle of electromagnetic wave propagation being limited by the location accuracy and complex indoor environment, traditional positioning technology is difficult to meet the demand of positioning. Ultra-wideband (UWB) technology with its unique advantages, can satisfy the requirement of indoor high-precision positioning.

However, the study of two-dimensional plane indoor static positioning is enough, and the research of three dimensional space indoor real-time dynamic positioning is relatively less. And the former is difficult to meet the needs of user location applications, three-dimensional space indoor real-time dynamic positioning has more practical significance and application prospect [2, 3]. Such as building fire rescue, only get the precise three-dimensional position of the people, can we carry out effective rescue. Warehousing logistics management, is generally the spatial distribution of goods, only to realize 3D positioning for storage of goods, handling, and outbound links to realize effective management pattern. In addition, the mine safety production, precious materials monitoring, shopping malls, require three dimensional space real-time dynamic positioning [4]. The UWB 3D indoor positioning technology is in the primary stage of development, the three dimensional space indoor real-time dynamic positioning algorithms still need further research and perfect.

So, this paper mainly based on kalman filter (KF) UWB indoor real-time 3D TOA positioning algorithm, in order to find a small calculation complexity, good real-time, high positioning accuracy, and effective algorithm.

Corresponding author: Shuhua Yang
Email: yangshuhua@ustb.edu.cn

II. UWB TOA 3D POSITIONING MODEL

The $M(M \geq 4)$ anchor nodes in 3D positioning are described by $AN_i(i=1,2,\cdots,M)$, the coordinate of i th node AN_i is (x_i, y_i, z_i) . Mobile node is used by MN , which position is (x,y,z) .Measure the TOA value d_i which is the distance of MN and $AN_i(i=2,\cdots,M)$,and $d_{i,1}$ is the relative distance, which is the short of distance MN to $AN_i(i=2,\cdots,M)$, and MN to AN_1.

$$d_i = \sqrt{(x_i - x)^2 + (y_i - y)^2 + (z_i - z)^2} \tag{1}$$

$$d_{i,1} = d_i - d_1 \tag{2}$$

A. TDOA LKF3D positioning algorithm

In the process of position tracking, because the time interval of adjacent distance is short, the position node moves slowly, mutation status generally will not happen, so we can assume that in unit time interval the mobile node is uniform motion [5]. Assuming that the motion parameters of mobile node for the 3D coordinates of target at a certain moment and the direction of the velocity components. Then model the LKF 3D algorithm.

Equation (2) is transformed into linear observation equation, the vector form is:

$$Z = HX \tag{3}$$

and

$$H = \begin{bmatrix} x_{2,1} & y_{2,1} & z_{2,1} & 0 & 0 & 0 \\ x_{3,1} & y_{3,1} & z_{3,1} & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{N,1} & y_{N,1} & z_{N,1} & 0 & 0 & 0 \end{bmatrix}_{(N-1)\times 6}$$

where $x_{i1} = x_i - x_1$, $y_{i1} = y_i - y_1$, $z_{i1} = z_i - z_1$,

$$Z = 0.5 \begin{bmatrix} K_2 - K_1 - d_{2,1}{}^2 - 2d_{2,1}d_1 \\ K_3 - K_1 - d_{3,1}{}^2 - 2d_{3,1}d_1 \\ \vdots \\ K_N - K_1 - d_{N,1}{}^2 - 2d_{N,1}d_1 \end{bmatrix}_{(N-1)\times 1}$$

and $K_i = x_i^2 + y_i^2 + z_i^2$.

In this positioning system, the motion parameters of MN are 3D position coordinates and the velocity components of different directions. So the state vector at time k for mobile node MN is $S_k = \begin{bmatrix} x_k & y_k & z_k & V_k^x & V_k^y & V_k^z \end{bmatrix}_{6\times 1}^T$, where each component is the location and speed of MN in the cartesian coordinate system.

The state equation of TOA LKF 3D algorithm is:

$$S_k = AS_{k-1} + W_{k-1} \tag{4}$$

where $A = \begin{bmatrix} 1 & 0 & 0 & \Delta T & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta T & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta T \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}_{6\times 6}$,

$\Delta T = t_k - t_{k-1}$ shows positioning system sampling time, $W_k = \begin{bmatrix} w_k^x & w_k^y & w_k^z & w_k^{V^x} & w_k^{V^y} & w_k^{V^z} \end{bmatrix}^T$ is a Gaussian white noise.

The observation equation of TDOA LKF 3D algorithm is:

$$Z_k = HS_k + V_k \tag{5}$$

where, Z_k is the value of Z at time k, V_k is the measurement noise vector of time k.

Thus, we can turn the above model parameters in LKF iterative process to realize TDOA LKF real-time 3D spatial orientation [6].

B. TDOA EKF3D positioning algorithm

To reduce the number of anchor nodes which participate in positioning, use Taylor series expansion linearization, Equation (2) can be expressed as nonlinear observation equation:

$$Z_k = h(S_k) + V_k \tag{6}$$

where $Z_k = [d_{2,1}, d_{3,1}, \cdots, d_{M,1}]^T$ is the observation vector of time k, V_k is the Gaussian white noise vector at time k.

$$h(S_k) = \begin{bmatrix} \sqrt{(x_2-x)^2+(y_2-y)^2+(z_2-z)^2} - \sqrt{(x_1-x)^2+(y_1-y)^2+(z_1-z)^2} \\ \sqrt{(x_3-x)^2+(y_3-y)^2+(z_3-z)^2} - \sqrt{(x_1-x)^2+(y_1-y)^2+(z_1-z)^2} \\ \vdots \\ \sqrt{(x_M-x)^2+(y_M-y)^2+(z_M-z)^2} - \sqrt{(x_1-x)^2+(y_1-y)^2+(z_1-z)^2} \end{bmatrix}_{(M-1)\times 1}$$

Because $h(S_k)$ is nonlinear, use Taylor series expansion, the Jacobi matrix at $\hat{S}_{k+1,k}$ of $h(S_k)$ is H_k:

$$H_k = \begin{bmatrix} \frac{\partial h_1(\hat{S}_{k+1,k})}{\partial x} & \frac{\partial h_1(\hat{S}_{k+1,k})}{\partial y} & \frac{\partial h_1(\hat{S}_{k+1,k})}{\partial z} & 0 & 0 & 0 \\ \frac{\partial h_2(\hat{S}_{k+1,k})}{\partial x} & \frac{\partial h_2(\hat{S}_{k+1,k})}{\partial y} & \frac{\partial h_2(\hat{S}_{k+1,k})}{\partial z} & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \frac{\partial h_{M-1}(\hat{S}_{k+1,k})}{\partial x} & \frac{\partial h_{M-1}(\hat{S}_{k+1,k})}{\partial y} & \frac{\partial h_{M-1}(\hat{S}_{k+1,k})}{\partial z} & 0 & 0 & 0 \end{bmatrix}_{(M-1)\times 6},$$

$$\frac{\partial h_1(\hat{S}_{k+1,k})}{\partial x} = \frac{\hat{x} - x_2}{\sqrt{(x_2-x)^2+(y_2-y)^2+(z_2-z)^2}} - \frac{\hat{x} - x_1}{\sqrt{(x_1-x)^2+(y_1-y)^2+(z_1-z)^2}}.$$

The state equation is the same with TOA LKF3D algorithm, according to Equation (4). Thus, we can put the above model parameters in EKF iterative process, which can realize TOA EKF real-time 3D spatial orientation.

EKF3D positioning algorithm iteration process is [7, 8]:

(1)Initialization, set the value of (S_0, P_0, Z_K, Q, R)

(2)Next predict: $\hat{S}_{K/K-1} = AS_{K-1}$.

(3)Mean square error: $\hat{P}_{k/k-1} = AP_{k-1}A^T + Q$.

(4)The filter gain: $K_k = \hat{P}_{k/k-1}H_k^T(H_k\hat{P}_{k/k-1}H_k^T + R)^{-1}$.

(5)State estimates: $S_k = \hat{S}_{k/k-1} + K_k(Z_k - h(\hat{S}_{k/k-1}))$.

(6)Error covariance estimates: $P_k = (I - K_kH_k)\hat{P}_{k/k-1}$.

Return the estimates S_k, P_k, and prepare the initial value for the next iteration.

C. TDOA UKF3D positioning algorithm

In this method, the state equation and observation equation is same with TDOA EKF3D algorithm, which is described as (4) and (6).

For N dimensional positioning system, transform the state vector X by UT, namely, according to the expectation and variance of X, select a group of sampling points χ_i symmetrically. The UT transformation formula is as follows [9, 10]:

$$\begin{cases} \chi_0 = \bar{X} \\ \chi_i = \bar{X} + \left(\sqrt{(N+\lambda)P_x}\right)_i & i = 1,2,\cdots,N \\ \chi_j = \bar{X} - \left(\sqrt{(N+\lambda)P_x}\right)_{j-N} & j = N+1, N+2, \cdots, 2N \end{cases} \tag{7}$$

where, $\bar{X}$ is the mean value of X, P_x is the variance matrix of X, $\lambda = \alpha^2(N+\gamma) - N$ shows the distribution parameters, which determines the sigma distribution around $\bar{X}$, α, γ are constant, α is ratio, (Take a small constant commonly, such as: $1 \geq \alpha \geq 10^{-4}$), γ is a secondary dimension parameters (commonly set $0 \leq \gamma \leq N$), $\left(\sqrt{(N+\lambda)P_x}\right)_i$ is the matrix square root of i th column.

This paper studies the three-dimensional positioning system, so $N = 3$, and set $\alpha = 0.7$, $\gamma = 3$. Q is the covariance matrix of process noise, set

$$Q = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \delta & 0 & 0 \\ 0 & 0 & 0 & 0 & \delta & 0 \\ 0 & 0 & 0 & 0 & 0 & \delta \end{bmatrix},$$

where δ is the standard deviation of process noise. R is the observation noise covariance matrix, set $R = diag(\sigma_{2,1}^2, \sigma_{3,1}^2, \cdots, \sigma_{M,1}^2)$, and, $\sigma_{i,1}$ is the standard deviation of noise.

Take each matrix vector into the following UKF3D localization algorithm iterative process, in order to realize the TDOA UKF3D positioning.

UKF3D localization algorithm iteration process is:

(a)Give a initial value of the algorithm, input $\hat{S}_0 = E[S_0]$, $P_0 = E\left[(S_0 - \hat{S}_0)(S_0 - \hat{S}_0)^T\right]$, Q and R. Where, $E[\cdot]$ means take a matrix average operation.

(b)According Equation (7) to do UT transform (where $X = S_0$), predict the state sampling points, get $2N+1$ sigma points $\chi_i, i = 0,1,\cdots,2N$, take the state vector dimension $N = 3$.

(c)Calculate the new state vector: $x_{k/k-1}^i = A\chi_i, i = 0,1,\cdots,2N$.

(d)Predict the mean and variance:

$$\hat{S}_{k/k-1} = \sum_{i=0}^{2N} w_i^m x_{k/k-1}^i, P_{k/k-1} = \sum_{i=0}^{2N} w_i^c (x_{k/k-1}^i - \hat{S}_{k/k-1})(x_{k/k-1}^i - \hat{S}_{k/k-1})^T + Q$$

where w_i^m is a weight number, w_i^c is covariance weight, calculating formula for weight coefficient is:

$$\begin{cases} w_0^m = \dfrac{\lambda}{N+\lambda}, w_0^c = \dfrac{\lambda}{N+\lambda} + 1 - \alpha^2 + \beta & i = 0 \\ w_i^m = w_i^c = \dfrac{1}{2(N+\lambda)} & i = 1,\cdots,2N \end{cases}$$

where β is commonly relative with the distribution of the state variables, this positioning system is Gaussian system, and $\beta = 2$.

(e)Predict measurement sampling points:

$$y_{k/k-1}^i = h(x_{k/k-1}^i), i = 0,1,\cdots,2N.$$

(f)Mean and variance of measurement value of prediction and measured values and the state vector covariance:

$$\begin{cases} \hat{Z}_{k/k-1} = \sum_{i=0}^{2N} w_i^m y_{k/k-1}^i \\ P_{ZZ} = \sum_{i=0}^{2N} w_i^c (y_{k/k-1}^i - \hat{Z}_{k/k-1})(y_{k/k-1}^i - \hat{Z}_{k/k-1})^T + R \\ P_{XZ} = \sum_{i=0}^{2N} w_i^c (x_{k/k-1}^i - \hat{S}_{k/k-1})(y_{k/k-1}^i - \hat{Z}_{k/k-1})^T \end{cases}$$

(g)Calculate UKF gain: $K = P_{XZ} P_{ZZ}^{-1}$.

(h)Get the update state vector: $S_k = \hat{S}_{k/k-1} + K(Z_k - \hat{Z}_{k/k-1})$.

(i)Get the estimation error of covariance matrix estimation: $P_k = P_{k/k-1} - KP_{ZZ}K^T$.

(j)Return the estimation of S_k, P_k, prepare the initial value for the next iteration.

III. IMPROVE THE COLLABORATIVE REAL-TIME POSITIONING

In the scene of actual location, it is generally intermittent interval, real-time locating and tracking. positioning interval maybe very big, but it requires high initial positioning rapid in each positioning, real-time positioning, high positioning accuracy and so on. Therefore, this article puts forward to using Chan3D localization algorithm to get the location of the initial value accurately, and provided it to the subsequent real-time 3D localization algorithm based on KF. In this way, can satisfy the initial positioning rapid calibration, and subsequent KF based 3D localization algorithm converges faster, so as to ensure the effect of truly achieve real-time accurate positioning, and meet the needs of rapid initial alignment. Improve the collaborative real-time positioning process is shown in figure 1.

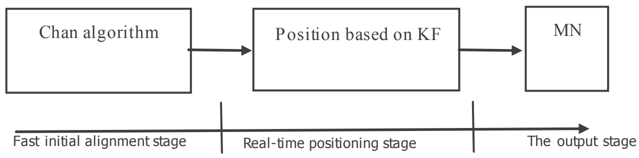

Figure 1. Improve the collaborative real-time positioning process

A. *Fast initial alignment*

The positioning algorithm based on KF needs given the current coordinates of the known or original coordinate in advance. Though we commonly set the observed value for the first time as the state of the initial value for iteration process, a diagonal matrix is the covariance matrix initial value of the filter estimate [11]. But in actual application, because it is hard to obtain relatively accurate initial value, several iterative arithmetic needs to return the actual location. So it is common to lead the start positioning with big error, iterative convergence speed is slow, poor real-time performance, positioning accuracy. When under the condition of the given initial value error is big, EKF algorithm is usually spread performance, estimate the result can't convergence.

To improve these problems, take the average value of beginning static sampling points as initial value, or take large state estimation covariance matrix initial value, in this way, even if the state of the initial value error is big, we can also make the algorithm faster convergence based on KF. But the above methods is not good, so it is necessary to explore new methods. This article puts forward to provide position to estimate the initial value by Chan localization algorithm, combined with the collaborative localization algorithm based on KF algorithm, can effectively achieve the starting location faster calibration requirements. TDOA algorithm, for example, the simulation verifies the good features. Initial alignment stage, sampling for the first time, when give an arbitrary initial value, the simulation results are shown in figure 2, the initial positioning estimated coordinates is shown in table 1.

Table 1. The initial location coordinates

Node coordinates	X(m)	Y(m)	Z(m)
Actual position	1.0000	0.5000	1.0000
Chan3D-TDOA	0.9493	0.3860	1.1035
LKF3D-TDOA	1.1337	0.2830	1.4836
EKF3D-TDOA	0.3499	-0.2184	2.4135
UKF3D-TDOA	2.0926	0.5190	1.8392

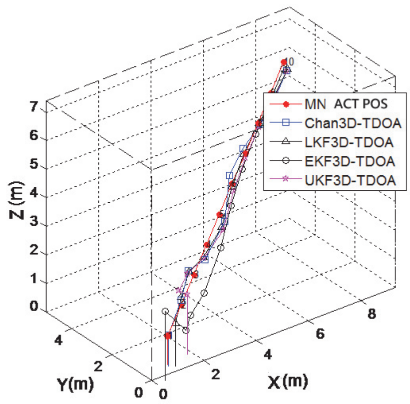

Figure 2. Arbitraty initial value simulation

The table 1 shows that the real-time positioning algorithm based on KF, when the initial value is given unaccurately, initial position precision is extremely low, relatively, Chan3D-TDOA algorithm estimation is relatively accurate. And the figure 2 shows that EKF3D-TDOA location accuracy serious decline, slow convergence.

When using Chan3D-TDOA localization algorithm provides the initial value of location estimate, the simulation result is shown in figure 3. Contrast figure 3 and figure 2 shows that the real-time positioning algorithm based on KF, due to get more accurate initial positioning coordinates, and greatly improve convergence speed, can quickly obtain high location estimation accuracy, improve the defects caused by the initial value uncertainty. Chan3D localization algorithm is demonstrated by the simulation results with real-time 3D localization algorithm based on KF, the improvement of the algorithm can effectively achieve initial positioning applications faster calibration requirements.

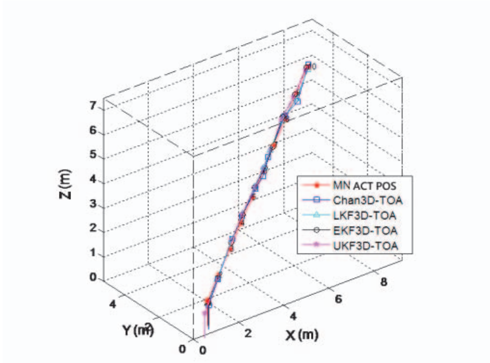

Figure 3. Chan algorithm provides initial value simulation

B. Dynamically switch of real-time positioning algorithm

In a real scenario, positioning in real-time dynamic positioning stage, the mobile node *MN* needs to build the scope of the anchor nodes dynamic list within to maintain a communication, the number of *AN* is refreshing at time n. Positioning accuracy and real-time requirements are always changing. So in order to meet the demand of practical orientation better, the positioning can be divided into three categories:

1） less *AN* (like $n=4$), general location accuracy, high real-time: Calculating *MN* coordinates when adopting EKF3D dynamic positioning algorithm, this algorithm can decrease in positioning anchor node number, save hardware cost.

2） less *AN* number, high location accuracy, general real-time: By UKF3D dynamic localization algorithm calculating *MN* coordinates, the algorithm computational complexity is slightly larger than EKF3D dynamic positioning algorithm, but the precision is high, require less number of anchor nodes, can save hardware cost.

3） more *AN* number(like $n \ge 6$), general location accuracy, high real-time: Calculating *MN* coordinates when adopting LKF3D dynamic positioning algorithm, the algorithm compute less, high real-time performance, general accuracy, need more anchor nodes to positioning.

Based on the above three kinds of orientation, set the algorithm switching module, set the number of positioning anchor nodes n, positioning accuracy σ (value 1: general; 2: higher), positioning real-time requirements (value 1: general; 2: higher).

$$\begin{cases} H_0: 4 \le n \le 5, \sigma = 1, \tau = 2 & \text{EKF3D算法} \\ H_1: 4 \le n \le 5, \sigma = 2, \tau = 1 & \text{UKF3D算法} \\ H_2: n \ge 6, & \text{LKF3D算法} \end{cases} \quad (8)$$

According to the type of ternary hypothesis test, according to a set of parameters σ τ , and the anchor node *AN* number on the list within communication scope, dynamic selection switch 3D dynamic positioning algorithm.

IV. LOCALIZATION ALGORITHM SIMUNLATION ANALYSIS

A.The contrast of 3D positioning error

In order to compare several positioning algorithms performance, this paper gives all kinds of localization algorithms simulation error under different noise measurement. The comparison of the 3D positioning error and position error is shown in figure 4, figure 5, figure 6, respectively set σ = 0.08m, 0.2m and 0.3 m.

When the observation noise standard deviation is constant, position the weight error and error curve shows the same trend. Under the same observation noise standard deviation σ , the position error of Chan+UKF3D-TDOA, Chan+EKF3D-TDOA and Chan+LKF3D-TDOA are much smaller than Chan3D-TDOA algorithm. Though it is fair with Chan+Taylor3D-TDOA algorithm, but it is more stable than Chan+Taylor3D-TDOA algorithm. When σ is small, the performance of Chan3D-TDOA positioning algorithm is better, but it has big volatility. When σ is large, the positioning accuracy of Chan3D-TDOA algorithm significantly lower and positioning error is bigger, the dynamic localization algorithm based on KF has more positioning effectiveness.

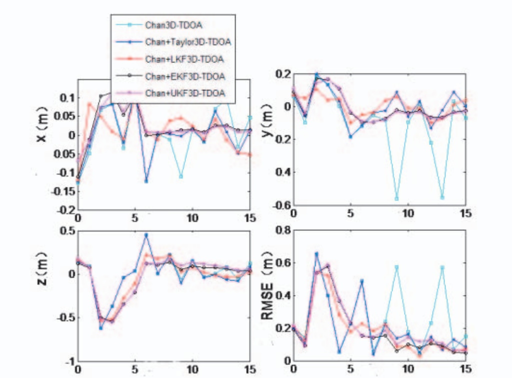

Figure 4. contrast of positioning component error and position error when σ = 0.08m

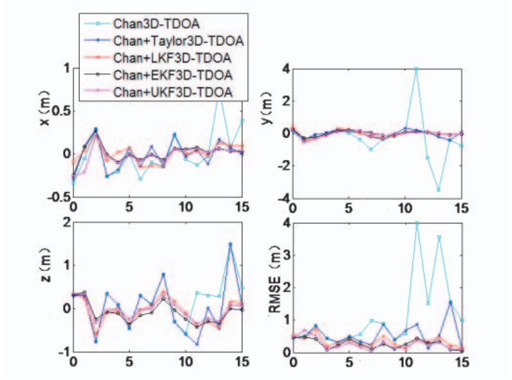

Figure 5. contrast of positioning component error and position error when σ = 0.2m

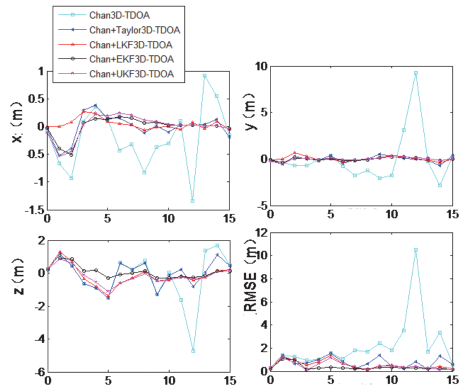

Figure 6. contrast of positioning component error and position error when σ = 0.3m

B.Operation efficiency and positioning accuracy contrast

From the above conclusions, the Chan+Taylor3D-TDOA algorithm location effect is not very good, location accuracy depends largely on the accuracy of the threshold method, the algorithm computational complexity is very big, not suitable for real-time dynamic positioning. So, we comparative analyze Chan3D-TDOA, Chan+LKF3D-TDOA, Chan+EKF3D-TDOA and Chan+UKF3D-TDOA algorithms by the CDF curves. As shown in figure 7, 8, and 9, the observation noise standard deviation, respectively set σ = 0.08m, 0.2m and 0.3m in various algorithms under different position precision corresponds to the CDF convergence curve. Simulation data by repositioning average estimate of 200 independent.

As shown in figure 8, take the observation noise σ = 0.2m, when the positioning accuracy within 0.4m, the CDF of Chan+LKF3D-TDOA, Chan+EKF3D-TDOA and Chan+UKF3D-TDOA algorithms reached more than 95%, is better than that of Chan algorithm is 40%. When positioning accuracy within 0.4m, Chan+LKF3D-TDOA, Chan+EKF3D-TDOA and Chan+UKF3D-TDOA algorithm CDF reached more than 95%, is better than that of Chan algorithm. When positioning accuracy within 0.2m, the CDF of Chan+EKF3D-TDOA and Chan+UKF3D-TDOA algorithm is above 85%, and Chan+LKF3D-TDOA algorithm is near to 15%, Chan algorithm is to be around 2%.

Contrast figure 7, figure 8 and figure 9, we can see that the positioning performance of four kinds of localization algorithms will reduce with the increase of the observation noise, but Chan+EKF3D-TDOA and Chan+UKF3D-TDOA algorithms can maintain relatively near the high positioning accuracy, especially Chan+UKF3D-TDOA algorithm, even when take the observation noise σ = 0.3 m, positioning accuracy within 0.25m, the CDF can reach above 80%. Chan3D-TDOA algorithm, when the observation noise is small, it is better to locate, but with the increase of the observation noise, the positioning performance fell sharply. Chan+LKF3D-TDOA performance is relatively common, although the positioning performance is better than Chan3D-TDOA algorithm, but it is not stable as Chan+EKF3D-TDOA and Chan+UKF3D-TDOA algorithm.

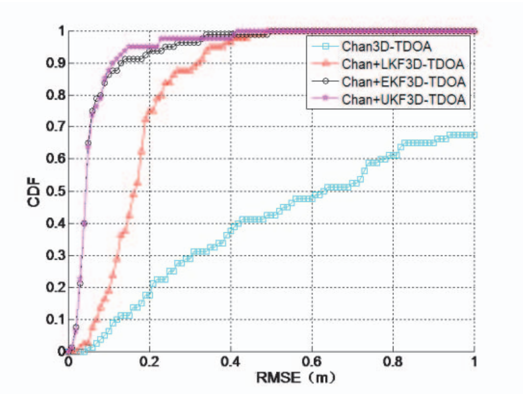

Figure 7. CDF contrast of 3D positioning error when $\sigma = 0.08$m

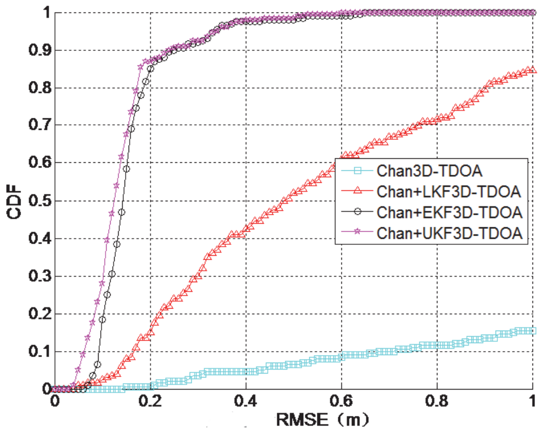

Figure 8. CDF contrast of 3D positioning error when $\sigma = 0.2$m

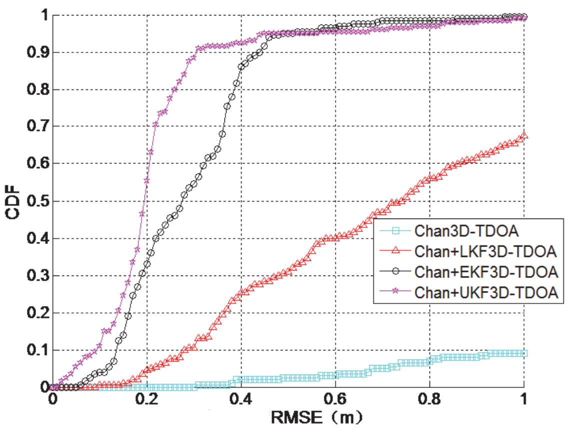

Figure 9. CDF contrast of 3D positioning error when $\sigma = 0.3$m

V. CONCLUSION

Chan3D-TDOA algorithm computational complexity is the smallest, in condition of less observation error the location accuracy is higher, but in the case of large observation error the positioning performance is greatly reduced. It is not suitable for the subsequent real-time dynamic positioning. Although Chan+LKF3D-TDOA algorithm belongs to the second category of equivalent linearization method, which without any approximation, only through the equation transformation, transform the nonlinear equations into linear equations, and solve it. The calculation is small, good real-time performance, but the location performance is less than Chan+EKF3D-TDOA and Chan+UKF3D-TDOA algorithms. Chan+EKF3D-TDOA and Chan+UKF3D-TDOA algorithms is the first kind of approximate linearization method, Chan+UKF3D-TDOA algorithm computational complexity greatly increased due to UT transformation, but the positioning precision is higher. In conclusion, the TDOA 3D dynamic positioning algorithm based on KF has better real-time performance and high positioning accuracy. It could be selected, which algorithm is suitable for dynamic positioning according to the requirements such as the specific location.

REFERENCES

[1] Wan Qun, Guo Xiansheng, Chen Zhangxin. Indoor positioning theory, method and application [M]. Beijing: Electronic industry press, 2012, 9.

[2] Onalaja O, Siyau M F, Ling S L, Ghavami M. UWB-based Indoor 3D Position Estimation for Future Generation Communication Applications[C]. IEEE International Conference on Future Generation Communication Technology, 2013: 16-20.

[3] Pan M S, Tsai C H, Tseng Y C. Emergency guiding and monitoring applications in indoor 3D environments by wireless sensor networks[J]. International Journal of Sensor Networks, 2006, 1(1): 2-10.

[4] Li Hui, Li Layuan, Li Fangyun. A new kind of WSN three-dimensional positioning mechanism [J]. Computer engineering and application, 2010, 46(14): 115-118.

[5] Zhang C, Kuhn M, Merkl B, Mahfouz M. Accurate UWB Indoor Localization System Utilizing Time Difference of Arrival Approach[J]. IEEE Radio and Wireless Symposium, 2006: 515-518.

[6] Kalman R E. A new approach to linear filtering and prediction problems[J]. Journal of Fluids Engineering, 1960, 82(1): 35-45.

[7] Hinsbergen C, Schreiter T, Zuurbier F S, et al. Localized extended kalman filter for scalable real-time traffic state estimation[J]. IEEE Transactions on Intelligent Transportation Systems, 2012, 13(1): 385-394.

[8] Gordon N J, almond D J, and Smith A F M. A Novel Approach to Nonlinear Non-Gaussian Bayesian State Estimation [J]. IEE Proceedings on Radar and Signal Processing, 1993, 140 (2): 107-113.

[9] Crassidis J L. Sigma-point Kalman filtering for integrated GPS and inertial navigation[J]. IEEE Transactions on Aerospace and Electronic Systems, 2006, 42(2): 750-756.

[10] Bosch M, Najar M. Unscented kalman filter for location in Non Line of Sight[J]. Vectors, 2006, 2.

[11] Fu Mengyin, Deng Zhihong, Zhang Jiwei. .Kalman filtering theory and its application in the navigation system [M]. Beijing: Science press, 2003.