A UWB Location Algorithm---Based on Adaptive Kalman Filter

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Abstract: In order to solve the problem of large fluctuations in UWB(Ultra Wide Band) positioning accuracy and solid-state deviations in the positioning results, which are in complex indoor environments, an adaptive Kalman filter method is introduced in the later stage of data processing. This method can better retain data information and obtain better filtering effects when the system noise is complex and measurement information is missing. Therefore providing better positioning accuracy. The experiment uses AGV trolley equipped with UWB sensors to obtain measurement data, uses traditional Kalman filtering and adaptive Kalman filtering methods to compare the filtering effects of the algorithms. The experimental results show that when the measurement information is missing, compared with the traditional Kalman filter algorithm, the adaptive Kalman filter method is a real-time high-precision indoor positioning algorithm with higher positioning accuracy.

Keywords: UWB; Indoor Positioning; positioning accuracy; Kalman filter; Adaptive Kalman filter

1. Introduction
With the rapid development in science technology, people are highly demanded on the accuracy of an indoor location. Locations can be estimated by traditional location techniques, such as infrared ray, ultrasonic, RFID(Radio Frequency Identification) and Wi-Fi, it becomes harder to satisfy the application needs in the refining industry because the accuracy of such techniques could be easily impacted by the local environment[1]. By contrast, UWB indoor location is a wireless technique with no carrier, which possesses high-speed transmission, low-power emission, and strong penetrability. Besides, it is based on short-duration pulse and has the advantages of such a technique, bringing favorable location in distance-of-sight transmission[2].
When equipment begins to run, UWB, owing to complex indoor transmission, often locates on a small area instead of a single point. Nowadays, it becomes a hot topic for learners to rectify and smooth locations Literature[3] studies error characteristic in one of UWB measurements--- based on round-trip time. It analyzes Non-gaussian noise in RTT measurement and verifies the advantage of the particle filter algorithm. However, it is overly computed given by a restriction in which algorithm itself uses plenty of samples to explore randomly. In order to forecast target location Literature [4] proposes an extended finite impulse response estimator based on UWB ranging information and time delay positioning model but the accuracy depends on the average level.

To better improve the accuracy of UWB location, this paper introduces a new location algorithm that adapts UWB. In addition, a small car--AGV, as sensor carriers, is adapted to verify the effectiveness of algorithm improvement[5]. The above method, combining with indoor environment, can provide better location accuracy, which is realized under systematic noise and inaccurate measuring information.

2. Traditional Kalman filter and Self-adapting Kalman filter

State equation of general linear discrete system can be represented as following one:

\[
X(k + 1) = \Phi(k + 1, k)X(k) + \Gamma(k + 1, k)\omega(k)
\]

(1)

\[
Z(k + 1) = H(k + 1)X(k + 1) + \nu(k + 1)
\]

(2)

This equation \(X(k)\) refers to n-dimensional state vector; \(\Phi(k+1, k)\) refers to state-transition matrix; \(\omega(k)\) refers to the noise vector of system; \(\Gamma(k+1, k)\) refers to the excitation transfer matrix; \(Z(k)\) refers to m-dimensional observation matrix; \(H(k+1)\) refers to the predicted output transmission matrix at \(k+1\) moment; \(\nu(k)\) refers to the measurement of noise vector.

The following are different kinds of equations:

Optimal filter estimation equation, Optimal gain matrix equation, Covariance equation of single-step prediction error, and Covariance equation of filtered prediction error.

\[
\hat{X}(k + 1 \mid k + 1) = \Phi(k + 1, k)\hat{X}(k \mid k) + K(k+1, k+1)\left[Z(k + 1) - H(k + 1)\Phi(k + 1, k)\hat{X}(k \mid k)\right]
\]

(3)

\[
K(k+1, k+1) = P(k+1 \mid k)H(k + 1)\left[H(k + 1)P(k+1 \mid k)H(k + 1) + R(k+1)\right]^{-1}
\]

(4)

\[
P(k + 1 \mid k) = \Phi(k + 1, k)P(k \mid k)\Phi^T(k + 1, k) + \Gamma(k + 1, k)Q(k)\Gamma^T(k + 1, k)
\]

(5)

\[
P(k + 1, k + 1) = \left[I - K(k + 1)H(k + 1)\right]P(k + 1 \mid k)
\]

(6)

In this equation, \(K\) refers to Kalman gain matrix; \(P\) refers to error covariance matrix; \(Q(k)\) refers to covariance matrix of \(\omega(k)\); \(R(k)\) refers to covariance matrix of \(\nu(k)\).

In practical applications, mathematical models and noise estimation, which described characteristics of system dynamics, sometimes are far from accuracy when they are under complex environments as well as other factors[6]. As a result, physics process cannot be reflected directly. Meanwhile, Kalman filtering is a recursive process. With the improving filtering steps, round-off error will be accumulated, which makes filter gain matrix lose its weighting function. Thus, the growing number of measurements magnified both mean value and covariance of evaluated error. The result is that smoothing will become less accurate when it is evaluating. Or worse is that Kalman filter will diverge. In order to control its divergence and improve precision, this paper introduces methods of adaptive Kalman filter[7].


Sage-Husa adaptive Kalman filter estimates estimator via time-varying noise when it uses measured data for recursive filtering. It estimates and corrects the statistical characteristics of system noise and measurement noise in real-time, so as to reduce the system model error, suppress filter divergence and improve the filtering accuracy [8-9].

Sage-Husa adaptive Kalman filter can be described as:

\[ \hat{x}_{k,k-1} = \Phi_{k,k-1} \hat{x}_{k-1} + \hat{q}_{k-1} \]  

\[ \hat{z}_{k} = z_{k} - H_{k} \hat{x}_{k,k-1} - \hat{r}_{k} \]  

\[ K_{k} = P_{k,k-1} H_{k} \left( H_{k} P_{k,k-1} H_{k}^{T} + \hat{R}_{k} \right)^{-1} \]  

\[ P_{k,k-1} = \Phi_{k,k-1} P_{k,k-1} \Phi_{k,k-1}^{T} + \hat{Q}_{k-1} \]  

\[ P_{k} = (I - K_{k} H_{k}) P_{k,k-1} \]

among the rest, \( \hat{r}_{k} \), \( \hat{R}_{k} \), \( \hat{q}_{k} \) and \( \hat{Q}_{k} \) can be gained through statistical estimators of time-varying noise:

\[ \hat{r}_{k+1} = (1-d_{k}) \hat{r}_{k} + d_{k} (z_{k+1} - H_{k+1} \hat{x}_{k+1,k}) \]

\[ \hat{R}_{k+1} = (1-d_{k}) \hat{R}_{k} + d_{k} (\hat{z}_{k+1} \hat{z}_{k+1}^{T} - H_{k+1} P_{k+1,k} H_{k+1}^{T}) \]

\[ \hat{q}_{k+1} = (1 - d_{k}) \hat{q}_{k} + d_{k} (x_{k+1} - \Phi_{k+1,k} \hat{x}_{k}) \]

\[ \hat{Q}_{k+1} = (1-d_{k}) \hat{Q}_{k} + d_{k} (K_{k+1} \hat{z}_{k+1} \hat{z}_{k+1}^{T} + P_{k+1,k} - \Phi_{k+1,k} P_{k,k} \Phi_{k+1,k}^{T}) \]

Of which: \( d_{k} = \frac{1-b}{1-b^{k+1}} \), \( 0 < b < 1 \) refers to forgotten factors.

3. Simulation experiment

3.1. Modeling and parameter setting
In this paper, the vehicle trajectory is filtered. State variables are set as \( x(k) \), it uses 4 state variables, that is \( X(k) = [x_1(k), x_2(k), x_3(k), x_4(k)]^T \), in which \( x \) represents separately direction displacement, direction velocity, and \( y \)-direction displacement, and direction velocity. The initial estimated value of speed is expressed by the observed value[10-11].

Setting the acceleration \( u_1(k) u_2(k) \) of \( x, y \) meet within the \( T \) of two sampling intervals: submit to average distribution within \([-M,M]\), its possible density is \( f(u)\frac{M}{2} \), variance is \( \sigma_u^2 \frac{M^2}{3} \); the average value of observation noise \( v_1(k), v_2(k) \) is 0; Variance is \( \sigma_v^2 = 0.05 \). Sampling time during the procedure is interval of \( T=1, M=0.001 \), So the state equation is:

\[
\begin{bmatrix}
x_1(k + 1)
x_2(k + 1)
x_3(k + 1)
x_4(k + 1)
\end{bmatrix} = \begin{bmatrix}
1 & T & 0 & 0
0 & 1 & 0 & 0
0 & 0 & 1 & T
0 & 0 & 0 & 1
\end{bmatrix} \begin{bmatrix}
x_1(k)
x_2(k)
x_3(k)
x_4(k)
\end{bmatrix} + \begin{bmatrix}
\frac{T^2 u_1(k)}{2}
\frac{T^2 u_2(k)}{2}
\end{bmatrix}
\]

(17)

Measurement equation is:

\[
\begin{bmatrix}
y_1(k)
y_2(k)
\end{bmatrix} = \begin{bmatrix}
1 & 0 & 0 & 0
0 & 0 & 1 & 0
\end{bmatrix} \begin{bmatrix}
x_1(k)
x_2(k)
x_3(k)
x_4(k)
\end{bmatrix} + \begin{bmatrix}
v_1(k)
v_2(k)
\end{bmatrix}
\]

(18)

Correspondingly, variance matrix can be written, which corresponds to the process noise \( \omega_k \) \( \mathbf{V}_k \).

\[
Q_k = \begin{bmatrix}
\frac{T^2 \sigma_u^2}{4} & \frac{T^2 \sigma_u^2}{2} & 0 & 0 \\
\frac{T^2 \sigma_u^2}{2} & T^2 \sigma_u^2 & 0 & 0 \\
0 & 0 & \frac{T^2 \sigma_v^2}{4} & \frac{T^2 \sigma_v^2}{2} \\
0 & 0 & \frac{T^2 \sigma_v^2}{2} & T^2 \sigma_v^2
\end{bmatrix}
\]

(19)

\[
R_k = \begin{bmatrix}
\sigma_v^2 & 0 \\
0 & \sigma_v^2
\end{bmatrix}
\]

(20)

Besides, in order to obtain estimated value with invariant state by Kalman filter, it has to provide initial value \( X_0, P_0 \) from both state variate and mean square value of estimated errors. It
shows $X_0 P_0$ by adapting the first two sets of data and combining with the equation of state and the equation of both sides[12].

Estimated value of initial state variate:

$$
X_0 = \begin{bmatrix}
\hat{x}_1(2) \\
\hat{y}_1(2) - y_1(1) \\
\hat{y}_2(2) \\
\hat{y}_3(2) - y_2(1)
\end{bmatrix}
= \begin{bmatrix}
y_1(2) \\
y_1(2) - y_1(1) \\
y_2(2) \\
y_2(2) - y_2(1)
\end{bmatrix}
\begin{bmatrix}
\dot{x}_1(1) + T \dot{x}_1(1) + \frac{T^2 u_1(1)}{2} + v_1(2) \\
\dot{y}_1(1) + T \dot{y}_1(1) + \frac{T^2 u_1(1)}{2} + v_2(1) \\
\dot{x}_2(1) + T \dot{x}_2(1) + \frac{T^2 u_2(1)}{2} + v_1(2) \\
\dot{y}_2(1) + T \dot{y}_2(1) + \frac{T^2 u_2(1)}{2} + v_2(1)
\end{bmatrix}
(21)
$$

The exact value $x$ of the state variate at the corresponding time can be written by the equation of state, so the mean square matrix $P$ of the initial error can be obtained:

$$
P = \mathcal{E}((X - X_0)(X - X_0)^T)
= \begin{bmatrix}
\sigma_x^2 & \frac{\sigma_y^2}{T} & 0 & 0 \\
\frac{\sigma_y^2}{T} & \frac{T^4 \sigma_x^2}{4} + \frac{2\sigma_y^2}{T^2} & 0 & 0 \\
0 & 0 & \sigma_y^2 & \frac{\sigma_y^2}{T} \\
0 & 0 & \frac{\sigma_y^2}{T} & \frac{T^4 \sigma_y^2}{4} + \frac{2\sigma_y^2}{T^2}
\end{bmatrix}
(22)
$$

Experiment of UWB Positioning Based on Adaptive Kalman Filter

The position data generated by AGV vehicle with UWB sensor, which around the target for 24 laps, is used as the initial measurement data. It respectively used Kalman filter and adaptive Kalman filter. The following contents are experimental image and results of data processing:

![Fig.1 AGV platform with uwb sensors](image1.png)

![Fig.2 Results of round 10 bypass](image2.png)
Fig. 3 results of zoom on the lower left of the tenth circle

P3 shows the results of processing data through traditional Kalman filter and adaptive Kalman filter. As P3 shows, both methods ensured the convergence of the filtering. However, by localizing P2 to P3, Kalman filter, compared with the adaptive Kalman filter algorithm, weakens the information of outliers and loses more effective information. In UWB location, partial data mutation, caused by inadequate data, is slower and less accurate.

4. Conclusion
This paper studies the UWB indoor positioning algorithm. Aiming at the large fluctuations in positioning accuracy of UWB positioning and the lack of measurement information when they are in the case of complex system noise, the adaptive Kalman filter algorithm is introduced in the later stage of data processing to further improve the measurement information. Filtering and correction. It compared the original position data measured in a complex noise environment with the data processed by traditional Kalman filtering and adaptive Kalman filtering methods. The results show that the adaptive Kalman filtering method is better than conventional Kalman filtering. It has better filters effect on missing location information, therefore makes positioning more accurate.

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