International Journal of Database Theory and Application
Vol.9, No.4 (2016), pp.45-54
http://dx.doi.org/10.14257/ijdta.2016.9.4.03

Indoor Location Algorithm Based on Kalman Filter and Multi-Source Data Integration

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Abstract

For onboard single-station passive direction-finding and location, if there is any abnormal error in the observation data, the extended Kalman filter (EKF) algorithm adopted thereby will cause inaccurate location result. In order to improve algorithm robustness, the robust equivalent gain matrix is constructed according to the standardized prediction residual error and the robust EKF algorithm is applied to the onboard single-station passive direction-finding and location. In allusion to the low efficiency of the robust EKF algorithm, the single-station passive location algorithm based on the improved extended Kalman filter is proposed in this article on the basis of combining F distribution statistic, and meanwhile single abnormal error and continuous abnormal error are added in the observation value to test the algorithm resistance to different abnormal errors. The simulation shows that the algorithm proposed in this article can well weaken the influence of abnormal errors on position estimation and the algorithm based on F distribution discriminant can improve location efficiency.

***Keywords**: Indoor location; Robust EKF filter; F distribution discriminant; Location accuracy*

1. Introduction

Due to strong concealment and good flexibility, the onboard single-station passive location has wide application prospect in such fields as electronic warfare **Error! Reference source not found.**. In some complex environments, angle information may be the observed information uniquely obtained by the detection equipment, so it is significant to research the angle information based onboard single-station passive location.

Common location algorithms include least square algorithm, Kalman filter algorithm, *etc.*, wherein the least square algorithm and the improved algorithms thereof are widely applied to direction-finding and location, such as linear weighted least square algorithm and total least square algorithm, and these algorithms are more or less effective to conquer the random error following zero-mean normal distribution; but the abnormal error in the observation value can significantly influence location accuracy. For solving these problems, the robust estimation theory is introduced into the improved least square algorithm in literature [2] to improve algorithm resistance to abnormal errors, but the state equation of dynamic carriers is not considered. In consideration of system state equation, Kalman filter algorithm can be adopted, and such algorithms as robust Kalman filter algorithm, rank-defect Kalman filter algorithm and robust self-adaptive Kalman filter algorithm are proposed in literature [4], thus to introduce the robust estimation theory into the standard Kalman filter algorithm and the improved algorithms thereof. However, these algorithms are currently mainly applied to satellite clock error fitting and estimation **Error! Reference source not found.**, precise point location **Error! Reference source not found.**, integrated navigation **Error! Reference source not found.**, *etc.* In the aspect of passive location algorithm, there are few researches on the application of the robust estimation theory for improving algorithm resistance to abnormal errors. Moreover, the location efficiency shall be considered for the application of the robust EKF algorithm in the onboard passive direction-finding and location. Therefore, it is necessary to further research algorithm robustness and effectiveness.

In allusion to the low efficiency of the robust EKF algorithm, the single-station passive location algorithm based on the improved extended Kalman filter is proposed in this article on the basis of combining F distribution statistic, and meanwhile single abnormal error and continuous abnormal error are added in the observation value to test the algorithm resistance to different abnormal errors. The simulation shows that the algorithm proposed in this article can well weaken the influence of abnormal errors on position estimation and the algorithm based on F distribution discriminant can improve location efficiency.

2. Onboard Single-Station Passive Direction-Finding and Location Model

For convenient calculation, the two-dimensional onboard single-station passive direction-finding and location model is taken as an example for relevant analysis, the state equation and the observation equation of the location model are also established, and meanwhile the observation equation is linearized. As shown in Figure1, the target radiation source T is located at (x_t, y_t). An airplane is assumed to start from the origin and make uniform linear motion at speed v and meanwhile change motion direction, wherein the coordinate of the k th observation point of the airplane is (x_k, y_k), and ϕ_k is the azimuth angle measured at the k th observation point.

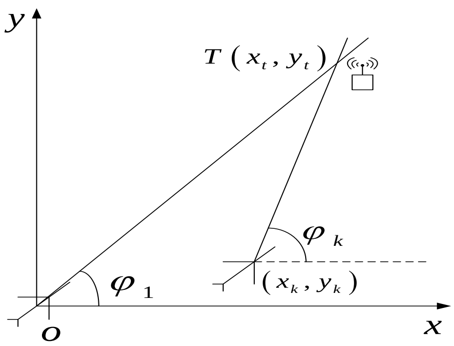

Figure 1. Location model

If the airplane is taken as the reference system, then the state equation of the target radiation source is as follows:

$$X(k) = \Phi X(k-1) + \Gamma W(k) \tag{1}$$

Therein:

$$W(k) \sim N(0, Q(k))$$

$$X(k)=\left[x(k),\dot{x}(k),y(k),\dot{y}(k)\right]^T$$
$$=\left[x_t-x_k,-v_x,y_t-y_k,-v_y\right]^T$$
$$\Phi=\begin{bmatrix}1 & T & 0 & 0\\0 & 1 & 0 & 0\\0 & 0 & 1 & T\\0 & 0 & 0 & 1\end{bmatrix}$$
$$\Gamma=\begin{bmatrix}T^2/2 & 0\\T & 0\\0 & T^2/2\\0 & T\end{bmatrix}$$

The observation equation of the onboard single-station passive direction-finding and location can be expressed by the following formula:

$$Z(k)=h\left[k,X(k)\right]+V(k) \tag{2}$$

In the above formula,

$$V(k)\sim N\left(0,R(k)\right)$$
$$Z(k)=\left[\phi_1,\phi_2,\cdots,\phi_n\right]^T$$
$$X(k)=\left[x_t-x_k,-v_x,y_t-y_k,-v_y\right]^T \quad h\left[k,X(k)\right]=\arctan\left(\frac{y_t-y_k}{x_t-x_k}\right)$$

When the airplane is taken as the reference system, the location model can be converted into the problem that the fixed single-station tracks the target radiation source under uniform motion, and Kalman filter algorithm can be adopted for calculation.

The motion model can be converted as follows:

$$X(k)=\Phi X(k-1)+\Gamma W(k) \tag{3}$$
$$Z(k)=\arctan\left(\frac{y_t-y_k}{x_t-x_k}\right)+V(k) \tag{4}$$

According to the model, the state equation is linear while the observation equation is nonlinear, and the linearized observation matrix is as follows:

$$\begin{aligned}H&=\frac{\partial Z(k)}{\partial X(k)}\\&=\left[\frac{\partial Z(k)}{\partial x(k)},\frac{\partial Z(k)}{\partial \dot{x}(k)},\frac{\partial Z(k)}{\partial y(k)},\frac{\partial Z(k)}{\partial \dot{y}(k)}\right]\\&=\left[\frac{-(y_t-y_k)^2}{(x_t-x_k)^2+(y_t-y_k)^2},0,\frac{-(x_t-x_k)^2}{(x_t-x_k)^2+(y_t-y_k)^2},0\right]\end{aligned} \tag{5}$$

The extended Kalman filter algorithm can realize the linear approximation of the nonlinear system to improve location accuracy. For a given model, the extended Kalman filter therefore is further predicted as follows:

$$\bar{X}(k+1|k)=\Phi\hat{X}(k|k) \tag{6}$$
$$\bar{Z}(k+1)=h\left[k+1,\bar{X}(k+1|k)\right] \tag{7}$$

The prediction covariance matrix is as follows:

$$P\left(k+1|k\right)=\Phi P\left(k|k\right)\Phi^{T}+Q\left(k\right) \tag{8}$$

The filter estimation and the corresponding covariance matrix thereof are as follows:

$$\hat{X}\left(k+1|k+1\right)=\hat{X}\left(k+1|k\right)+ K\left(k+1\right)\left[Z\left(k+1\right)-\hat{Z}\left(k+1\right)\right] \tag{9}$$

$$P\left(k+1|k+1\right)=\left[I-K\left(k+1\right)H\left(k+1\right)\right] P\left(k+1|k\right) \tag{10}$$

The observation estimation is as follows:

$$\hat{Z}\left(k+1\right)=h\left[k+1,\hat{X}\left(k+1|k+1\right)\right] \tag{11}$$

EKF gain matrix is as follows:

$$K\left(k+1\right)=P\left(k+1|k\right)H^{T}\left(k+1\right)\left[H\left(k+1\right) P\left(k+1|k\right)H^{T}\left(k+1\right)+R\left(k+1\right)\right]^{-1} \tag{12}$$

For a given nonlinear location model, EKF algorithm can effectively solve nonlinear problem to obtain a relatively optimal state estimation.

3. Robust Extended Kalman Filter Algorithm

3.1 Robust EKF Filter Algorithm

At time k, the parameter vector $\hat{X}\left(k+1|k\right)$ of the prediction state is assumed to follow normal distribution, the observation vector $Z\left(k\right)$ includes abnormal errors and follows contaminated normal distribution, namely:

$$Z\left(k\right)\sim\left(1-\varepsilon_k\right)N_k+\varepsilon_k h_{Z(k)} \tag{13}$$

In the above formula, N_k stands for following normal distribution; $h_{Z(k)}$ is contaminated distribution source; ε_k $\left(0<\varepsilon_k<1\right)$ is contamination rate. The robust EKF algorithm is adopted, wherein the robust M estimation is adopted for the observation vector, and the least square estimation is adopted for the state parameter, namely M-LS filter.

The robust EKF algorithm process includes the construction of equivalent gain matrix and the iterative calculation. Therein, it is important to construct the suitable equivalent weight function for the robust estimation in order to make the weight factor reduced or as zero when there are any abnormal observation data, thus to reduce the influence of abnormal data on estimation. Specifically, the equivalent weight functions usually used for robust estimation include Huber weight function, Danish weight function, IGG I weight function, IGG Ⅲ weight function, *etc.* In this article, IGG Ⅲ weight function is selected as the equivalent weight function, namely:

$$\bar{p}_i=\begin{cases}1 & \left|\tilde{s}_i\right|\le k_1\\ \dfrac{k_1}{\left|\tilde{s}_i\right|}\left(\dfrac{k_2-\left|\tilde{s}_i\right|}{k_2-k_1}\right)^2 & k_1<\left|\tilde{s}_i\right|\le k_2\\ 0 & \left|\tilde{s}_i\right|>k_2\end{cases} \tag{14}$$

In the above formula, $\tilde{s}_i$ ($\tilde{s}_i=\hat{s}_i/\sigma_v$) is the standard residual error of the i th observation value, σ_v is the standard deviation of the residual error and can be calculated through a prior method. k_1 and k_2 are constants and reflect the algorithm sensitivity to abnormal data; generally, $k_1 \in [1.0,\ 1.5]$, $k_2 \in [2.5,\ 8.0]$.

The robust solution $\hat{X}\left(k+1|k+1\right)$ of the state parameter, the covariance matrix $P\left(k+1|k+1\right)$ and the robust EKF gain $K_{MLS}\left(k+1\right)$ are respectively as follows:

$$\hat{X}\left(k+1|k+1\right)=\hat{X}\left(k+1|k\right)+K_{MLS}\left(k+1\right)\left(Z\left(k+1\right)-\hat{Z}\left(k+1\right)\right) \tag{15}$$

$$P\left(k+1|k+1\right)=\left[I-K_{MLS}\left(k+1\right)H\left(k+1\right)\right]P\left(k+1|k\right) \tag{16}$$

$$K_{MLS}\left(k+1\right)=P\left(k+1|k\right)H^{T}\left(k+1\right)\left[H\left(k+1\right)P\left(k+1|k\right)H^{T}\left(k+1\right)+\bar{R}\left(k+1\right)\right]^{-1} \tag{17}$$

In the above formula, $\bar{R}\left(k+1\right)=\left[R\left(k+1\right)\bar{P}_k\right]^{-1}$; $\bar{P}_k$ is equivalent weight matrix; I is unit matrix.

In the robust EKF algorithm, the robust M estimation is adopted for the observation vector while the least square estimation is adopted for the state parameter. When there is any abnormal error in the observation value, the algorithm can reduce the weight of the abnormal data through the robust equivalent gain matrix in order to weaken the influence of abnormal data on the location estimation.

3.2. Robust EKF Algorithm Based on F Distribution Discriminant

The error equation of the state prediction information vector is as follows:

$$V_{\bar{X}_k}(k)=\hat{X}\left(k|k\right)-\bar{X}\left(k|k-1\right) \tag{18}$$

$$\varepsilon\left(k\right)=\left(V_{\bar{X}_k}^{T}\left(k\right)\right)\left(P\left(k|k-1\right)\right)^{-1}\left(V_{\bar{X}_k}\left(k\right)\right) \tag{19}$$

Then, the statistic **Error! Reference source not found.**:

$$\varepsilon\left(k\right)=\left(V_{\bar{X}_k}^{T}\left(k\right)\right)\left(P\left(k|k-1\right)\right)^{-1}\left(V_{\bar{X}_k}\left(k\right)\right) \tag{19}$$

Follows χ^2 distribution with DOF (Degree of Freedom) as 4.

The error equation of the observation vector is as follows:

$$V\left(k\right)=Z\left(k\right)-\hat{Z}\left(k\right) \tag{20}$$

$$\eta\left(k\right)=\left(V^{T}\left(k\right)\right)\left(P\left(k|k\right)\right)^{-1}\left(V\left(k\right)\right) \tag{21}$$

Then, the statistic:

$$\eta\left(k\right)=\left(V^{T}\left(k\right)\right)\left(P\left(k|k\right)\right)^{-1}\left(V\left(k\right)\right) \tag{21}$$

Follows χ^2 distribution with DOF (Degree of Freedom) as 1.

The following statistic is constructed:

$$F\left(k\right)=\frac{\varepsilon\left(k\right)}{4}\Big/\frac{\eta\left(k\right)}{1} \tag{22}$$

If there is no abnormal error in the observation value and the state prediction value, the observation residual error and the state error follow zero-mean normal distribution, and the statistic $F\left(k\right)$ follows central F distribution with DOF as (4, 1); if there is any abnormal error in the observation value or the state prediction value, the observation residual error or the state error follows non-zero-mean normal distribution, and the statistic $F(k)$ follows non-central F distribution with DOF as (4, 1).

Test method is as follows:

(1) When the state error follows zero-mean normal distribution and the observation value includes abnormal error:

Original hypothesis H_0: no abnormal error in the observation value; alternative hypothesis H_1: abnormal error in the observation value. The significance level is α, and if $F(k) > F_\alpha(4,1)$ is true, then original hypothesis H_0 is accepted; or else, alternative hypothesis H_1 is accepted and original hypothesis H_0 is refused. Therein, $F_\alpha(4,1)$ is upper α-quantile of $F(4,1)$.

(2) When the observation residual error follows zero-mean normal distribution and the state prediction value includes abnormal error:

Original hypothesis H_0: no abnormal error in the state observation value; alternative hypothesis H_1: abnormal error in the state observation value. The significance level is α, and if $F(k) \le F_\alpha(4,1)$ is true, then original hypothesis H_0 is accepted and the test is qualified; or else, alternative hypothesis H_1 is accepted and original hypothesis H_0 is refused.

Only the abnormal error in the observation value is considered in this article, so the above method can be adopted for the test before robust iteration. If there is any abnormal error, then the robust iteration shall be carried out in order to obtain accurate location estimation; if there is no abnormal error, then there is no need to carry out robust iteration, and the location estimation obtained through EKF algorithm shall be regarded as the estimation result.

4. Simulation Analysis

4.1. Simulation Parameter Setting

The simulation parameter is set as follows: a certain radiation source target T is located at (5km, 10km), an airplane travels from (0, 0) along the positive x-axis at the speed of 600m/s and meanwhile changes the direction, the measurement period is 1s, and the measurement noise follows the normal distribution with the mean as 0 and the variance as 0.1°. In order to increase location speed and ensure robust EKF algorithm convergence, the initial value of the recursive estimation of the target position is calculated according to the previous measurement values. The initial value of matrix $\boldsymbol{P}$ is $\boldsymbol{P}(0) = diag(10^6, 0, 10^6, 0)$, and if the airplane is taken as the reference system and the target speed is known, then the initial variance of the speed is set as 0. In the improved EKF algorithm, the significance level is α=0.005, and the discriminant threshold value can be found in the table as $F_\alpha(4,1)$=22500. In order to accurately analyze the algorithm performance, it is necessary to carry out several Monte-Carlo simulations and adopt RMSE performance index, namely:

$$\text{RMSE} = \sqrt{\frac{1}{M}\sum_{i=1}^{M}\left[\left(x_t - x_k - \hat{x}_i\right)^2 + \left(y_t - y_k - \hat{y}_i\right)^2\right]} \tag{18}$$

In the above formula, M is the times of Monte-Carlo simulations, and is set as 200 in this article. Additionally, the simulation time is set as 200s.

4.2. Result and Analysis

4.2.1. Performance Comparison of EKF Algorithm and Least Square Algorithm

The comparison of EKF algorithm and least square algorithm is as shown in Figure2. According to Figure2, the location accuracy and the convergence rate of EKF algorithm are superior to those of the least square algorithm. After convergence, the location accuracy difference between the two algorithms is about 150m, because the system state equation is considered in EKF algorithm to obtain more information and accordingly make the position estimation more accurate.

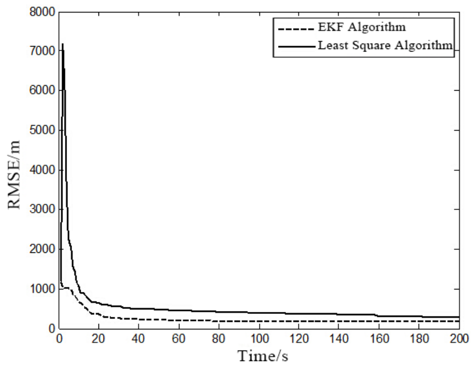

Figure 2. Performance Comparison of EKF Algorithm and Least Square Algorithm

4.2.2. Performance Comparison under the Condition of No Abnormal Error

If there is no abnormal error, the performance comparison of EKF algorithm, robust EKF algorithm and robust EKF algorithm based on F distribution discriminant is as shown in Figure3. According to Figure3, under the condition of no abnormal error, EKF algorithm and the robust EKF algorithm are gradually converged along with the increment of observation time. Specifically, the robust EKF algorithm has greater convergence rate than EKF algorithm, and after convergence, its location accuracy is lower than that of EKF algorithm. Actually, the location accuracy difference between the two algorithms are about 20m, because the robust EKF algorithm needs to execute robust iteration for the observation value at each moment, thus increasing the calculation time and reducing the location accuracy. However, EKF algorithm based on F distribution discriminant and EKF algorithm have similar performance, the convergence rate and the location accuracy of the two algorithms are superior to those of the robust EKF algorithm, and the location accuracy between the two algorithms is about 3m. In conclusion, when there is no abnormal error, compared with the robust EKF algorithm, the robust EKF algorithm based on F distribution discriminant can improve location accuracy and convergence rate.

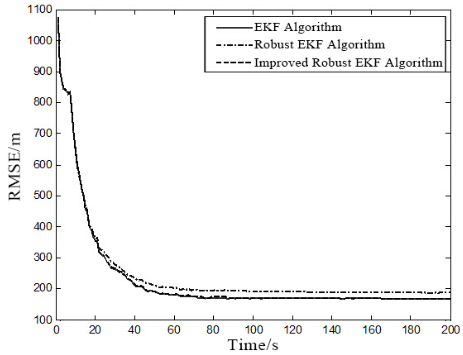

Figure 3. Performance Comparison of Different Algorithms (No Abnormal Error)

4.2.3. Performance Comparison under the Condition of Abnormal Error

Single abnormal error and continuous abnormal error are added in the observation value, and the abnormal error is set as shown in Table 1. The performance comparison of EKF algorithm, robust EKF algorithm and robust EKF algorithm based on F distribution discriminant is as shown in Figure4. According to Figure4, when the abnormal error is not added, the robust EKF algorithm based on F distribution discriminant and EKF algorithm have similar performance, with the performance superior to that of the robust EKF algorithm; if continuous abnormal error is added during the period $T = 100 \sim 110s$, the convergence rate of EKF algorithm is reduced due to the influence of abnormal error, but the robust EKF algorithm and the robust EKF algorithm based on F distribution discriminant are slightly influenced by the abnormal error, and the location accuracy difference between common algorithm and robust algorithm is about 100m. When single abnormal error is added respectively at time $T = 130,140,160s$, the location accuracy and the convergence rate of EKF algorithm are reduced due to the influence of abnormal error, and the location accuracy difference between this algorithm and the robust EKF algorithm and the robust EFK algorithm based on F distribution discriminant is more than 100m; especially, when the abnormal error is added at time $T = 160s$, EKF algorithm is significantly influenced and suffers from serious distortion, but the robust EKF algorithm and the robust EKF algorithm based on F distribution discriminant can execute robust iteration for the abnormal data, namely reducing the weight of the abnormal observation value or eliminating such value, thus to reduce the influence of the abnormal value on location estimation and make the algorithm have good convergence performance and high location accuracy. Generally speaking, the robust algorithm can well weaken the influence of abnormal error on position estimation to ensure algorithm performance; the performance of the robust EKF algorithm based on F distribution discriminant is superior to that of the robust EKF algorithm, because the statistical model is introduced in the robust EKF algorithm based on F distribution discriminant to construct the test statistic following F distribution for discriminant, thus to improve algorithm efficiency and make the algorithm have greater convergence rate and higher location accuracy.

Table 1. Abnormal Error Setting

Observation Point	100 ~ 110s	130s	140s	160s
Standard Deviation Setting of Abnormal Error	5σ	10σ	20σ	25σ

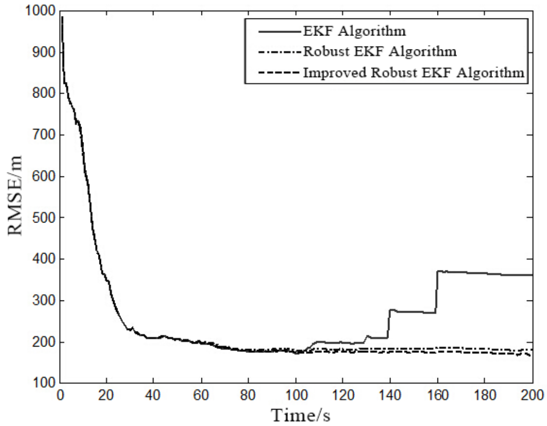

Figure 4. Performance Comparison of Different Algorithms (with Abnormal Error)

5. Conclusion

In this article, the robust EKF algorithm is applied to the onboard single-station passive location, and meanwhile the robust EKF algorithm based on F distribution discriminant is also proposed. The simulation shows that this algorithm can resist to the influence of abnormal error and has good location performance. When significant abnormality exists between the state equation and the onboard motion curve and both the observation equation and the state equation are influenced by abnormal error, the passive location estimation will also be significantly influenced and accordingly have deviation. In future, these complex environments will be considered in order to further improve algorithm robustness.

Acknowledgement

This work was supported by the Shaanxi Provincial Science and Technology Department of Agricultural science and technology innovation and research project(2015ny047), Yulin Municipal Science and Technology Bureau of research projects(2014CXY-3-03), National Natural Science Foundation of China (No. 51408442).

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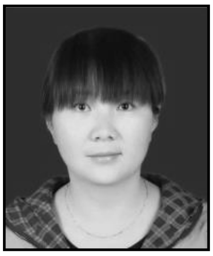

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