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Full Length Research Paper

A novel robust two-stage extended Kalman filter for bearings-only maneuvering target tracking

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A novel robust filter is proposed via embedding extended Kalman filter into an optimal two-stage Kalman filter, which is improved through a modified Sage-Husa noise statistics estimator. Meanwhile, strong tracking multiple fading factors are introduced in this paper to improve the tracking performance for high maneuvering targets. The new method provides an optimal estimation of the target state through a combination of the output of the first stage (a "bias-free" filter) and that of the second stage (a "bias-compensating" filter). Furthermore, the unknown statistical parameters of virtual noises are estimated online, and the predicted covariance can be adjusted in real time by fading factors when high maneuvers occur. Simulation results of tracking a maneuvering target by 3 passive sensors show that the proposed algorithm has advantages over the conventional method in terms of the numerical accuracy with only a little additional computational cost.

Key words: Target tracking, two-stage Kalman filter, noise statistics estimator, multiple fading factors.

INTRODUCTION

Considering the problem of a maneuvering target tracking with both unknown maneuvers and dynamic uncertainties, to avoid the influence of maneuvers which is usually assumed as an unknown bias sequence, the common method is to ignore the bias or to keep it as a prior constant, leading to a simplified dynamic model. However, this simplification may yield to performance degradation of the filter. An effective compensating strategy is to use the multiple model (MM) method by constructing the dynamic model with more than one discrete prior bias (Kowalczuk and Sankowski, 2010; Li and Jilkov, 2010). However, the MM approach has much more computational cost due to the recursive processes of multiple model-matched filter. Another method is augmented state Kalman filter (ASKF) (Freidland, 1969; Garcia et al., 2002; Khaloozadeh and Karsaz, 2009), which treats the maneuver as a part of the target state, whose computational burden increases with the dynamic dimension. To maintain the computational burden at a lower level and to avoid the numerical inaccuracy introduced by computations of large vectors and matrices. Friedland (1969) suggested employing the two-stage Kalman estimator. His idea is to decouple the augmented filter into two parallel filters.

The first stage, called "bias-free" filter, is based on the assumption that the bias is weak enough to be ignored. The second stage, the "bias" filter, producing the remaining states, is combined with the output of the first stage to reconstruct the original system state estimation. Under an algebraic constraint, the optimal estimate of the system state can be obtained. Unfortunately, this algebraic constraint is seldom satisfied for target tracking systems (Hsieh and Chen, 1999; Hsieh, 2000). The optimal two-stage Kalman filter (OTSKF) (Hsieh, 2000; Lo et al, 2002) gives the optimal solution of the two-stage estimator, in which the algebraic constraint is removed. As to the uncertainties of the dynamic model with unknown statistical parameters, a homologous method is to replace the unknown parameters with conservative prior estimates. Because of the decrease of estimation precision introduced by this conservative method, it is desirable to estimate prior statistics online along with the recursive estimate of the state and to use these estimates in implementation of the optimum estimation algorithms. One of the prevailing methods is developed by Sage and Husa (1969), which is a sequential robust Bayes

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estimation algorithm for prior statistics of the unknown noises. All these approaches can track low maneuvering targets well, however, the tracking performance will degenerate badly for high maneuvering targets. To solve the aforementioned problem, a new robust two-stage extended Kalman filter (RTSEKF) is proposed on the basis of OTSKF (Hsieh and Chen, 1999) for a maneuvering target tracking.

A modified Sage-Husa noise statistics estimator and strong tracking multiple fading factors are introduced in the two-stage extended Kalman filter for a passive maneuvering targets tracking. Simulations show that the proposed algorithm has a better tracking accuracy than the conventional OTSEKF method in tracking a maneuvering target with low maneuvers and/or high maneuvers.

PROBLEM FORMULATION

Consider the nonlinear discrete-time tracking system in two-dimensional case represented by:

$$\begin{aligned} \boldsymbol{x}_k &= \boldsymbol{F}_{k,k-1}\boldsymbol{x}_{k-1} + \boldsymbol{B}_{k,k-1}\boldsymbol{u}_{k-1} + \boldsymbol{w}^{\mathrm{x}}_{k-1} \\ \boldsymbol{u}_k &= \boldsymbol{u}_{k-1} + \boldsymbol{w}^{\mathrm{u}}_{k-1} \\ z_k &= \mathrm{h}_k(\boldsymbol{x}_k) + \boldsymbol{v}_k \end{aligned} \quad (1)$$

Where $\mathbf{x}_k = [x_k, y_k, \dot{x}_k, \dot{y}_k]^T \in \mathrm{R}^{n_x}$ is the target state, $\mathbf{u}_k = [u_{x,k}, u_{y,k}] \in \mathrm{R}^{n_u}$ is maneuvering disturbances, which is treated as an unknown bias sequence. $\mathbf{z}_k = [\cdots, \alpha_{k,i}, \cdots]^T \in \mathrm{R}^{n_z}$ is the measurement vector. The process noise $\mathbf{w}^{\mathrm{x}}_k$, the bias noise $\mathbf{w}^{\mathrm{u}}_k$, and the measurement noise $\mathbf{v}_k$ are assumed as independently identically distributed stochastic sequences, with statistical parameters $\mathbf{q}^{\mathrm{x}}_k, \mathbf{Q}^{\mathrm{x}}_k, \mathbf{q}^{\mathrm{u}}_k, \mathbf{Q}^{\mathrm{u}}_k, \mathbf{r}_k$, and $\mathbf{R}_k$ respectively.

$\mathrm{h}_k(\boldsymbol{x}_k)$ is the nonlinear measurement function:

$$\mathrm{h}_k(\boldsymbol{x}_k) = [0 \quad \arctan(\Delta x_{k,i}/\Delta y_{k,i}) \quad 0]^T$$

$$\Delta x_{k,i} = (x_k - x_{s,i}), \quad \Delta y_{k,i} = (y_k - y_{s,i}) \quad (2)$$

Where $(x_{s,i}, y_{s,i})$ is the location of sensor s_i, $i = 1, \cdots, n$, n denotes the number of sensors.

One of the effective approaches for this nonlinear obstacle is Taylor linearization shown as follows:

$$\mathbf{H}_k = \left.\frac{\partial \mathrm{h}_k(\mathbf{x})}{\partial \mathbf{x}}\right|_{\mathbf{x}=\hat{\mathbf{x}}_{k|k-1}} = \begin{bmatrix} & \vdots & & \\ \dfrac{\Delta y_{k,i}}{\Delta x^2_{k,i} + \Delta y^2_{k,i}} & \dfrac{-\Delta x_{k,i}}{\Delta x^2_{k,i} + \Delta y^2_{k,i}} & 0 & 0 \\ & \vdots & & \end{bmatrix} \quad (3)$$

ROBUST TWO-STAGE EXTENDED KALMAN FILTER (RTSEKF)

The main idea of the novel robust two-stage extended Kalman filter (RTSEKF) is to redesign an optimal two-stage extended Kalman filter for bearings-only maneuvering target tracking shown by Equation 1, in which both the unknown bias input and virtual system noises are estimated online to modify the original tracking output. Moreover, strong tracking multiple fading factors are introduced to enhance the tracking capability for high maneuvers. The structure of the RTSEKF method is depicted in Figure 1. The unknown statistical parameters of the system noises are estimated online with the two-stage extended Kalman filtering technique. The new modified Sage-Husa time-varying noise statistics is given by:

$$\begin{aligned} \hat{\boldsymbol{q}}^{\mathrm{x}}_{k|k} &= (1-d^{\mathrm{x}}_k)\hat{\boldsymbol{q}}^{\mathrm{x}}_{k-1|k-1} + d^{\mathrm{x}}_k \tilde{\boldsymbol{x}}^{\mathrm{x}}_{k|k} \\ \hat{\boldsymbol{q}}^{\mathrm{u}}_{k|k} &= (1-d^{\mathrm{u}}_k)\hat{\boldsymbol{q}}^{\mathrm{u}}_{k-1|k-1} + d^{\mathrm{u}}_k \tilde{\boldsymbol{u}}_{k|k} \\ \hat{\boldsymbol{r}}_{k|k} &= (1-d^{\mathrm{z}}_k)\hat{\boldsymbol{r}}_{k-1|k-1} + d^{\mathrm{z}}_k \tilde{\boldsymbol{z}}^{\mathrm{x}}_k \\ \boldsymbol{Q}^{\mathrm{x}}_{k|k} &= (1-d^{\mathrm{x}}_k)\boldsymbol{Q}^{\mathrm{x}}_{k-1|k-1} + d^{\mathrm{x}}_k[\boldsymbol{K}^{\mathrm{x}}_k\tilde{z}^{\mathrm{x}}_k(\boldsymbol{K}^{\mathrm{x}}_k\tilde{z}^{\mathrm{x}}_k)^T + \boldsymbol{P}^{\mathrm{x}}_{k|k} - \boldsymbol{F}_{k,k-1}\boldsymbol{P}^{\mathrm{x}}_{k-1|k-1}\boldsymbol{F}^T_{k,k-1}] \\ \boldsymbol{Q}^{\mathrm{u}}_{k|k} &= (1-d^{\mathrm{u}}_k)\boldsymbol{Q}^{\mathrm{u}}_{k-1|k-1} + d^{\mathrm{u}}_k[\boldsymbol{K}^{\mathrm{u}}_k\tilde{z}^{\mathrm{u}}_k(\boldsymbol{K}^{\mathrm{u}}_k\tilde{z}^{\mathrm{u}}_k)^T + \boldsymbol{P}^{\mathrm{u}}_{k|k} - \boldsymbol{P}^{\mathrm{u}}_{k-1|k-1}] \\ \boldsymbol{R}_{k|k} &= (1-d^{\mathrm{z}}_k)\boldsymbol{R}_{k-1|k-1} + d^{\mathrm{z}}_k[\boldsymbol{H}_k\boldsymbol{P}^{\mathrm{x}}_{k|k}\boldsymbol{H}^T_k + (\boldsymbol{I}-\boldsymbol{H}_k\boldsymbol{K}^{\mathrm{x}}_k)\tilde{z}^{\mathrm{x}}_k(\tilde{z}^{\mathrm{x}}_k)^T(\boldsymbol{I}-\boldsymbol{H}_k\boldsymbol{K}^{\mathrm{x}}_k)^T] \end{aligned} \quad (4)$$

Where $\mathbf{K}^{\mathrm{x}}_k$ and $\mathbf{K}^{\mathrm{u}}_k$ are Kalman gain matrices, $\tilde{\mathbf{x}}^{\mathrm{x}}_{k|k}$ and $\tilde{\mathbf{u}}_{k|k}$ are residues of state prediction, $\tilde{\mathbf{z}}^{\mathrm{x}}_k$ and $\tilde{\mathbf{z}}^{\mathrm{u}}_k$ are measurements of the two stages. d^{x}_k, d^{u}_k and d^{z}_k are adjustment coefficients which can be obtained by Equation 5.

$$d_k = (1-b)/(1-b^{k+1}), \quad 0<b<1 \quad (5)$$

Equations 4 and 5 can estimate the unknown system noises online to improve the tracking performance for low maneuvering targets, but when high maneuvers occur to the tracking system, the tracking accuracy is still low, even divergence may happen. Hence, we introduce strong tracking multiple fading factors based on Equations 4 and 5 to further improve the tracking performance of the proposed method for high maneuvering targets.

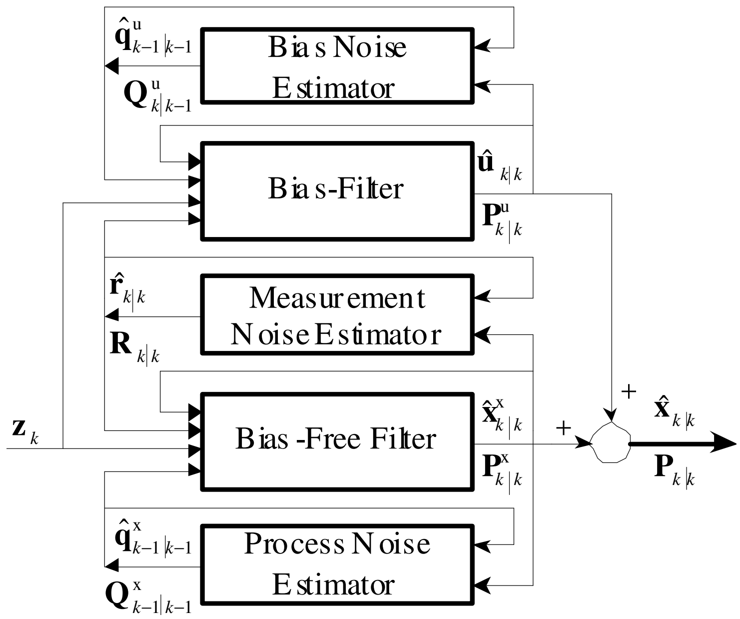

Figure 1. Structure of RTSEKF.

Then, the proposed method can not only track low maneuvering targets well, but also can track high maneuvering targets accurately. In order to ensure that the proposed approach has a strong tracking filter performance, the filter gains must satisfy the orthogonal principle in the light of the design of strong tracking filter (Zhou and Frank, 1996; Zhou, 1999; Yang and Ji, 2010).

$$E\left\{[\boldsymbol{X}_{k+1}-\hat{\boldsymbol{X}}_{k+1|k+1}]\cdot[\boldsymbol{X}_{k+1}-\hat{\boldsymbol{X}}_{k+1|k+1}]^{\mathrm{T}}\right\}=\min \quad (6)$$

$$E[\boldsymbol{d}_{k+1}^{\mathrm{T}}\cdot\boldsymbol{d}_{k+1+j}]=0, k=0,1,\cdots, j=1,2,\cdots. \quad (7)$$

Where $\boldsymbol{d}_{k+1}$ denotes the residue.

$$\boldsymbol{d}_{k+1}=\boldsymbol{Z}_{k+1}-\boldsymbol{H}_{k+1}\hat{\boldsymbol{X}}_{k+1|k} \quad (8)$$

To obtain the appropriate time-varying gain $\boldsymbol{K}_{k+1}^{x}$, $\boldsymbol{P}_{k+1|k}^{x}$ needs to be adjusted in real time in the filtering process according to Equation 9.

$$\boldsymbol{P}_{k+1|k}^{x}=\boldsymbol{\Lambda}(k+1)\boldsymbol{F}_{k}\boldsymbol{P}_{k|k}^{x}\boldsymbol{F}_{k}^{\mathrm{T}}+\boldsymbol{Q}_{k}^{x} \quad (9)$$

Where $\boldsymbol{\Lambda}(k+1)$ stands for a multiple fading factor matrix, which can adjust the prediction covariance of the different data channels at different rate in real time, and thereby adjust the corresponding filter gain $\boldsymbol{K}_{k+1}^{x}$. Through some derivations, $\boldsymbol{\Lambda}(k+1)$ can be obtained.

$$\boldsymbol{\Lambda}(k+1)=\mathrm{diag}[\lambda_1(k+1),\lambda_2(k+1),\cdots,\lambda_n(k+1)] \quad (10)$$

Where $\lambda_i(k+1), i=1,2,\cdots,n$ denote the fading factors.

$$\lambda_i(k+1)=\max\{1,\ a_i c(k+1)\} \quad (11)$$

$$c(k+1)=tr[\boldsymbol{N}(k+1)]\Big/\sum_{i=1}^{n}a_i\boldsymbol{M}_{ii}(k+1) \quad (12)$$

$$\boldsymbol{N}(k+1)=\boldsymbol{S}_0(k+1)-\beta\boldsymbol{R}_{k+1}-\boldsymbol{H}_{k+1}\boldsymbol{Q}_k^{x}\boldsymbol{H}_{k+1}^{\mathrm{T}} \quad (13)$$

$$\boldsymbol{M}(k+1)=\boldsymbol{F}_k\boldsymbol{P}_{k|k}^{x}\boldsymbol{F}_k^{\mathrm{T}}\boldsymbol{H}_{k+1}^{\mathrm{T}}\boldsymbol{H}_{k+1} \quad (14)$$

Where $\boldsymbol{N}(k+1)$ and $\boldsymbol{M}(k+1)$ are derived to ensure that the residues at different time can remain approximate to orthogonality, without specific meaning.

$$\boldsymbol{S}_0(k+1)=E[\boldsymbol{d}_{k+1}\boldsymbol{d}_{k+1}^{\mathrm{T}}]=\begin{cases}\boldsymbol{d}_1\boldsymbol{d}_1^{\mathrm{T}}, & k=0\\ [\rho\boldsymbol{S}_0(k)+\boldsymbol{d}_{k+1}\boldsymbol{d}_{k+1}^{\mathrm{T}}]/(1+\rho), & k\geq 1\end{cases} \quad (15)$$

In Equation 11 to 15, $0<\rho\leq 1$ is a forgetting factor, generally taking 0.95; $\beta\geq 1$ is a softening factor, which can make the state estimated value smoother; $\boldsymbol{S}_0(k)$ is a residual second-order moment; $a_i\geq 1, i=1,2,\cdots,n$ are pre-determined coefficients. If a component of the state changes rapidly, a larger a_i will be selected to further

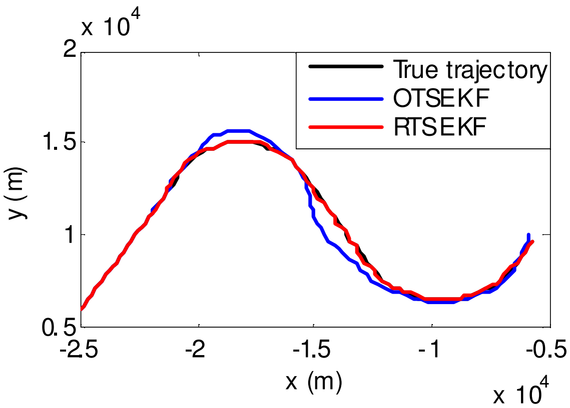

Figure 2. True trajectory and estimated trajectory.

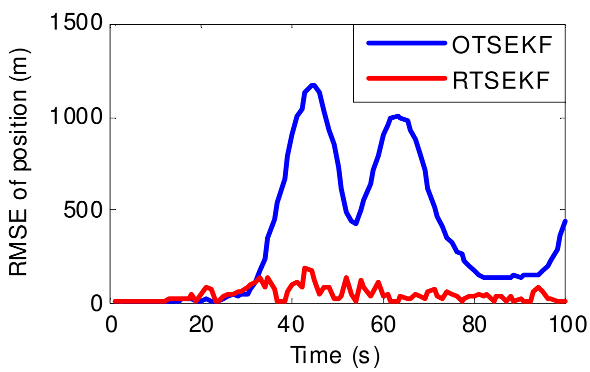

Figure 3. RMSE of the estimated position.

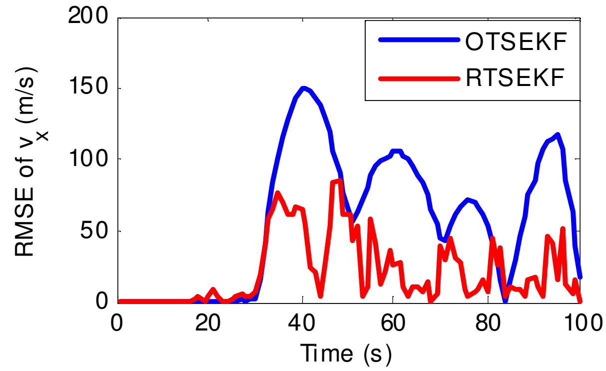

Figure 4. RMSE of the estimated velocity in x-axis direction.

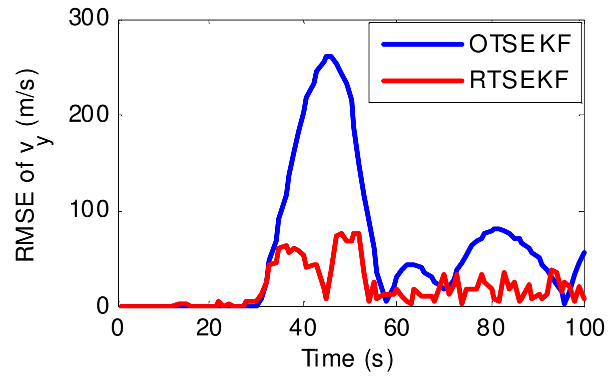

Figure 5. RMSE of the estimated velocity in y-axis direction.

improve the tracking performance of the filter. If $a_i = 1, i = 1, 2, \cdots, n$, then, the multiple fading factors will degenerate into a single fading factor. For the selection of some parameter values, please refer to the literature (Zhou and Frank, 1996; Zhou, 1999). When the system is in stable state, $\Lambda(k+1)$ will approximate to unit matrix, nevertheless, the filtering algorithm is still able to maintain the tracking capability for a general uniform or low maneuvering target due to the modified Sage-Husa noise statistics estimator.

SIMULATION RESULTS AND ANALYSES

The performances of the proposed algorithms are evaluated in the scenarios of maneuvering target tracking for passive multiple sensors. Assume there is a target maneuvering with $\omega = 0.1 rad/s$ during 30 to 50th seconds and $\omega = 0.14 rad/s$ during 71 to 95th seconds by coordinate turn (CT), the tangential velocity of which is 300m/s. State noise and observation noises are 1m and 0.5mrad, respectively. The performances of the OTSEKF and RTSEKF are shown in Figures 2 to 5. Averagely over 100 Monte Carlo simulations are adopted by 3 passive sensors. The locations of the 3 sensors are (0, 0 km), (2.5, 4.3 km), and (5, 0 km), respectively.

Figure 2 illustrates the estimated trajectory by the OTSEKF method and the proposed algorithm (RTSEKF). It is clear that the estimated trajectory by the proposed method has a higher accuracy than the OTSEKF approach. Figure 3 illustrates the root mean square errors (RMSE) of estimated position, it can also be seen that the RTSEKF method performs far more effectively than OTSEKF because of the modified Sage-Husa noise statistics estimator and the multiple fading factors. Furthermore, RMSEs of velocity are illustrated in Figures 4 and 5, respectively. The same conclusions are drawn for the assumption of constant statistic parameters of noises in the OSTEKF, the flexibility for maneuvering is worse when the prior variances are less accurate. Therefore, the adjustment of the novel robust filer is significative.

The runtime of RTSEKF is 0.56 second, only 0.16 second slower than that of OSTEKF. Because of the robust processes, the new robust filter is synthetically preferable.

CONCLUSIONS

An improved filter algorithm is proposed for a maneuvering target tracking by bearings-only measurements based on an optimal two-stage extended Kalman filter and a modified Sage-Husa adaptive statistical noises parameters estimator. Moreover, strong tracking multiple fading factors are introduced to further improve the tracking performance for high maneuvering targets. Simulations show that the proposed method has a better performance for passive maneuvering target tracking than the conventional method. In future work, the proposed method can also be applied in some prevailing techniques such as UKF, QKF, CKF (Ienkaran and Simon, 2009), linear fractional transformation (LFT) (Pasha et al., 2010) and particle filter (PF) to improve the performance for nonlinear systems.

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