Enhanced Sequential Nonlinear Tracking Filter with Denoised Pseudo Measurements

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Abstract – Sequential nonlinear tracking filter using pseudo measurements has been proposed to solve the tracking problem with range-rate measurements. Replacing the range-rate measurement by pseudo measurement constructed by the product of range and range-rate measurements can reduce nonlinearity, but large covariance of the error of pseudo measurements may be introduced. A denoising method based on a debiased Kalman filter is proposed in this paper to reduce the error of pseudo measurements. Then the denoised pseudo measurements are processed sequentially with position measurements to establish a new tracking filter with range-rate measurements. The proposed filtering method can reduce not only the nonlinearity but also the error of pseudo measurements. Monte Carlo simulations show that the performance of the new tracking filter is better than the sequential filter using pseudo measurement without denoising.

Keywords: range-rate measurements, sequential filtering, pseudo measurements, denosing, second-order EKF.

1 Introduction

Target tracking is usually performed in a Cartesian coordinate system despite the fact that sensors measure target parameters in a polar or spherical coordinate system. In this case, tracking in Cartesian coordinates using sensor measurements is a nonlinear state estimation problem. A basic idea is to convert the sensor measurements, such as range, bearing, and elevation into a pseudo-linear form in the Cartesian coordinates to avoid using nonlinear filters. This is the so called CMKF (converted measurements Kalman filtering) method. A lot of research has been attracted to obtain the bias and covariance of the converted measurement errors (e.g., [1][6]) in different ways. In practical situations, target Doppler or range rate measurements are also available which may provide additional information about target kinematic state and therefore can be incorporated into the tracker to enhance tracking performance. When target Doppler is included as part of the measurement vector, nonlinear estimators have to be used to cope with the nonlinearity between the target kinematic state (e.g. position, velocity, etc.) and the range rate measurement. The extended Kalman filter (EKF) [7][8] is a conventional method to solve the tracking problem with Doppler measurements. However, because of the strong nonlinearity between measurements and states, the EKF may potentially introduce stability and performance issues which are inherently associated with the EKF [2][9][11].

In [9][10], a pseudo measurement is constructed by the product of the range and range-rate measurements to reduce the nonlinearity of the range-rate measurement with respect of target state. But the statistics of the converted measurement errors are obtained by the linearization method which has been proved to be not consistent estimates[11]. [12] proposes a sequential filtering method to process position and range-rate measurements sequentially. The range-rate measurement is processed directly by a first order extended Kalman filter. Then in [13][14] position measurement and a pseudo measurement, constructed by the product of the range and Doppler measurements to reduce nonlinearity, are used to update the target state sequentially based on a second order extended Kalman filter to obtain filtering enhancement. However, the pseudo measurement may magnify the error of the range rate and larger variance of the error of pseudo measurement can be introduced. The range-rate measurements are utilized by unscented Kalman filter (UKF)[15][16] instead of using pseudo measurement to deal with the nonlinear state estimation problem.

To use the range-rate measurement more sufficiently and reasonably, the pseudo measurement is denoised by a debiased Kalman filter and then used to enhance state estimation based on a sequential second order EKF. Performance improvement of the new filtering method is demonstrated by means of Monte-Carlo simulations.

The rest of this paper is organized as following. Target dynamic model and sensor measurement equation are presented in Section 2. Section 3 describes the statistics of the converted measurement errors introduced by the range-rate measurements. Following in Section 4 is the derivation of pseudo measurement denoising procedure. Sections 5 presents the whole sequential filtering progress after the denoising of pseudo measurement. Monte Carlo simulations are performed in Section 6 and conclusions are presented in Section 7.

2 Problem Description
2.1 Target Motion Model

In Cartesian coordinates, the target motion model can be modeled as

\[ X_k = \Phi_{k-1} X_{k-1} + G_{k-1} u_{k-1} + \Gamma_{k-1} w_{k-1} \]

(1)

where \( X_k \triangleq [x_k, y_k, \dot{x}_k, \dot{y}_k, s_{k(n-4)}]^T \), \( X_k \in \mathbb{R}^n \) is the state vector consisting of the position components and corresponding velocity components along the \( x \) and \( y \) directions at time step \( k \), respectively. \( s_{k(n-4)} \) is other state components such as acceleration. \( \Phi_{k-1} \in \mathbb{R}^{n \times n} \) is the state transition matrix, \( u_k \) is process noise assumed as zero-mean Gaussian noise with known covariance \( Q_k \). \( G_k \) and \( \Gamma_k \) are deterministic input matrix.

2.2 Measurement Equation

Assuming a two-coordinated radar located at the origin of the polar coordinates, the radar measurement equation can be expressed as

\[ z_k = [r_k^m, \theta_k^m, \dot{r}_k^m]^T = f_k(x_k) + v_k^m = [r_k, \theta_k, \dot{r}_k]^T + v_k^m \]

(2)

Where

\[
\begin{align*}
    r_k &= \sqrt{x_k^2 + y_k^2} \\
    \theta_k &= \arctan \left( \frac{y_k}{x_k} \right) \\
    \dot{r}_k &= \frac{(x_k \dot{x}_k + y_k \dot{y}_k)}{\sqrt{x_k^2 + y_k^2}} \\
    v_k^m &= [r_k, \theta_k, \dot{r}_k]^T
\end{align*}
\]

\( r_k^m, \theta_k^m, \dot{r}_k^m \) are radar measurements of the true target range, bearing and range-rate respectively; \( \tilde{r}_k, \tilde{\theta}_k, \tilde{\dot{r}}_k \) are the corresponding measurement noises, which are all assumed to be zero-mean white Gaussian noises with known variances \( \sigma_r^2, \sigma_\theta^2, \sigma_{\dot{r}}^2 \) respectively. It is assumed that \( \tilde{\theta}_k \) and \( \tilde{\dot{r}}_k \) are statistically independent, \( \tilde{r}_k \) and \( \tilde{\dot{r}}_k \) are correlated with correlation coefficient \( \rho \).

3 Measurement Conversion

3.1 Measurement Conversion with Range-rate Measurement

3.1.1 Conversion Equation of Position Measurements

The position measurements including range and bearing in polar coordinates can be transformed into the pseudo-linear form in the Cartesian coordinates by

\[
\begin{align*}
x_k &= r_k^m \cos \theta_k^m = x_k + \tilde{x}_k \\
y_k &= r_k^m \sin \theta_k^m = y_k + \tilde{y}_k
\end{align*}
\]

(3)

where \( \tilde{x}_k \) and \( \tilde{y}_k \) are the position conversion measurement errors along \( x \), \( y \) directions in Cartesian coordinates, respectively.

3.1.2 Conversion Equation of Pseudo Measurement

The pseudo measurement conversion equation can be expressed as

\[
\eta_k^c = r_k^m \dot{r}_k^m = x_k \dot{x}_k + y_k \dot{y}_k + \tilde{\eta}_k
\]

(4)

where \( \tilde{\eta}_k \) is the error of the converted pseudo measurement \( \eta_k^c \) in the Cartesian coordinates.

3.1.3 Conversion Equation of Measurements

From (3) to (4), conversion of the radar measurements from the polar coordinates to the Cartesian coordinates can be totally expressed as

\[
z_k^c = [x_k, y_k, \dot{x}_k, \dot{y}_k]^T = h_k(X_k) + \eta_k^c
\]

\[
= [x_k, y_k, x_k \dot{x}_k + y_k \dot{y}_k]^T + [\tilde{x}_k, \tilde{y}_k, \tilde{\dot{x}}_k, \tilde{\dot{y}}_k]^T
\]

(5)

3.2 Statistics of Converted Measurement Errors

3.2.1 True Bias and Covariance

Under the assumptions in (2), we can get (as derivation in [13])

\[
E[\tilde{r}_k \tilde{r}_k] = E[\tilde{\theta}_k \tilde{\theta}_k] = 0
\]

(6)

\[
E[\tilde{\dot{r}}_k \tilde{\dot{r}}_k] = (1 + 2\rho^2) \sigma_{\dot{r}}^2
\]

(7)

Using (6), (7) and (2), we can derive the true bias and covariance of the converted measurement errors conditioned on the true position and range-rate as

\[
\begin{align*}
\mu_{k,i} &= E[z_k^c \mid r_k, \theta_k, \dot{r}_k] \\
&= [\mu^r_{i}, \mu^\theta_{i}, \mu_{i, \dot{r}}]^T \\
R_{k,i} &= \text{cov}[z_k^c \mid r_k, \theta_k, \dot{r}_k] \\
&= \begin{bmatrix}
    R_{r,r} & R_{r,\theta} & R_{r,\dot{r}} \\
    R_{\theta,r} & R_{\theta,\theta} & R_{\theta,\dot{r}} \\
    R_{\dot{r},r} & R_{\dot{r},\theta} & R_{\dot{r},\dot{r}}
\end{bmatrix}
\end{align*}
\]

(8)

where \( \mu^r_{i}, \mu^\theta_{i}, \mu_{i, \dot{r}} \) and \( R_{r,r}, R_{r,\theta}, R_{r,\dot{r}} \) are expressed as (9) to (12). (The same as in [14])

\[
\begin{align*}
\mu^r_{i} &= r \cos \theta \left( e^{-\frac{\sigma_r^2}{2}} - 1 \right) \\
\mu^\theta_{i} &= r \sin \theta \left( e^{-\frac{\sigma_\theta^2}{2}} - 1 \right)
\end{align*}
\]

(9)
\[ R_{\text{true}} = \text{var} \left[ \tilde{x} \mid r, \theta \right] \]
\[ = r^2 e^{-\sigma^2} \left[ \cos^2 \theta \left( \cosh \left( \sigma^2 \right) - 1 \right) \right] \]
\[ + r^2 e^{-\sigma^2} \left[ \sin^2 \theta \cosh \left( \sigma^2 \right) \right] \]
\[ + \sigma^2 e^{-\sigma^2} \left[ \cos^2 \theta \cosh \left( \sigma^2 \right) \right] \]
\[ + \sigma^2 e^{-\sigma^2} \left[ \sin^2 \theta \cosh \left( \sigma^2 \right) \right] \]
\[ R_{\text{true}} = \text{var} \left[ \tilde{y} \mid r, \theta \right] \]
\[ = r^2 e^{-\sigma^2} \left[ \sin^2 \theta \left( \cosh \left( \sigma^2 \right) - 1 \right) \right] \]
\[ + r^2 e^{-\sigma^2} \left[ \cos^2 \theta \sinh \left( \sigma^2 \right) \right] \]
\[ + \sigma^2 e^{-\sigma^2} \left[ \sin^2 \theta \cosh \left( \sigma^2 \right) \right] \]
\[ + \sigma^2 e^{-\sigma^2} \left[ \cos^2 \theta \sinh \left( \sigma^2 \right) \right] \]
\[ R_{\text{true}} = \text{cov} \left[ \tilde{x}, \tilde{y} \mid r, \theta \right] \]
\[ = \sin \theta \cos \theta e^{-\sigma^2} \left[ \sigma^2 + r^2 \left( 1 - e^{-\sigma^2} \right) \right] \]

And we can get
\[
\begin{align*}
\mu_{k,a} &= \rho_{a} \sigma_{a} \\
R_{k,a} &= \rho_{a} \sigma_{a} + \left( \sigma_{2}^{2} \rho_{a} + r_{k} \rho_{a} \sigma_{a} \right) \cos \theta_{k} e^{-\sigma^2/2} \\
R_{k,a} &= \left( \sigma_{2}^{2} \rho_{a} + r_{k} \rho_{a} \sigma_{a} \right) \sin \theta_{k} e^{-\sigma^2/2} \\
R_{k,a} &= r_{k}^{2} \sigma_{2}^{2} + \sigma_{2}^{2} r_{k}^{2} + \left( 1 + r_{k}^{2} \right) \sigma_{a}^{2} r_{k}^{2} + 2 r_{k} \sigma_{a} r_{k} \rho_{a} \sigma_{a} \\
\end{align*}
\]

3.2.2 Average True Bias and Covariance

Since \( (8) \) is conditioned on the true position and range-rate of the target, which are not available in practice, they can not be used directly. To make them more practicable, the expected value of the true bias and covariance are evaluated conditioned on the measured position and range-rate.

\[
\begin{align*}
\mu_{k,a} &= E \left[ \mu_{k,a} \mid r_{k}^{\text{m}}, \theta_{k}^{\text{m}}, \tilde{r}_{k}^{\text{m}} \right] \\
R_{k,a} &= E \left[ R_{k,a} \mid r_{k}^{\text{m}}, \theta_{k}^{\text{m}}, \tilde{r}_{k}^{\text{m}} \right] \\
\end{align*}
\]

where \( \mu_{k,a} \) and \( R_{k,a} \) are expressed as(16) to (19). (The same as in [14])

\[
\begin{align*}
\mu_{k,a} &= r_{k}^{\text{m}} \cos \theta_{k} \left( e^{-\sigma^2} - e^{-\sigma^2/2} \right) \\
\mu_{k,a} &= r_{k}^{\text{m}} \sin \theta_{k} \left( e^{-\sigma^2} - e^{-\sigma^2/2} \right) \\
\end{align*}
\]

And we can also get

\[
\begin{align*}
\mu_{k,a} &= \rho_{a} \sigma_{a} \\
R_{k,a} &= \left( \sigma_{2}^{2} \rho_{a} + r_{k}^{\text{m}} \rho_{a} \sigma_{a} \right) \cos \theta_{k}^{\text{m}} e^{-\sigma^2/2} \\
R_{k,a} &= \left( \sigma_{2}^{2} \rho_{a} + r_{k}^{\text{m}} \rho_{a} \sigma_{a} \right) \sin \theta_{k}^{\text{m}} e^{-\sigma^2/2} \\
R_{k,a} &= \left( r_{k}^{\text{m}} \right)^{2} \sigma_{2}^{2} + \sigma_{a} \left( r_{k}^{\text{m}} \right)^{2} \\
&+ 3 \left( 1 + r_{k}^{2} \right) \sigma_{a}^{2} r_{k}^{2} + 2 r_{k}^{\text{m}} \rho_{a} \sigma_{a} \\
\end{align*}
\]

(14) and (15) are consistent estimates of the first two moments of the converted measurement errors. In practical tracking, the converted measurement (5) can be used to substitute (2).

4 Denoising of Pseudo Measurement

The error of the range rate measurement maybe magnified by the range measurement (as shown in equation 20), therefore large covariance of the error of pseudo measurement can be introduced especially for long range cases. A basic idea is seek to reduce the error of pseudo measurement to enhance the filtering precision. Under the assumption of a target with a constant velocity motion, the motion state of the target \( x_{k} \) and \( y_{k} \) is a linear function of time step. Since velocity is a constant variable for CV model, the pseudo measurement \( n_{k} = r_{k}^{\text{m}} = x_{k} \dot{x}_{k} + y_{k} \dot{y}_{k} + \eta_{k} \) is also a linear function of time step \( k \). Therefore a Kalman filter can give the consistent estimate of the pseudo measurement.

The state vector can be set as \( X_{k} = \left[ \eta_{k}, \dot{\eta}_{k} \right]^{\text{T}} \) and observation is \( Z_{k} = \eta_{k} \).

The state transition equation and the systematic observation equation are given by

\[
\begin{align*}
X_{k} &= \Phi_{k-1} X_{k-1} + G_{k-1} u_{k-1} + \Gamma_{k-1} w_{k-1} \\
Z_{k} &= H_{k} X_{k} + v_{k} \\
\end{align*}
\]
where $\Phi_k^n = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix}$, $H_k^n = \begin{bmatrix} 1 & 0 \end{bmatrix}$, $\text{cov}[\omega_k^n] = Q_k^n$, and 
\[ \text{cov} [\nu_k^n] = R_k^n. \]
As the range and range rate measurement are statistically correlated with correlation coefficient $\rho$, the pseudo measurement covariance is set as equation (20)
\[ R_k^n = R_{\text{ke}} = \left( r_k^n \right)^2 \sigma_i^2 + \sigma_y^2 \left( r_k^n \right)^2 + 3 \left( 1 + \rho^2 \right) \sigma_i^2 + 2 \tau_k^n \tau_k^n \rho \sigma_i \sigma_y. \]
Time update and measurement update of the target state can be implemented as follows:
\[ X_{k-1} = \Phi_{k-1} X_{k-1} + \Gamma_{k-1}^T Q_{k-1}^T \Gamma_{k-1} \]
\[ P_{k-1} = \Phi_{k-1} P_{k-1} \Phi_{k-1}^T + \Gamma_{k-1}^T Q_{k-1}^T \Gamma_{k-1}. \]
\[ R_k^n = R_{\text{ke}} = \left( r_k^n \right)^2 \sigma_i^2 + \sigma_y^2 \left( r_k^n \right)^2 + 3 \left( 1 + \rho^2 \right) \sigma_i^2 + 2 \tau_k^n \tau_k^n \rho \sigma_i \sigma_y. \]
\[ \tilde{X}_k^n = X_{k-1} + K_k^n \left( Z_k^n - X_{k-1} \right). \]
\[ P_{k|k} = \left[ I_{k|k} - K_k^n H_k^n \right] P_{k|k-1} \]
As the converted measurement bias $\mu_{\text{ke}}$ is subtracted from the pseudo measurement in (26) and measurement correlation is also considered in the filtering procedure, the filtering result will be a consistent estimation.

5 Tracking Filter

It can be seen from (5) that the converted measurements are still nonlinear function of the target state. The conventional filtering method for this issue is the EKF, in which $h_k (X_k)$ is linearized by the Taylor series expansion around $X_{k|k-1}$. Since the position converted measurements are linear functions of the target state, sequential filtering may be taken to solve this problem. The position conversion measurements can be processed firstly to obtain the target state estimate $X_{k|k}$, then the nonlinear function is linearized by the Taylor series expansion around $X_{k|k}^p$, so the linearization errors will be reduced.

5.1 Decorrelation between Position and Pseudo Measurement

From (15), the converted measurement errors of position and pseudo measurement $\eta_k$, are correlated, so they should be decorrelated first before sequential filtering.
Covariance matrix $R_{\text{ke}}$ of the converted measurement errors can be rewritten as
\[ R_{\text{ke}} = \begin{bmatrix} R_{\text{ke}}^p & \left( R_{\text{ke}}^p \right)^T \\ R_{\text{ke}}^p & R_{\text{ke}}^p \end{bmatrix} \]
Set
\[ L_k = -R_{\text{ke}}^p \left( R_{\text{ke}}^p \right)^{-1} = \begin{bmatrix} L_k^1 \\ L_k^2 \end{bmatrix} \]
Pre-multiplying $L_k$ on both sides of (5), from Cholesky factorization [11], one can get
\[ \left[ \begin{array}{c} \xi_k^p = H_k^p X_k + v_k^p \\ \xi_k^p = h_k (X_k) + \tilde{\xi}_k \end{array} \right. \]
where
\[ \left[ \begin{array}{c} \xi_k^p = [x_k^p, y_k^p]^T \\ H_k^p = \left[ I_2, 0_{2 \times 2} \right] \end{array} \right. \]
\[ v_k^p = [\tilde{x}_k, \tilde{y}_k]^T \]
\[ E[v_k^p] = \mu_{\text{ke}}^p, \text{cov}[v_k^p] = R_{\text{ke}}^p \]
\[ \tilde{X}_k^p = X_{k|k}^p + K_k^p \left( Z_k^n - X_{k|k}^p \right) \]
\[ P_{k|k} = \left[ I_{k|k} - K_k^p H_k^p \right] P_{k|k-1} \]

5.2 Sequential Filtering

5.2.1 Position Measurement Filtering

Time update and measurement update of the target state by position measurement $Z_k^n$ can be implemented as follows.
\[ \left\{ \begin{array}{l} \tilde{X}_{k|k-1} = \Phi_{k|k-1} X_{k|k-1} + G_{k|k-1} \nu_k \end{array} \right. \]
\[ P_{k|k-1} = \Phi_{k|k-1} P_{k|k-1} \Phi_{k|k-1}^T + \Gamma_{k|k-1}^T Q_{k|k-1} \Gamma_{k|k-1}. \]
\[ K_k^p = P_{k|k-1} \left( H_k^p \right)^T \left[ H_k^p P_{k|k-1} \left( H_k^p \right)^T \right]^{-1} \]
\[ \tilde{X}_k^p = \tilde{X}_{k|k-1} + \left( \xi_k^p - \mu_{\text{ke}}^p - H_k^p \tilde{X}_{k|k-1} \right) \]
\[ P_{k|k} = \left( I_{k|k} - K_k^p H_k^p \right) P_{k|k-1} \]

5.2.2 Update with Denoised Pseudo Measurement

From (30), the pseudo measurement $\xi_k^p$ is a quadratic function of the target state, and so the nonlinear filtering estimation for the target state can be achieved by the second-order EKF in [9] as
\[ \left\{ \begin{array}{l} \tilde{X}_k^p = X_{k|k} + K_k^p \left( \xi_k^p - \xi_k^p - H_k^p \tilde{X}_{k|k} \right) - \frac{1}{2} \delta_k^2 \end{array} \right. \]
\[ P_{k|k} = \left( I_{k|k} - K_k^p H_k^p \right) P_{k|k} \]
Here $R_{k,a}$ can be replaced by the first element of the $P_{k,k}^p$ in (27) and $\varepsilon_i^*$ should be replaced by the first element of the $\hat{X}_{k}^n$ in (26), so they could be rewritten as

$$R_{k,a} = P_{k,k}^p (1,1) - P_{k,k}^p (R_{k,a})^{-1} (R_{k,a})^T$$

Moreover, because denoising processing is an unbiased Kalman filter, we can assume $\mu_{k,a} = 0$ and then get

$$\mu_{k,a} = L_\eta \mu_{k,a}$$

$H_k^e$ is the Jacobian of $h_k^e (X_k)$ around $\hat{X}_{k|k}$ and

$$H_k^e = [\hat{L}_k, \hat{x}_{k|k}^e, \hat{y}_{k|k}^e, h_{k|k}, 0_{l(s-4)}]$$

$\delta_k^e$ consists of the second-order derivative of $h_k^e (x_k)$ and

$$\delta_k^e = 2P_{k,k}^p (1,3) + 2P_{k,k}^p (2,4)$$

$$A_k = P_{k,k}^p (1,1) P_{k,k}^p (3,3) + P_{k,k}^p (2,2) P_{k,k}^p (4,4)$$

$$+ 2P_{k,k}^p (1,2) P_{k,k}^p (3,4) + 2P_{k,k}^p (1,4) P_{k,k}^p (2,3)$$

$$+ [P_{k,k}^p (3,1)]^T [P_{k,k}^p (4,2)]^T$$

$P_{k,k}^P (i,j)$ represents the element located at the $i$th row and $j$th column of $P_{k,k}^p$.

5.2.3 Final Filtering

The final target state filtering estimate and corresponding error covariance at time $k$ are then given by

$$\hat{X}_{k|k} = \hat{X}_{k|k}$$

$$P_{k|k} = P_{k|k}$$

(34)

6 Simulation and Comparison

In order to evaluate the performance of the new nonlinear tracking filter with denoised pseudo measurement, a target with a constant velocity motion is considered. The target dynamic model can be set as follows.

$$X_{k+1} = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} X_k + \begin{bmatrix} \frac{\sigma}{\tau} \\ 0 \\ T \end{bmatrix} \begin{bmatrix} w_k^x \\ 0 \\ w_k^y \end{bmatrix}$$

where $X_k = [x_k \ y_k \ \dot{x}_k \ \dot{y}_k]^T$, $T = 200s$, $w_k^x$ and $w_k^y$ are zero-mean uncorrelated Gaussian white process noises and the standard deviation $q_k^x = q_k^y = 0.0005m/s$.

The starting position is (10km,200km). The true velocity is 10m/s and the orientation is 145 degree. A Doppler radar is located at the origin of the polar coordinate, which measures the tracker-to-target range, bearing and range rate with standard measurement noise deviation $\sigma_r = 1000m$, $\sigma_\theta = 1.5deg., \sigma_v = 0.5m/s$. The correlation coefficient between the range and range-rate measurement noises is $\rho = 0.3$.

The performance of the denoising Kalman filter(KF-D) and the sequential EKF with denoised pseudo measurement are tested. One time run of the KF-D result and RMS pseudo measurement error of 100 runs Monte-Carlo simulation are displayed in Fig. 1 and Fig. 2. It is shown that the denoising Kalman filter smooth the pseudo measurement sequence well and the error is significantly reduced.

RMS position and velocity errors of the final sequential filter with denoised pseudo measurement (DPSEKF), compared with the pseudo measurement based sequential EKF (PSEKF) in [13], are shown in Fig. 3-6 and Fig.7-8. As can be seen, compared with the PSEKF, the proposed tracking filter performs better both in position filtering and in velocity estimation. This proves that the denoising processing of the pseudo measurement enhances the precision of tracking filter greatly.
7 Conclusions
A new sequential nonlinear tracking filter with denoising of the pseudo measurement is presented in this paper. Linear model of pseudo measurement constructed by the product of range and range-rate measurements is derived for constant velocity target motion. A debiased converted measurement KF is then used to reduce the error of the pseudo
measurements and enhance the whole second order EKF based sequential filtering precision consequentially. The Monte Carlo simulations show that the denoising of pseudo measurement method can improve the state estimation performance significantly. Only constant velocity motion is considered in this paper, future work will utilize a multiple model filter to deal with pseudo measurement denoising of maneuvering target tracking.

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