Unbiased converted measurement manoeuvering target tracking under maximum correntropy criterion

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Abstract: In this study, the manoeuvering target tracking problem is addressed by using the unbiased converted measurements from a two-dimensional radar system. Due to the fact that radar measurements are usually expressed in polar coordinates while the target motion is described in the Cartesian coordinates, the unbiased converted measurements are utilised to linearise the system model of the manoeuvering target tracking problem in the Cartesian coordinates. The manoeuver acceleration is modelled as the unknown input of the constant velocity kinematic model of the target. First, it is pointed out that the converted measurement noise no longer satisfies Gaussian distribution, even if the raw radar measurement noise is Gaussian noise. In order to solve the manoeuvering target tracking problem with non-Gaussian disturbances, a joint estimation method for the target state and the unknown input is presented under the maximum correntropy criterion. In the simulation, the proposed manoeuvering target tracking method is compared with the one developed on the basis of the traditional Kalman filter. The simulation results verify the effectiveness of the method proposed in this study.

1 Introduction

The radar system is a widely used target tracking measurement system in various military and civilian fields [1–4]. As well known radar measurement is usually expressed in polar coordinates, while the target kinematic model is described in the Cartesian coordinates. They are usually converted into the same coordinate system. However, the non-linear conversion possibly makes the Gaussian noise no longer obey Gaussian distribution. It is one of the important issues that need to be solved for target tracking with radar platforms.

The target tracking problem based on the radar platform has received extensive attention from researchers, and some important results have been achieved. The existing results mainly include two categories. (i) Re-express the radial distance and the pitch angle in radar measurement with the position of the target, then the target-tracking problems are considered as non-linear filtering problems [9–12]. In this context, the famous Kalman filter was utilised to estimate the state of the target. However, the converted measurement noise no longer satisfies Gaussian distribution, after being transformed by a non-linear function. The filtering method based on Gaussian system may reduce the target tracking accuracy. On the other hand, the manoeuvering target tracking problems have also attracted considerable attention in recent years [13–19]. The manoeuvering target tracking methods were studied on the basis of different target manoeuvering models. Based on the Singer model, a manoeuvering target tracking method was presented, in [13], by using the Kalman filter. With the help of three-dimensional constant-turn models, the EKF and the UKF were used to design the manoeuvering target-tracking methods in [14]. By modelling the manoeuvering target with multiple models, the interacting multiple model approaches were studied for the manoeuvering target tracking problems, by considering discrete-time hybrid systems with Gaussian system noises in [15–17]. Taking the target manoeuvering acceleration as the unknown input, the target state and the manoeuvering acceleration were simultaneously estimated in [18, 19]. A common characteristic of these above-mentioned works is that the measurement noises were assumed satisfying Gaussian distribution. However, the converted measurement noise no longer satisfies Gaussian distribution. In addition, the manoeuvering target tracking research with non-Gaussian noise has been seldom reported.

In this paper, a manoeuvering target tracking method is studied with the converted measurements from a two-dimensional radar system. The radar measurement in polar coordinates is firstly converted into an unbiased conversion measurement in the Cartesian coordinates. It is shown that the converted measurement noises no longer obey the Gaussian distribution, even if the raw radar measurement noise is Gaussian noise. The target kinematic equation is modelled as a constant velocity motion with an unknown manoeuvering acceleration. Then, with the help of the information-theoretic learning theory [20], the target state and the unknown manoeuvering acceleration are estimated, simultaneously, under the maximum correntropy criterion. The effectiveness of the proposed method is illustrated by numerical simulation, on comparing with the method developed on the basis of the Kalman filter.

The main contributions of this paper are two-fold. (i) It is pointed out that the converted measurement noises no longer obey the Gaussian distribution, even if the raw radar measurement noise is Gaussian noise, due to the non-linear measurement conversion. (ii) A non-Gaussian joint state and unknown input estimation method are presented under the maximum correntropy criterion, to estimate the target state and the unknown manoeuvering acceleration.

The rest of this paper is organised as follows. Section 2 introduces the manoeuvering target tracking system with unbiased converted measurement and points out that the converted measurement noises no longer satisfy the Gaussian distribution. In Section 3, the target state and the unknown manoeuvering acceleration are estimated under the maximum correntropy criterion. Simulation is provided, in Section 4, to illustrate the effectiveness of the proposed method. Section 5 concludes this paper.
2 Problem formulation

Consider the following discrete maneuvering target tracking model

\[ X(k) = F(k, k - 1)X(k - 1) + G(k, k - 1)u(k - 1) + w_r(k - 1) \]  

where \( X(k) \) represents the state of the target at \( k \), including its positions and velocities on the \( x \) and \( y \) axes. Namely, \( X(k) = [x(k) \ x'(k) \ y(k) \ y'(k)]^T \) is the unknown maneuvering acceleration, the evolution equation of which is given by

\[ u(k) = u(k - 1) + w_r(k - 1) \]  

In (1), \( F(k, k - 1) \) and \( G(k, k - 1) \) are, respectively, the state transition matrix and the maneuvering acceleration transition matrix

\[ F(k, k - 1) = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad G(k, k - 1) = \begin{bmatrix} T^2/2 & 0 & 0 & 0 \\ 0 & T & 0 & 0 \\ 0 & 0 & T & 0 \end{bmatrix} \]  

The process noise \( w_r(k - 1) \) and \( w_\theta(k - 1) \) satisfy the zero-mean Gaussian distributions with the covariance \( Q_r(k - 1) \) and \( Q_\theta(k - 1) \). The discretisation period, \( T \), is the discretisation period.

The target is observed by a two-dimensional radar platform. As well known, the measurement of the radar platform is obtained in the polar coordinates. In addition, the measurement function is modelled as follows in this paper

\[ \begin{bmatrix} r_{\text{rad}}(k) \\ \theta_{\text{rad}}(k) \end{bmatrix} = \begin{bmatrix} r(k) + \bar{v}_r(k) \\ \bar{v}_\theta(k) \end{bmatrix} \]  

where \( r(k) \) is the radial distance between the radar system and the target and \( r_{\text{rad}}(k) \) is its measurement obtained by the radar system. \( \theta_{\text{rad}}(k) \) is the pitch angle between the radar system and the target, \( \theta_{\text{rad}}(k) \) is its measurement, as well as the noises \( v_r(k) \sim \text{N}(0, \sigma_r^2(k)), v_\theta(k) \sim \text{N}(0, \sigma_\theta^2(k)) \).

Converting the measurement in the polar coordinates into the one in the Cartesian coordinates, it yields

\[ \begin{bmatrix} x_{\text{rad}}(k) \\ y_{\text{rad}}(k) \end{bmatrix} = \begin{bmatrix} r_{\text{rad}}(k)\cos(\theta_{\text{rad}}(k)) \\ r_{\text{rad}}(k)\sin(\theta_{\text{rad}}(k)) \end{bmatrix} \]  

Using the trigonometric formula, we can obtain

\[ \begin{bmatrix} x_{\text{rad}}(k) \\ y_{\text{rad}}(k) \end{bmatrix} = \begin{bmatrix} x(k) \\ y(k) \end{bmatrix} + \begin{bmatrix} v_r(k) \\ v_\theta(k) \end{bmatrix} \]  

in which \[ v_r(k) = r(k)\cos(\theta(k))(\cos(v_\theta(k)) - 1) - v_\theta(k)\sin(\theta(k))\sin(v_\theta(k)) \]  

\[ -r(k)\sin(\theta(k))\sin(v_\theta(k)) + v_\theta(k)\cos(\theta(k))\cos(v_\theta(k)) \]  

Remark 1: From (8) and (9), it is noted that the converted measurement noises \( v_r(k) \) and \( v_\theta(k) \) no longer obey the Gaussian distribution, even if the raw radar measurement noises \( v_r(k) \) and \( v_\theta(k) \) are Gaussian noise.

Under the condition of the first \( k \) measurements

\[ (r_j, \theta_j^2) = \begin{bmatrix} r_{\text{rad}}(j) \\ \theta_{\text{rad}}(j) \end{bmatrix}, \quad j = 1, 2, \ldots, k \]  

where

\[ R_{\text{rad}}(k) = \begin{bmatrix} R_{rr}(k) & R_{r\theta}(k) \\ R_{\theta r}(k) & R_{\theta\theta}(k) \end{bmatrix} = \begin{bmatrix} R_{r}(k) & R_{r}(k) \\ R_{r}(k) & R_{r}(k) \end{bmatrix} \]  

where

\[ R_{r}(k) = \begin{bmatrix} e^{2\sigma_r^2(k)} \sin^2(\theta_{\text{rad}}(k)) \sin^2(\theta_{\text{rad}}(k)) \\ e^{2\sigma_r^2(k)} \sin^2(\theta_{\text{rad}}(k)) \sin^2(\theta_{\text{rad}}(k)) \end{bmatrix} \]  

Denote the augmented state \( X'(k) \) and the augmented process noise \( w'(k - 1) \) as follows:

\[ X'(k) = \begin{bmatrix} X(k) \\ u_r(k) \\ u_\theta(k) \end{bmatrix}, \quad w'(k - 1) = \begin{bmatrix} w_r(k - 1) \\ w_\theta(k - 1) \end{bmatrix} \]  

It yields

\[ X'(k) = F'(k, k - 1)X'(k - 1) + w'(k - 1) \]  

where \( w'(k - 1) \sim \text{N}(0, Q'(k - 1)) \) and

\[ Q'(k - 1) = \begin{bmatrix} Q(k - 1) & 0 \\ 0 & Q_\theta(k - 1) \end{bmatrix} \]  

The unbiased converted measurement can be further re-written as

\[ Z(k) = HX'(k) + v(k), \]  

where
As mentioned in the Remark 1, the measurement noises in (8) and (9) do not satisfy the Gaussian distribution, even if \( v_i(k), v_y(k) \) are Gaussian noises. Therefore, the estimator of the target state and the manoeuvering acceleration with the above unbiased converted measurements should not be designed on the basis of the famous Kalman filter and its evolution methods, which are proposed for the systems with Gaussian noises. In the next section, without assuming the converted measurement noises satisfy Gaussian distribution, the manoeuvering target tracking approach is studied under the maximum correntropy criterion.

3 Manoeuvring target tracking under maximum correntropy criterion

In this section, the manoeuvring target tracking approach is studied with unbiased converted measurement, under the maximum correntropy criterion.

Without loss of generality, assume the augmented state estimate and its estimation error covariance at \( k - 1 \) are \( \hat{X}(k - 1|k - 1) \) and \( P(k - 1|k - 1) \). According to (16), the augmented state of the target at \( k \) can be predicted by

\[
\hat{X}(k|k - 1) = F^r(k, k - 1)\hat{X}(k - 1|k - 1) \tag{20}
\]

and

\[
P(k|k - 1) = F^r(k, k - 1)P(k - 1|k - 1)F^{rT}(k, k - 1) + Q^r(k - 1) \tag{21}
\]

Combining (20) and (18), it yields

\[
\begin{bmatrix}
\hat{X}(k|k - 1) \\
Z(k)
\end{bmatrix} = \begin{bmatrix}
I \\
H
\end{bmatrix} X(k) + \begin{bmatrix}
\hat{X}(k|k - 1) - X(k) \\
v(k)
\end{bmatrix} \tag{22}
\]

with

\[
E \left[ \begin{bmatrix}
\hat{X}(k|k - 1) - X(k) \\
v(k)
\end{bmatrix} \right] = \begin{bmatrix}
P(k|k - 1) & 0 \\
0 & R(k)
\end{bmatrix} \tag{23}
\]

\[
= \begin{bmatrix}
B_{\alpha}(k|k - 1)B_{\alpha}(k|k - 1) & 0 \\
0 & B_{\alpha}(k)B_{\alpha}(k)
\end{bmatrix}
\]

Under the maximum correntropy criterion, the cost function is given by [20, 22]

\[
J_{X^*:L} = \sum_{i=1}^{L} G(d_i(k) - W_i(k)X^*(k)) \tag{24}
\]

where \( d_i(k), W_i(k) \) are the \( i \)th row of \( D(k), W(k) \), \( L \) is the dimension of \( D(k) \), and \( G(\cdot) \) is the Gaussian kernel which is given by

\[
G_{\delta}(x) = \frac{1}{\sqrt{2\pi}\delta} e^{-\frac{x^2}{2\delta^2}} \tag{25}
\]

and

\[
D(k) = B^{-1}(k) \begin{bmatrix}
\hat{X}(k|k - 1) \\
Z(k)
\end{bmatrix} \tag{26}
\]

\[
W(k) = B^{-1}(k) \begin{bmatrix}
I \\
0
\end{bmatrix}
\]

Therefore, the optimal estimate of the augmented state \( X^*(k) \) is the solution of

\[
X^*(k) = \arg\max_{X^*(k)} \left[ J_{X^*:L} \right] = \arg\max_{X^*(k)} \sum_{i=1}^{L} G(d_i(k) - W_i(k)X^*(k)) \tag{27}
\]

Thus the optimal estimate is the one satisfying (28). Further, it yields

\[
X^*(k) = (W^T(k)C(k)W(k))^{-1}W^T(k)C(k)D(k) \tag{29}
\]

where

\[
C(k) = \begin{bmatrix}
C_{X^*(k)} & 0 \\
0 & C_{Z(k)}
\end{bmatrix} \tag{30}
\]

with

\[
C_{X^*(k)} = \text{diag}(G(d_i(k) - W_i(k)X^*(k))), \ldots, G(d_i(k) - W_i(k)X^*(k)))
\]

\[
C_{Z(k)} = \text{diag}(G(d_i(k) - W_i(k)X^*(k))), \quad G(d_i(k) - W_i(k)X^*(k))
\]

Substituting (26) and (30) into (29), we have

\[
X^*(k) = \hat{X}(k|k - 1) + K(k) (Z(k) - H\hat{X}(k|k - 1)) \tag{31}
\]

in which

\[
K(k) = P^*(k|k - 1)H(HP^*(k|k - 1)H^T + R^*(k))^{-1}
\]

\[
P^*(k|k - 1) = B_{\beta}(k|k - 1)C_{X^*(k)}B_{\beta}(k|k - 1)
\]

\[
R^*(k) = B_{\beta}(k)C_{Z(k)}B_{\beta}(k)
\]

It should be noted that the augmented state \( X^*(k) \) is included in \( C_{X^*(k)}, C_{Z(k)} \), as shown in (29) and (30). Namely, (31) is a fixed point function with respect to \( X^*(k) \). Taking its prediction as the initial solution \( \hat{X}(k|k) = \hat{X}(k|k - 1) \), the iterative solution of the fixed point function results into an iterative non-Gaussian filtering algorithm [22].

The \( r \)th iterative updating augmented state estimate is
The filter gain is obtained by

\[
K_{r}(k) = P_{r}(k|k-1)H[H_{r}P_{r}(k|k-1)H^{T} + R_{r}(k)]^{-1} \\
P_{r}(k|k-1) = B_{r}(k|k-1)C_{r}^{-1}(k)B_{r}^{T}(k|k-1) + R_{r}(k) \\
C_{r}(k) = \text{diag}(G_{r}(d(k), W_{r}(\hat{x}_{r}^{c}(k|k))), \ldots, G_{r}(d(k), W_{r}(\hat{x}_{r}^{c}(k|k)))) \\
G_{r}(d(k), W_{r}(\hat{x}_{r}^{c}(k|k))) = \text{diag}(G_{r}(d(k), W_{r}(\hat{x}_{r}^{c}(k|k)) \ldots, G_{r}(d(k), W_{r}(\hat{x}_{r}^{c}(k|k))))
\]

(34)

The final augmented state estimate is obtained by

\[
\hat{x}(k|k) = \hat{x}^{c}(k|k) + K_{r}(k)(Z(k) - H\hat{x}^{c}(k|k) - 1)
\]

(37)

where

\[
K_{r}(k) = P_{r}(k|k-1)H[H_{r}P_{r}(k|k-1)H^{T} + R_{r}(k)]^{-1} \\
P_{r}(k|k-1) = B_{r}(k|k-1)C_{r}^{-1}(k)B_{r}^{T}(k|k-1) + R_{r}(k) \\
\hat{x}^{c}(k|k-1) = F^{c}(k|k-1)\hat{x}(k|k-1) - 1
\]

(38)

The estimation error covariance is given by

\[
P_{r}(k|k) = P_{r}(k|k-1) - P_{r}(k|k-1)H[H_{r}P_{r}(k|k-1)H^{T} + R_{r}(k)]^{-1}H^{T}P_{r}(k|k-1)
\]

(35)

Given a small scalar \( \varepsilon > 0 \), the final augmented state estimate is obtained by \( \hat{x}(k|k) = \hat{x}^{c}(k|k) \), if the following inequality holds

\[
\frac{\| \hat{x}^{c}(k|k) - \hat{x}_{r}^{c}(k|k) \|}{\| \hat{x}_{r}^{c}(k|k) \|} < \varepsilon
\]

(36)

The final augmented state estimate \( \hat{x}(k|k) \) includes the manoeuvering acceleration estimate as its 5th, 6th components, and the estimate of the target position and velocity \( \hat{x}(k|k) \) as its first four components.

Remark 2: For the method developed from the Kalman filter, the converted measurement noise \( v(k) \) is assumed to obey the zero-mean Gaussian distribution. Denote the noise variance as \( R_{r}(k) \).

The augmented system state is estimated by the following method

\[
\hat{x}^{c}(k|k) = \hat{x}^{c}(k|k) + K_{r}(k)(Z(k) - H\hat{x}^{c}(k|k) - 1)
\]

(37)

The final augmented state estimate \( \hat{x}^{c}(k|k) \) includes the manoeuvering acceleration estimate as its 5th, 6th components, and the estimate of the target position and velocity \( \hat{x}(k|k) \) as its first four components.

Remark 2: For the method developed from the Kalman filter, the converted measurement noise \( v(k) \) is assumed to obey the zero-mean Gaussian distribution. Denote the noise variance as \( R_{r}(k) \).

The augmented system state is estimated by the following method

\[
\hat{x}^{c}(k|k) = \hat{x}^{c}(k|k) + K_{r}(k)(Z(k) - H\hat{x}^{c}(k|k) - 1)
\]

(37)

where

\[
K_{r}(k) = P_{r}(k|k-1)H[H_{r}P_{r}(k|k-1)H^{T} + R_{r}(k)]^{-1} \\
P_{r}(k|k-1) = B_{r}(k|k-1)C_{r}^{-1}(k)B_{r}^{T}(k|k-1) + R_{r}(k) \\
\hat{x}^{c}(k|k-1) = F^{c}(k|k-1)\hat{x}(k|k-1) - 1
\]

The estimation error covariance is given by

\[
P_{r}(k|k) = P_{r}(k|k-1) - P_{r}(k|k-1)H[H_{r}P_{r}(k|k-1)H^{T} + R_{r}(k)]^{-1}H^{T}P_{r}(k|k-1)
\]

(35)

Given a small scalar \( \varepsilon > 0 \), the final augmented state estimate is obtained by \( \hat{x}(k|k) = \hat{x}^{c}(k|k) \), if the following inequality holds

\[
\frac{\| \hat{x}^{c}(k|k) - \hat{x}_{r}^{c}(k|k) \|}{\| \hat{x}_{r}^{c}(k|k) \|} < \varepsilon
\]

(36)

The final augmented state estimate \( \hat{x}(k|k) \) includes the manoeuvering acceleration estimate as its 5th, 6th components, and the estimate of the target position and velocity \( \hat{x}(k|k) \) as its first four components.

Remark 2: For the method developed from the Kalman filter, the converted measurement noise \( v(k) \) is assumed to obey the zero-mean Gaussian distribution. Denote the noise variance as \( R_{r}(k) \).

4 Simulation

Consider the following manoeuvering target tracking system.

\[
T = 0.1, \begin{bmatrix} w_{x}(k, k-1) \\ w_{y}(k, k-1) \end{bmatrix} \sim \mathcal{N}(0, Q_{w}), \begin{bmatrix} v_{x}(k) \\ v_{y}(k) \end{bmatrix} \sim \mathcal{N}(0, R) \quad \text{and} \quad Q_{w} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, \quad Q = \begin{bmatrix} 0.3 & 0 \\ 0 & 0.3 \end{bmatrix}
\]

(40)

\[
\begin{bmatrix} x(k+1) \\ y(k+1) \\ \theta(k+1) \end{bmatrix} = \begin{bmatrix} T/2 & 0 \\ 0 & T/2 \\ 0 & T \end{bmatrix} \begin{bmatrix} u(k) + w_{x}(k, k-1) \\ w_{y}(k, k-1) \end{bmatrix}
\]

(41)

where (see equation below). The idea position of the radar platform is \((0, 0)\). The initial estimate of the target manoeuver value is \((0, 1, 0.2)\). The initial state of the target is \([100, 2.5, 200, 2.5]\) and the initial estimate covariance is \(10^{-2} \times \text{diag}[1, 1, 1, 1, 0.1, 0.1]\).

In this simulation, the proposed method is compared with the one developed from Kalman filter as shown in Remark 2. The proposed method is denoted as manoeuvering target maximum correntropy Kalman filter (MTMCKF)-based method, and the one developed from Kalman filter is denoted as KF-based method. The simulation results are shown in Table 1, Figs. 1 and 2.

As shown in Figs. 1 and 2, the effectiveness of the proposed method is illustrated. In this simulation, the radar measurements on the polar coordinates are converted into the one on the Cartesian coordinates. The converted measurement noise is taken as Gaussian noise in the method developed from Kalman filter, but is not in the proposed tracking method. Therefore, the distance between the real target and the estimate obtained by the proposed method is smaller than the one obtained by the Kalman filter based method. The mean of absolation estimation error of the proposed method is 0.18811, which improves 16.5%, compared with the one obtained by the method developed from Kalman filter, whose mean of absolation estimation error (MAE) is 0.22525.

5 Conclusion

In this paper, the manoeuvering target tracking problem is addressed based on the unbiased conversion of the radar measurement. The converted measurement noise no longer obeys the Gaussian distribution, even if the raw measurement noise is Gaussian noise. Therefore, in this paper, a manoeuvering target tracking method is developed for the non-Gaussian measurements. The manoeuvering target tracking system is modelled as a CV motion with the target manoeuvering acceleration which is taken as an unknown input. Under the maximum correntropy criterion, a state and unknown input joint estimation approach is given to solve the manoeuvering target tracking problem. The final simulation illustrates the effectiveness of the proposed approach. How to avoid the singular matrix that appears in the Cholesky decomposition is an important direction in our next work. The square root filtering methods give us meaningful inspiration.

6 Acknowledgments

This work was supported in part by the National Natural Science Foundation of China (U1604149).
Table 1  Mean of absolution estimation error

|                  | MTMCKF-based method | KF based method |
|------------------|----------------------|-----------------|
| MAEE             | 0.18811              | 0.22525         |

Fig. 1 Position curves of the target and its estimates

Fig. 2 Distance curves between the target and its estimates

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