Research Article

Maneuvering Target Tracking Algorithm Based on Interacting Multiple Models

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Aiming at improving the accuracy and quick response of the filter in nonlinear maneuvering target tracking problems, the Interacting Multiple Models Cubature Information Filter (IMMCIF) is proposed. In IMMCIF, the Cubature Information Filter (CIF) is brought into Interacting Multiple Model (IMM), which can not only improve the accuracy but also enhance the quick response of the filter. CIF is a multisensor nonlinear filtering algorithm; it evaluates the information vector and information matrix rather than state vector and covariance, which can reduce the error of nonlinear filtering algorithm. IMM disposes all the models simultaneously through Markov Chain, which can enhance the quick response of the filter. Finally, the simulation results show that the proposed filter exhibits fast and smooth switching when disposing different maneuver models; it performs better than the IMMCKF and IMMUKF on tracking accuracy.

1. Introduction

Nowadays, target tracking has broad application in different areas, such as radar tracking, aircraft surveillance, and vehicle navigation [1–4]. In order to improve the tracking precision when the motion of the target is complex, many filtering algorithms have been proposed based on specifically physical model [5–7]. Blom and Bar-Shalom propose the IMM algorithm based on generalized pseudorandom algorithm to depress the error of the single model algorithm [8]. The IMM algorithm processes all the models simultaneously and then switches to different models by checking the weight of each filter [9]. Analysis shows that IMM algorithm is more robust and more exact than the single model algorithm when tracking the maneuvering target [10, 11].

In order to enhance the performance of IMM algorithm, many nonlinear filters have been designed. For example, Interacting Multiple Models Extended Kalman Filter (IMMEKF) and Interacting Multiple Models Unscented Kalman Filter (IMMUKF) [4, 10, 12–14] are proposed as IMM-based nonlinear filtering algorithm. The results show that, in maneuvering targets tracking problems, IMMUKF performs better than IMMEKF in stability and precision [11]. It is because

Extended Kalman Filter (EKF) carries on the filtering procession by linearizing the state equation, which inevitably induces the linearization error even divergence of filter. However, when Unscented Kalman Filter (UKF) [15] is used in higher order system, the weights of the sigma points will turn into negative which will result in the divergence of the filter. In order to overcome these issues and improve the performance of filter, Cubature Kalman Filter (CKF) is introduced in IMM to track the maneuvering target [14, 16]. And analysis shows that the IMMCKF exhibits better performance than IMMUKF and IMMEKF in enhancing the accuracy and reducing the computational complexity [14]. In this paper, the Interacting Multiple Models Cubature Information Filter (IMMCIF) based on IMM and the CIF [17, 18] is proposed to improve the tracking accuracy and quick response of maneuvering target. In IMMCIF, the state estimation variables including position and velocity of different models are disposed simultaneously through Markov Chain; then the combined state estimate and covariance of each filter are fed back when the cycle completes. The proposed filter evaluates the information vector and information matrix instead of the state vector and covariance; it propagates in the information space which makes the filter easy to initialize and more

precise [17]. Therefore, the accuracy of the IMM is improved, and the novel algorithm in this paper is a promising approach for maneuvering target tracking. The numerical simulation results show that the IMMCIF exhibits better than IMM-CKF and IMMUKF on accuracy, robustness, and switching response.

The remainder of this paper is organized as follows. In Section 2, the Cubature Information Filter is briefly reviewed. The whole procession of IMMCIF used in target tracking problem is derived in Section 3. In Section 4, the performance of IMMCIF is better than IMMCKF and IMMUKF, they are compared in a benchmarked target tracking problem, and the results are analyzed. Conclusions are given in Section 5.

2. Cubature Information Filter

The CIF is different with conventional filtering algorithms which are based on Kalman filter. It estimates information state vector and information matrix instead of state vector and covariance matrix, from which the measurement update is simpler than CKF.

2.1. Time Update. Consider

$$[Y_{k-1|k-1}]^{-1} = S_{k-1|k-1} S_{k-1|k-1}^T, \quad (1)$$

where $Y_{k-1|k-1}$ is information matrix. $S_{k-1|k-1}$ can be obtained by factorizing the inverse information matrix, which is used to evaluate the cubature points.

Then the cubature point can be obtained as follows:

$$\begin{aligned} X_{i,k-1|k-1} &= S_{k-1|k-1} \xi_i + \hat{x}_{k-1|k-1}, \\ X_{i,k-1|k-1}^* &= f(X_{i,k-1|k-1}, u_{k-1}), \end{aligned} \quad (2)$$

where $\{\xi_i\}$ is the matrix with a set of unit vector as shown in

$$\sqrt{n} \left\{ \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix}, \dots, \begin{pmatrix} 0 \\ \vdots \\ 0 \\ 1 \end{pmatrix}, \begin{pmatrix} -1 \\ 0 \\ \vdots \\ 0 \end{pmatrix}, \dots, \begin{pmatrix} 0 \\ \vdots \\ 0 \\ -1 \end{pmatrix} \right\}. \quad (3)$$

The predicted state and predicted error covariance can be obtained based on CKF:

$$\begin{aligned} \hat{x}_{k|k-1} &= \frac{1}{2n} \sum_{i=1}^{2n} X_{i,k-1|k-1}^*, \\ P_{k|k-1} &= \frac{1}{2n} \sum_{i=1}^{2n} X_{i,k-1|k-1}^* X_{i,k-1|k-1}^{*T} - \hat{x}_{k|k-1} \hat{x}_{k|k-1}^T \\ &\quad + Q_{k-1}, \end{aligned} \quad (4)$$

where $i = 1, 2, \dots, 2n$, n is the dimension of state vector x_k .

From (4), the predicted information matrix and the predicted information state vector can be derived:

$$Y_{k|k-1} = P_{k|k-1}^{-1}, \quad (5)$$

$$\begin{aligned} y_{k|k-1} &= P_{k|k-1}^{-1} \hat{x}_{k|k-1} = Y_{k|k-1} \hat{x}_{k|k-1} \\ &= \frac{1}{2n} \left[Y_{k|k-1} \sum_{i=1}^{2n} X_{i,k-1|k-1}^* \right]. \end{aligned} \quad (6)$$

2.2. Measurement Update. Consider

$$[Y_{k|k-1}]^{-1} = S_{k|k-1} S_{k|k-1}^T, \quad (7)$$

where $S_{k|k-1}$ can be obtained by factorizing the inverse predicted matrix $Y_{k|k-1}$.

The cubature points are evaluated as

$$\chi_{i,k|k-1} = S_{k|k-1} \xi_i + \hat{x}_{k|k-1}. \quad (8)$$

The propagated cubature points are evaluated as

$$Z_{i,k|k-1} = h(\chi_{i,k|k-1}). \quad (9)$$

The predicted measurement is estimated:

$$\hat{z}_{k|k-1} = \frac{1}{2n} \sum_{i=1}^{2n} Z_{i,k|k-1}. \quad (10)$$

The cross-covariance matrix is estimated:

$$P_{xz,k|k-1} = \frac{1}{2n} \sum_{i=1}^{2n} \chi_{i,k|k-1} Z_{i,k|k-1}^T - \hat{x}_{k|k-1} \hat{z}_{k|k-1}^T. \quad (11)$$

Then information state distribution and information matrix can be obtained from (5) and (11):

$$\begin{aligned} i_k &= Y_{k|k-1} P_{xz,k|k-1} R_k^{-1} [v_k + P_{xz,k|k-1}^T Y_{k|k-1}^T \hat{x}_{k|k-1}], \\ I_k &= Y_{k|k-1} P_{xz,k|k-1} R_k^{-1} P_{xz,k|k-1}^T Y_{k|k-1}^T, \end{aligned} \quad (12)$$

where $v_k = z - \hat{z}_{k|k-1}$.

From (5) and (12), the updated information matrix and updated information can be given, respectively:

$$Y_{k|k} = Y_{k|k-1} + I_k, \quad (13)$$

$$y_{k|k} = y_{k|k-1} + i_k. \quad (14)$$

Then the estimated state vector $\hat{x}_{k|k}$ and estimated error covariance $P_{k|k}$ can be derived as follows:

$$\hat{x}_{k|k} = Y_{k|k}^{-1} y_{k|k}, \quad (15)$$

$$P_{k|k} = Y_{k|k}^{-1} I_n,$$

where I_n is the n dimensional unit matrix.

3. Interacting Multiple Models Cubature Information Filtering Algorithm

As the information filter can be extended straight to design multisensory fusion algorithm, in this paper, the proposed IMMCIF includes the merits of CIF algorithm and IMM algorithm. The main factor of IMMCIF is that it calculates the state distribution and error covariance matrix by choosing the cubature points with equal weight and then processes the filter update by calculating the information vector and information matrix. The IMMCIF algorithm includes input integration, CIF, model probability update, and output integration. The structure diagram is shown as in Figure 1.

The detailed filtering processes are as follows.

3.1. *Input Integration.* Consider

$$\begin{aligned} u_{k-1|k-1}^{i/j} &= \frac{p_{ij} u_{k-1}^i}{C_j}, \\ \widehat{X}_{k-1|k-1}^{0j} &= \sum \widehat{X}_{k-1|k-1}^i u_{k-1|k-1}^{i/j}, \\ P_{k-1|k-1}^{0j} &= \sum_{i=1}^r u_{k-1|k-1}^{i/j} \left\{ P_{k-1|k-1}^i \right. \\ &\quad \left. + \left[\widehat{X}_{k-1|k-1}^i - \widehat{X}_{k-1|k-1}^{0j} \right] \left[\widehat{X}_{k-1|k-1}^i - \widehat{X}_{k-1|k-1}^{0j} \right]^T \right\}, \end{aligned} \quad (16)$$

where $C_j = \sum_{i=1}^r p_{ij} u_{k-1}^i$, $u_{k-1|k-1}^{i/j}$ is the conditional probability of model i at $k-1$, u_{k-1}^i is the probability of model i at $k-1$, $\widehat{X}_{k-1|k-1}^{0j}$ is the initial mean value of model j , $P_{k-1|k-1}^{0j}$ is the initial error covariance, $\widehat{X}_{k-1|k-1}^i$ is the estimated value of model i at $k-1$, and $P_{k-1|k-1}^i$ is the relative covariance.

3.2. *Cubature Information Filtering.* Let the mixed initial value and the measure value (z) as the input of each filter at k . Then new state vector $\widehat{X}_{k|k}^j$, the error covariance $P_{k|k}^j$, the predicted measured value $\widehat{z}_{k|k-1}^j$, and the residual v_k^j can be obtained from the CIF which have been derived in Section 2.

The likelihood value L_k^j is

$$\begin{aligned} L_k^j &= N(z; \widehat{z}_{k|k-1}^j, V_k^j) \\ &= \frac{1}{\sqrt{2\pi V_k^j}} \\ &\quad \cdot \exp\left(-\frac{1}{2} [z_k - \widehat{z}_{k|k-1}^j]^T (V_k^j)^{-1} [z_k - \widehat{z}_{k|k-1}^j]\right), \end{aligned} \quad (17)$$

where V_k^j is the associated covariance of residual v_k^j .

3.3. *Model Probability Update.* Bayesian hypothesis testing method is used to evaluate the model probability and calculate the residual of each filter. It is known that once the filter model matches with the actual model, the filtering residual

FIGURE 1: IMMCIF structure diagram.

is zero mean, and the variance $v(k)$ is Gaussian White Noise. Therefore from the likelihood function of model matching m_i at k , the model probability can be updated from

$$u_k^j = \frac{L_k^j C_j}{\sum_{j=1}^{n_m} L_k^j C_j}. \quad (18)$$

3.4. *Output Integration.* The probabilities of model are fused with the estimated value of each filter based on the given weights; then the final output of the IMMCIF is calculated as

$$\begin{aligned} \widehat{X}_{k|k} &= \sum_{j=1}^r \widehat{X}_{k|k}^j u_k^j, \\ P_{k|k} &= \sum_{j=1}^r u_k^j \left\{ P_{k|k}^j + \left[\widehat{X}_{k|k}^j - \widehat{X}_{k|k} \right] \left[\widehat{X}_{k|k}^j - \widehat{X}_{k|k} \right]^T \right\}. \end{aligned} \quad (19)$$

4. Results and Discussion

In this section, we consider a classical target tracking scenario where the target trajectory is shown in Figure 2. Let the state vector at time k be $X_k = [x, \dot{x}, y, \dot{y}]^T$, where x and y are the position variable in X - and Y -bearing and $\dot{x}$ and $\dot{y}$ are the velocity variable in X - and Y -bearing.

FIGURE 2: Target trajectory.

The CT (coordinated turn) model is

$$F2 = \begin{bmatrix} 1 & \frac{\sin(\omega T)}{\omega} & 0 & \frac{(\cos(\omega T) - 1)}{\omega} \\ 0 & \cos(\omega T) & 0 & -\sin(\omega T) \\ 0 & \frac{(1 - \cos(\omega T))}{\omega} & 1 & \frac{\sin(\omega T)}{\omega} \\ 0 & \sin(\omega T) & 0 & \cos(\omega T) \end{bmatrix}, \quad (20)$$

where ω is the turn rate of the target and T is the sampling interval.

The right turn rate is defined as -3° , and the left turn rate is defined as 3° .

The measure equation of the system is

$$Z = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} + R, \quad (21)$$

where R is the measurement noise of the system.

The initial state is $X_0 = [1000 \text{ m}, 200 \text{ m/s}, 1000 \text{ m}, 200 \text{ m/s}]^T$, and the initial associate covariance is $P_0 = \text{diag}([1000, 10, 1000, 10])$, the process noise $Q \sim N(0, q)$, with $q = [10, 0, 0, 10]$, and the process noise weight matrix is $G = [T^2/2, 0; T, 0; 0, T^2/2; 0, T]$. The measurement noise $R \sim N(0, r)$, with $r = \text{diag}([200, 0.1])$. The simulation time is $\text{simTime} = 100 \text{ s}$, and the step time $T = 1 \text{ s}$. The target turns right during 20 s~40 s, turns left during 60 s~80 s, and maintains uniform motion during the other time. The model transition probability is

$$p_{ij} = \begin{bmatrix} 0.9 & 0.05 & 0.05 \\ 0.1 & 0.8 & 0.1 \\ 0.05 & 0.15 & 0.8 \end{bmatrix}. \quad (22)$$

FIGURE 3: RMSEs of (a) X-position and (b) Y-position.

TABLE 1: The RMSEs of IMMCIF, IMMCKF, and IMMUKF.

	IMMCIF	IMMCKF	IMMUKF
RMSE_X (m)	4.9371	6.6262	9.6817
RMSE_X_V (m/s)	2.8419	3.2512	4.2409
RMSE_Y (m)	5.7319	9.0982	9.1862
RMSE_Y_V (m/s)	4.5933	5.6901	5.8375

The root-mean square error (RMSE) of position and velocity is used to compare the performance of two filtering algorithms. The RMSE defined in state vector X at k is

$$\text{RMSE} = \sqrt{\frac{\sum_{n=1}^n (1/k) \sum_{k=1}^k (X_{k,n} - \hat{X}_{k,n})^2}{n}}, \quad (23)$$

where $X_{k,n}$ is the real state vector of n Monte Carlo simulation and $\hat{X}_{k,n}$ is the estimated state vector of n Monte Carlo simulation. The simulation results are shown in Figures 2, 3, and 4.

Figures 2, 3, and 4 and Table 1 show the contrast of the tracking accuracy with IMMCIF, IMMCKF, and IMMUKF. It can be seen clearly from the figures that IMMCIF does better in tracking precision than IMMCKF and IMMUKF, while all of them exhibit stable characteristics and there is no error divergence.

Figures 5(a), 5(b), and 5(c) show the mode probabilities of IMMCIF, IMMCKF, and IMMUKF, which demonstrate that all of them can effectively track the target maneuvering characteristics at preliminary stage. And the mode probabilities correspond well to the maneuvering target, which will

FIGURE 4: RMSEs of (a) X-velocity and (b) Y-velocity.

FIGURE 5: Mode probabilities of IMMs.

FIGURE 6: Comparisons of mode probability of IMMs.

change when motion state transforms from CV trajectory to CT trajectory and vice versa. Mode 1 is constant velocity (CV) mode, Mode 2 is right coordinate turn (CT) mode, and Mode 3 is left coordinate turn (CT) mode.

The comparisons of mode probabilities of IMMCIF, IMMCKF, and IMMUKF are shown in Figures 6(a), 6(b), and 6(c). The figures show that the IMMCIF, IMMCKF, and IMMUKF can capture the kinematics of maneuvering in time once the motion state changes when $t = 20$ s, $t = 40$ s, $t = 60$ s, and $t = 80$ s. However as time goes by, IMMCKF and IMMUKF cannot track the maneuvering target well while the IMMCIF is more stable.

5. Conclusion

In this paper, the Interacting Multiple Models Cubature Information Filtering (IMMCIF) algorithm is proposed to enhance the precision and quick response of nonlinear maneuvering target tracking problem. This algorithm introduces Cubature Information Filter based on Interacting Multiple Models, which disposes all the models simultaneously through Markov Chain. And it evaluates the information vector and information matrix instead of the state vector and covariance to deal with nonlinear filtering. The simulation results show IMMCIF outperforms IMMCKF and IMMUKF

which exhibits potential applications in nonlinear target tracking.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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