Research on Radar/Infrared Fusion Algorithm Based on IMM/MS-MDPDAF

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Abstract: In the clutter environment, radar/infrared sensors are used to track the background of maneuvering targets. Aiming at the shortcomings of traditional probabilistic data association theory in solving multiple target echoes and numbers in measurement, it is presented by combining interactive multiple model (IMM) and multiple detection probabilistic data association filter (MDPDAF) in a multi-sensor (radar and infrared) scenario known as IMM/MS-MDPDAF algorithm. The IMM algorithm has the ability to adapt to the target high maneuver and clutter environment. The MS-MDPDAF algorithm can detect multiple effective target echoes, considering various uncertainties in the clutter environment. According to the multi-detection mode of radar sensor, the target is effectively measured and the state vector is updated. Then the data fusion and probability data association theory are used to calculate the corresponding probability and state prediction, estimation and update under the Bayesian framework. The simulation results show that the IMM/MS-MDPDAF algorithm can improve the effectiveness and tracking accuracy of target, and has better tracking performance than IMM/MSPDAF.

1. Introduction

In the modern age of informationization, the battle for the electromagnetic spectrum has gradually been the key to winning the war. As an active sensor, radar can provide complete target position information and Doppler information by sending electromagnetic wave to capture the relevant information of the target. Therefore, radar plays an important role in target tracking and detection. However, as radar radiates high-power electromagnetic waves into the air, it is easy to expose the carrier, and it is attacked by anti-radiation missiles and electronic interference; At the same time, there is also a low blind area. When the target takes stealth measures or releases chaff shells around to reduce the backscattering of radar radiation, the detection distance and precision of the radar to the target will be greatly reduced. These inherent defects of radar expose it to a variety of threats, such as "electronic interference, anti-radiation strike, stealth aircraft, ultra-low altitude penetration" [1]. As a passive sensor, infrared sensor does not radiate any energy into the air. By receiving the radiation generated by the target, it can get the relevant information of the target. Therefore, it is not easy to be detected or positioned. Therefore, how to make full use of the advantages of radar and infrared sensors to complement each other in maneuvering target tracking in the face of clutter environment is the hot spot of domestic and foreign experts in recent years.

In the clutter interference environment, the tracking of information fusion using multiple sensors
has been studied by many scholars. In 1970, R.A.Singer first proposed a simple multi-sensor path
fusion algorithm based on the assumption that the estimation errors of each sensor were independent
from each other. However, the fusion results were not globally optimal. On this basis, Y.Bar.Shalom et
al. proposed a path fusion algorithm based on covariance weighting [2-3], which increased the
computational complexity of the algorithm and was not conducive to implementation. Subsequently,
Willner et al. proposed the centralized multi-sensor Kalman filtering algorithm by using Kalman
filtering technology [4]. To reduce the sophistication of the calculation, Simon Julier and others have
proposed the covariance crossover algorithm based on the optimal target function, and the S.Mc Clean
and the others have proposed a weighted fusion algorithm that is simple and easy to implement. In
order to improve the self-adaptability of the system, Shizhong Li et al. proposed an algorithm based on
sequential filtering and interactive multi-model fusion, and Beugnon et al. proposed an adaptive path
fusion algorithm based on threshold selection [5-7]. In recent years, Jian Rong et al. proposed a target
fusion tracking algorithm based on fuzzy system based on adaptive fuzzy theory and Kalman filtering
to achieve flight path fusion [8], and improved the tracking accuracy of maneuvering target by
adjusting system parameters through adaptive. On this basis, Yunong Zhang et al. proposed a fusion
algorithm [9-10] to determine weight using neural network and spline approximation theory, which
improved the stability and computational efficiency of the system.

In fact, due to the scalability of maneuvering targets, the radar receives more than one echo per
scan. In view of the uncertainty in the origin and number of tracking measurements of maneuvering
targets, this paper uses multiple detection probability data association algorithm (MDPDAF) to solve
the above uncertainty problem. IMM algorithm can improve the self-adaptability of maneuvering
target model and process the measurement data of multiple sensors through sequential filtering,
reducing the computational complexity. On the above basis, this paper proposes a fusion algorithm
based on interactive multi-model and multi-sensor multi-detection probability data association
(IMM/MS-MDPDAF). Through simulation verification, it is found that it has better tracking accuracy
than IMM/MSPDAF algorithm.

2. Description of the problem
It is assumed that the target dynamics are stated by hypothesis models as \( M_n = \{1,...,n\} \). The model
\( j \) in the sampling period \((t_{k-1},t_k] \) is denoted by the event \( M'_j \). The state equation and sensor
measurement equation for the \( j \) model are described as:

\[
\begin{align*}
x_k &= F'_j x_{k-1} + G'_j v'_{k-1} \\
z'_k &= h'(x_k) + w'_k, \quad l = 1,...,q
\end{align*}
\]

(1)

Where, \( x_k \) is the state vector at time \( t_k \), \( z'_k \) is the validated measurement vector of the sensor \( 1, q \) is
the number of sensors; In this paper, the Taylor formula of the measurement function \( h'(x_k) \) is
expanded at the prediction state \( x_k \), so that the nonlinear measurement model is linearized. The linear
formula is as follows:

\[
z'_k = H'_j(x_k) + w'_k, \quad l = 1,...,q
\]

(3)

Where, \( H'_j(x_k) \) is Jacobian of \( h'(x_k) \). The process noise \( v'_{k-1} \) and the measurement noise \( w'_k \)
are zero mean gaussian white noise which are not related to each other, and they have covariance
matrix \( Q'_l \) and \( R'_l \) respectively.

The initial gaussian random variable is denoted as \( x'_0 \), and the covariance is denoted as \( P'_0 \).
According to markov state transition matrix, the conditional probability that the initial probability
\( \mu'_i = P[M'_j] \) of the target motion model \( j \) is transferred from model \( i \) to model \( j \) is denoted as
\( p'_{ij} = P[M'_j | M'_{i-1}] \) at time \( t_0 \). The state estimation and error covariance matrix of the target are as follows:
\[ \hat{x}_{k|k} = E[x_k | Z^k] \quad (4) \]
\[ P_{k|k} = E[(x_k - \hat{x}_{k|k})(x_k - \hat{x}_{k|k})^T | Z^k] \quad (5) \]

Where, \( Z^k \) is the total set of measurements (not validated) of all sensors until the time \( k (\gamma^k) \).

3. MDPDA filter

3.1 Multi-detection model

If the target is detected and its measurement falls into the tracking door, it is considered that the group data is related to the target track. As the Multiple-detection model considers all events that associate a set of measurements to the target track, the uncertainty of the exact number of targets and the uncertainty of the origin of the measurements can be well resolved.

It is assumed in the time step \( k \) the total number of measurements (not validated) is \( m_k \) and the total number of validated measurements is \( \tilde{m}_k (m_k \geq \tilde{m}_k) \). When the radar has multiple effective measurement data in each scan, it is assumed that \( \varphi \) is the correlation event of \( \tilde{m}_k \) in the effective measurement. Here \( \varphi \) ranges from 1 to the maximum number of measured values of the target source, \( \varphi_{\text{max}} \). Therefore, the total number of association events of the measurement set to the track formula equals:

\[ N = \sum_{i=1}^{\varphi_{\text{max}}} C_i^{m_k} \quad (6) \]

3.2 MDPDA filtering algorithm

The standard PDAF [11] calculates the correlation probability based on the assumption that there is at most one effective measurement from the target each time, and the rest are clutter or invalid measurement. Due to the scalability of the target, multiple sets of measurement data can be obtained at the same time, this algorithm divides the weight among all validated measurements based on the assumption. In this case, the weight of invalid measurement data generated by clutter is neglected. Thus, this method does not associate proper probabilities to the validated measurements.

MDPDA [12] compared with PDAF filter calculation of each group of measurement data from the interested target. First, the effective measurement data is extracted through the multi-detection model in the previous section, and then the corresponding correlation probability is calculated through MDPDAF. For the sake of simplicity of calculation, it is assumed that a maximum of two sets of measured data from the target are obtained for each scan (\( \varphi_{\text{max}} = 2 \)). The specific steps [13] are as follows:

**Step 1:** state and measurement prediction

The state prediction, covariance and measurement prediction formulas are as follows:

\[ \hat{x}_{k|k-1} = F_{k-1} \hat{x}_{k-1|k-1} \quad (7) \]
\[ P_{k|k-1} = F_{k-1} P_{k-1|k-1} F_{k-1}^T + G_{k-1} Q_{k-1} G_{k-1}^T \quad (8) \]
\[ \tilde{z}_{k|k-1} = h(\hat{x}_{k|k-1}) \quad (9) \]

Using (9) the measurement prediction for multiple-detection pattern (\( \varphi = 1 \) and \( \varphi = 2 \)) is described as:

\[ \tilde{z}_{k|k-1}^{(1)} = \tilde{z}_{k|k-1} \quad (10) \]
\[ \tilde{z}_{k|k-1}^{(2)} = \begin{bmatrix} \tilde{z}_{k|k-1}^{(1)} \\ \tilde{z}_{k|k-1}^{(2)} \end{bmatrix} \quad (11) \]

Innovation process and corresponding covariance are calculated as:

\[ v_{k}^{(i)} = z_{k}^{(i)} - \tilde{z}_{k|k-1}^{(i)} \quad (12) \]
\[ s_k^1 = H_k^1 p_{z_k|z} (H_k^1)^T + R_k^1 \]
\[ v_{k}^{2,m} = z_{k}^{2,m} - \hat{z}_{k}^{2,m} \]
\[ \tilde{s}_k = H_k (p_{z_k|z} (H_k)^T) \left[ \begin{array}{c} R_k^1 \ 0 \end{array} \right] \]

Where, \( z_{k}^{1,m} \), \( z_{k}^{2,m} \) are derived from target and are single and double measurements of the target respectively. \( H_k \), \( R_k^1 \) are the jacobian matrix and the measurement noise covariance matrix.

**Step 2:** Measurement validation and multiple detection pattern formation

In this paper, the ellipsoid tracking door is adopted. According to the measurement in the previous step, the threshold \( \gamma \) of the tracking door can be obtained by predicting \( \hat{z}_{k|k-1} \) and the Innovation process covariance matrix \( s_k^1 \), satisfying the inequality:
\[ [\hat{z}_{k|k-1} - \hat{z}_{k|k-1}]^{T} s_{k}^{1} [\hat{z}_{k|k-1} - \hat{z}_{k|k-1}] < \gamma \quad (i = 1, ..., m) \]
\[ V_k = c_n \gamma^{1/2} |s_k^{1}|^{1/2} \]

Where, \( n \) is the measurement vector dimension, \( c_n \) is the volume of the unit hypersphere with this dimension.

**Step 3:** state estimation with multiple detection

In the previous step of the multi-detection mode formed in use, the measured value of the correlation event (hypotheses) tracked at time \( k \) is defined as:
\[ \theta_{k}^{m_0} : \text{chosen} \quad \phi \text{ measurements are caused by the target}, \quad n_0 = 1, ..., C_0^{m} . \]
\[ \theta_{k}^{m_0} : \text{None of the other measurements are caused by the target.} \]

The association probabilities are defined as:
\[ \beta_{k}^{m_0} = P[\theta_{k}^{m_0}|Y^k, Z^{k-1}] \]

On the basis of the standard PDAF, the association probability of the event can be further calculated by using the non-parametric model [14]. The steps are as
\[ \beta_{k}^{0,n_0} = c \left( 1 - P_{d} P_{G} \right), \quad \phi = 0, n_0 = 1 \]
\[ \beta_{k}^{1,n_0} = c \left( P_{d} P_{G} \right) N[y_{k}^{1,n_0};0, S_{k}^{1}] \]
\[ \beta_{k}^{2,n_0} = c \left( P_{d} P_{G} \right) N[y_{k}^{2,n_0};0, S_{k}^{2}] \]

Where, \( P_{d} \) are one and two times valid probabilities of detection in each scan of radar. \( P_{d} \) is the total target detection probability, \( P_{d} = P_{d_1} + P_{d_2} \), \( P_{G} \) is the probability that the target is in the sensor tracking gate. \( c \) is the normalization constant as \( \sum_{\phi=0}^{c_n} \sum_{n_0=1}^{C_0} \beta_{k}^{m_0} = 1 \). \( N(x; y, P) \) is the Gaussian probability density function notation as follows:
\[ N(x; y, P) = [2\pi P]^{1/2} \exp[-\frac{1}{2} (x - y)^{T} P^{-1} (x - y)] \]

The likelihood function is as follows:
\[ \Lambda_k = p(Y^k|Z^{k-1}) = \sum_{\phi=0}^{c_n} \sum_{n_0=1}^{C_0} p(Y^k, \theta_{k}^{m_0}|Z^{k-1}) \]
By using the state estimation $\hat{x}_{k|k-1}$ and covariance $P_{k|k-1}$, the updated target state can be obtained:

$$\hat{x}^{x_{k}}_{k|k} = E[x_{k} | \theta_{k}^{x_{k}}, Z^{k-1}, Y^{k}] = \hat{x}_{k|k-1} + W^{\theta_{k}}_{k} v_{k}^{x_{k}}$$

Kalman gain is calculated as follows:

$$(25)$$

$$W^{\theta_{k}}_{k} = \begin{cases} W^{\theta_{k}}_{k} = 0, & \varphi = 0, n_{0} = 1 \\ W^{1}_{k} = P_{k|k-1}[ (H_{k}^{1})^{T}, (S_{k}^{1})^{-1}, 0], & \varphi = 1, n_{1} = 1, ..., n_{k} \\ W^{2}_{k} = P_{k|k-1}[ (H_{k}^{2})^{T}, (H_{k}^{2})^{T}(S_{k}^{2})^{-1}, 0], & \varphi = 2, n_{2} = 1, ..., C^{2}_{k} \end{cases}$$

Updating the target state estimation can be obtained:

$$\hat{x}_{k|k} = E[x_{k} | Y^{k}, Z^{k-1}] = \sum_{\varphi=0}^{C^{1}_{k}} \sum_{n_{\varphi}}^{C_{k}} \beta^{\theta_{k}}_{n_{\varphi}} \hat{x}^{x_{k}}_{k|k}$$

Accordingly, the covariance of the target state estimation is:

$$(27)$$

$$P_{k|k} = P_{k|k-1} - \sum_{\varphi=1}^{C^{1}_{k}} \sum_{n_{\varphi}}^{C_{k}} \beta^{\theta_{k}}_{n_{\varphi}} W^{\theta_{k}}_{k} S^{\theta_{k}}_{k} (W^{\theta_{k}}_{k})^{T} + \sum_{\varphi=1}^{C^{2}_{k}} \sum_{n_{\varphi}}^{C_{k}} \beta^{\theta_{k}}_{n_{\varphi}} W^{\theta_{k}}_{k} v_{k}^{x_{k}} (v_{k}^{x_{k}})^{T} W^{\theta_{k}}_{k}^{T} - \sum_{\varphi=1}^{C^{1}_{k}} \sum_{n_{\varphi}}^{C_{k}} \beta^{\theta_{k}}_{n_{\varphi}} W^{\theta_{k}}_{k} v_{k}^{x_{k}} (v_{k}^{x_{k}})^{T} W^{\theta_{k}}_{k}^{T}$$

$$(28)$$

4. IMM/MS-MDPDAF Algorithm

In order to improve the performance of radar and infrared tracking, and better track the maneuvering target in the clutter environment, the fusion system uses sequential filtering to process the measurement data of multiple sensors. The proposed algorithm like IMM/MS-PDAF in has eight steps that are different with it in third and fourth steps. The third step of the IMM/MS-MDPDAF algorithm is to form a multiple detection mode for the radar verification measurement results and the fourth step is to calculate the probability of the associated data of the different target maneuver models in the multiple detection mode. Finally, the target state estimation update and estimate covariance to realize the target of continuous. The structure of IMM/MS-MDPDAF is shown Figure 1.
In order to evaluate the proposed algorithm of interactive multi-model and multi-sensor multi-detection probabilistic data association (IMM/MS-MDPDAF), the corresponding simulation analysis is made for tracking the maneuvering target in the clutter environment. The details are as follows:

The target starts moving from $[2000,10000]$ in Cartesian coordinates in meters, the target specific maneuver is shown in Table 1, the flight path is shown in Figure 2.

| time | motor  | state            |
|------|--------|------------------|
| 0s ~ 19s | Uniform | $v = 400m/s$    |
| 20s ~ 39s | Left roll   | $a = 20m/s^2$   |
| 40s ~ 54s | Right roll | $a = 40m/s^2$   |
| 55s ~ 79s | Left roll     | $a = 32m/s^2$   |
| 80s ~ 99s  | accelerate     | $a = 60m/s^2$   |

In IMM algorithm three motion models are used ($r=3$), $M^1$ is the second order kinematic model (model with nearly constant velocity) in which the acceleration is modeled as white noise, the standard deviation of the process noise is $5m/s^2$. $M^2$, $M^3$ are third order kinematic models (model with nearly constant acceleration) with white noise acceleration increments, the standard deviation of the process noise are $7.5m/s^2$ and $40m/s^2$ respectively. The initial probability of the model, $\mu_0 = [0.8, 0.1, 0.1]$, also the conversion probability matrix between models are as follows:

$$ P = \begin{bmatrix} 0.8 & 0 & 0.2 \\ 0.3 & 0.3 & 0.4 \end{bmatrix} $$

It is hypothesized that radar and infrared sensors located at the origin, sampling time $T = 1s$. The detection probability of the radar is $P_{D_1} = 0.05$, $P_{D_2} = 0.95$. Assume that clutter relative to the radar and infrared Poisson distribution for $\lambda_1 = 13 \times 10^6$ and $\lambda_2 = 7 \times 10^4$, measurement validation gates for
both sensors with threshold $\gamma=16$. The corresponding probability of receiving the correct echo is $P_c=0.9997$. The radar measures distance $r$ and azimuth angle $\theta$, Infrared measures azimuth angle $\theta$ and elevation angle $e$. Nonlinear equations to distance, azimuth, and elevation Angle and state variables are as follows:

$$r = \sqrt{x^2 + y^2 + z^2}$$  \hspace{1cm} \text{(29)}$$

$$\theta = \tan(\theta_2)$$  \hspace{1cm} \text{(30)}$$

$$e = \tan(\theta_1)$$  \hspace{1cm} \text{(31)}$$

Covariance matrix of radar and infrared sensor are as follows:

$$R^1 = \begin{bmatrix} 400 & 0 \\ 0 & 49 \end{bmatrix} \hspace{1cm} R^2 = \begin{bmatrix} 4 & 0 \\ 0 & 4 \end{bmatrix}$$

Based on the above simulation scenarios and parameter setting, Monte Carlo simulation was performed for 200 times for IMM/MS-MDPDAF and IMM/MSPDAF. Simulation shows the target trajectory, fusion target position and azimuth and elevation angle and speed of root mean square error (RMSE) of curve, as shown from Figure 2 to Figure 6.

Figure 2. The trajectory of the maneuvering target  
Figure 3. Comparison between both algorithms in terms of RMSE in position
Figure 4. Comparison between both algorithms in terms of RMSE in azimuth angle $\theta$  

Figure 5. Comparison between both algorithms in terms of RMSE in elevation angle $\epsilon$

Figure 6. Comparison between both algorithms in terms of RMSE in velocity

From Figure 3 to Figure 6 respectively, azimuth angle, elevation angle, position and velocity error curve, we can conclude that in clutter environment IMM/MS-MDPDAF algorithm of estimation error is significantly lower than IMM/MSPDAF algorithm. By Figure 4 and Figure 5 shows two error curves of the algorithm is very close, it shows that this algorithm can accurately track for the target angle. While tracking of the position and velocity of the target, it can be seen from Figure 3 and Figure 6: When the target is moving at constant speed or uniformly accelerating, both algorithms can track the position and velocity of the target very well; When the target makes a maneuvering turn, it can be seen from the error curve that the error of IMM/MS-MDPDAF algorithm is significantly lower than that of IMM/MSPDAF algorithm. This indicates that the algorithm proposed in this paper can improve the positioning accuracy of the tracking target, and improve the tracking performance and stability of the system better.
Table 2. The quantitative comparison of two algorithms

| Algorithm                        | IMM/MS-MDPDAF | IMM/MDPDAF |
|----------------------------------|---------------|------------|
| RMSE Average in Position /m      | 33.4727       | 35.1382    |
| RMSE Average in Azimuth Angle /° | 0.128         | 0.1473     |
| RMSE Average in Elevation Angle /° | 0.09189     | 0.1009     |
| RMSE Average in Velocity /(m/s)   | 27.6527       | 28.0268    |
| Average Number of False Alarms (Radar Sensor) | 0.4157   | 0.4282     |
| Average Number of False Alarms (Infrared Sensor) | 0.7634 | 0.9025  |
| Number of Lost Tracks            | 0             | 0          |

The quantitative results of simulation consist of RMSE average in position, velocity, azimuth angle, elevation angle and average number of false alarms in radar and infrared sensors, number of lost tracks. From the Table 2, it can be seen that the number of lost targets of both algorithms is zero, so that the target motion model established by both algorithms can cover various maneuvers, considering the various changes of the target motion. From the analysis of other data, compared with the IMM/MS-MDPDAF algorithm, the tracking effect of this algorithm on position, azimuth, elevation angle and velocity are increased by 4.7%, 13.1%, 8.9% and 1.3%, respectively. To sum up, it is obvious that in tracking with multiple detection radar and infrared sensor, IMM/MS-MDPDAF algorithm has superior performance in all cases rather than IMMIMSPDAF.

6. Conclusion

In this paper, aiming at the tracking problem of maneuvering target in clutter environment, the traditional IMM/MSPDAF method cannot deal with the uncertainty problem in multiple target echo well, so IMM/MS-MDPDAF algorithm was proposed. Considering the origin of target tracking measurement and the uncertainty of the number, the multi-detection mode of radar and infrared sensor are used for joint observation and fusion processing. The simulation results show that compared with IMM/MSPDAF, the algorithm can improve tracking accuracy of maneuvering targets and improve anti-interference ability of the system, which verifies the effectiveness of the algorithm.

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