THE IMPROVED IMM TRACKING ALGORITHM FOR HIGH-SPEED MANEUVERING TARGET

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Abstract

This paper proposes an improved interacting multi-model (IMM) tracking algorithm based on the adaptive Markov transition probability matrix, which can be utilized in radar systems for high-speed maneuvering target tracking. The Markov transition probability matrix can be adaptive adjusted according to different characteristics of target motion state and the Markov transition probability matrix can be dynamically regulated between different models. The Monte Carlo simulation is carried out by software, which shows that the tracking performance of the algorithm is superior to the traditional method of IMM.

1 Introduction

Target tracking is the important research part in the modern radar technique field. The essence of target tracking problem is tracking and filtering problem of target state, namely the target state can be accurately estimated according to the measurement data obtained by the radar system. With the development of the technology and science, the maneuverability of target becomes more and more complicated and inconstant. The target changes the law of motion resulting in a serious decline in tracking performance. Therefore, the high-speed maneuvering ability of target becomes a serious challenge for radar.

The motion model for maneuvering target includes: CV model, CA model, Singer model, "current" statistical model and so on. Because of the maneuverability, when using adaptive filtering algorithm based on a single model, the model that needs priori sets can not preferably match the maneuvering motion of the target. With the help of multiple model adaptive control, Magill puts forward the model algorithm that the motion model is developed from single model to the multi model\cite{1}. The IMM algorithm is proposed by Blom and Bar-Shalom based on the generalized pseudo-Bayes algorithm\cite{2}. The basic idea of IMM algorithm is utilizes different motion models to match different motion states of the target, corresponding to each different filter in parallel, using Markov chains to achieve the switch of different models, the ultimate estimates of the filter is the weighted sum of each individual model estimation\cite{3,4}. The improved IMM algorithm has been proposed in recent years\cite{5-9}.

Traditional IMM algorithm achieves the fusion between the different motion models by regulate the weighted probability, and does not take into account the irrationality of Markov transition probability matrix designation. If the Markov transition probability matrix can be adaptive, that is to say, according to different characteristics of target motion state for dynamic adjustment, more optimal treatment can be achieved. Not only can be adaptively calculated the various transition probability models’ weighting coefficients by the formulation also Markov transition probability matrix can be dynamically regulated between different models.

The IMM algorithm for target tracking is introduced and the improved algorithm with an adaptive Markov transition probability matrix is proposed in the paper. The simulation results are shown. The simulation results show that Adaptive Markov transition probability matrix IMM tracking algorithm can track maneuvering target well.

2 IMM Algorithm to Target Tracking

Suppose that the target have r kinds of motion states, such as uniform linear motion, uniformly accelerated linear motion, etc., each state corresponds to a motion model, r kinds of motion models, denoted by $M_1, M_2, ..., M_r$.

The following procedures should be performed in the application of the IMM tracking algorithm\cite{3}: (I) Input interaction; (II) model-condition transition; (III) model probability updating; (IV) estimate fusion. Step 1. Input interaction; Calculate the mixed initial condition of various models $M_j (k)$ in IMM tracking model

$$\hat{X}^o (k-1 | k-1) = \sum_{i=1}^{N} \tilde{X} (k-1 | k-1) u_i (k-1 | k-1) \tag{1}$$

Where $\mu_i (k-1 | k-1)$ is mixed probability.

$$\mu_i (k-1 | k-1) = \frac{1}{C_j} P_{i,j} (k-1 | k-1) \tag{2}$$

Where $P_{i,j}$ is Markov state transition probability matrix and $u_i (k-1)$ is the probability of $M_i (k-1)$.

Mixed initial state covariance matrix is
\[
P^c(k-1|k-1) = \sum_{i=1}^{N} P^c(k-1|k-1) \\
+ \left\{ \begin{array}{l} \hat{X}^c(k-1|k-1) - \hat{X}^c(k-1|k-1) \\
\times \left[ \hat{X}^c(k-1|k-1) - \hat{X}^c(k-1|k-1) \right]^T \end{array} \right\} \\
\times u_c(k-1|k-1)
\]

(3)

\[
P^o(k-1|k-1) = \sum_{i=1}^{N} P^o(k-1|k-1) \\
+ \left\{ \begin{array}{l} \hat{X}^o(k-1|k-1) - \hat{X}^o(k-1|k-1) \\
\times \left[ \hat{X}^o(k-1|k-1) - \hat{X}^o(k-1|k-1) \right]^T \end{array} \right\} \\
\times u_o(k-1|k-1)
\]

(4)

Step II. Kalman filtering;
Corresponding to the model \( M_i(k) \), the state vector \( \hat{X}^o(k-1|k-1) \), the variance \( P^o(k-1|k-1) \) and \( Z(k) \) are as input to be filtered and proceeded with Kalman filtering.

Step III. Updating the model probability, probability is updated based on the likelihood function as:

\[
\Lambda_j(k) = \frac{1}{\sqrt{2\pi S_j(k)}} \exp\left[ -\frac{1}{2} (v_j(k)^T S_j(k)^{-1} v_j(k)) \right]
\]

(5)

Where \( v_j(k) \) is the filtering residual and \( S_j(k) \) is the corresponding covariance:

\[
\begin{aligned}
& v_j(k) = Z(k) - H_j(k) \hat{X}^o(k|k-1) \\
& S_j(k) = H_j(k) P^o(k|k-1) H_j(k)^T + R(k)
\end{aligned}
\]

(6)

Update the model probability as:

\[
\mu_j(k) = P\{ M_j(k) | Z(k) \} = P\{ Z(k) | M_j(k) \} P\{ M_j(k) \} \sum_{i=1}^{N} P^i(k|k-1)
\]

\[
= \frac{1}{C} \Lambda_j(k) \sum_{i=1}^{N} P^i(k|k) \mu_i(k-1)
\]

\[
= \frac{1}{C} \Lambda_j(k) \tilde{C}_j
\]

(7)

Where \( C = \sum_{i=1}^{N} \Lambda_i(k) \tilde{C}_i \).

Step IV. estimate fusion, the estimate and covariance matrices can be obtained as:

\[
\hat{X}(k|k) = \sum_{i=1}^{N} \hat{X}^i(k|k) u_i(k)
\]

(8)

\[
P(k|k) = \sum_{i=1}^{N} u_i(i) P^i(k|k) + \left\{ \hat{X}^i(k|k) - \hat{X}(k|k) \right\} \\
\times \left[ \hat{X}^i(k|k) - \hat{X}(k|k) \right]^T \}
\]

(9)

### 3 Adaptive Markov transition probability matrix

In the IMM model, Markov state transition probability matrix is used to describe the conversion between different models[11], Markov state transition probability matrix is

\[
P_r = \begin{bmatrix} p_{11} & \cdots & p_{r1} \\ \vdots & \ddots & \vdots \\ p_{1r} & \cdots & p_{rr} \end{bmatrix}
\]

(10)

Where \( p_{ij} (1 \leq i, j \leq r) \) denotes the probability from motion model \( i \) to \( j \).

\[
\sum_{j=1}^{r} p_{ij} = 1
\]

(11)

It is assumed that the target transition probability is fixed between different motion models in the traditional IMM algorithm, this assumption does not fully take into account the selectivity of the motion model, just utilizes a "hard rule" to set the transition probability to a fixed value. In fact, when the target motion state has a tendency to one of the motion models, traditional IMM algorithm achieves the "fusion" by adjusting the weighted probability but not takes into account the irrationality of the Markov transition probability matrix designation.

The example for two models \( M_1, M_2 \). Figure 1 gives the Structure diagram of improved IMM algorithm, assumes that there are only two motion models.

![Figure 1. The improved IMM algorithm structure](image-url)

The change of model probability

\[
\Delta \mu(k) = \mu(k) - \mu(k-1)
\]

(12)

\[
\Delta \mu(k) = - (\mu_2(k) - \mu_1(k-1))
\]

(13)

When \( \Delta \mu(k) > 0 \), it shows that the probability of model \( M_1 \) increases.
When the Δμ(k) < 0, it shows that the probability of model $M_2$ increases.

\[
p_{12}(k) = p_{12}(k-1) + \lambda \Delta \mu(k)
\]

\[
p_{11}(k) = 1 - p_{12}(k)
\]

Where

\[
\lambda = \begin{cases} 
\lambda_1 & \Delta \mu(k) \geq T_h \\
\lambda_2 & 0 < \Delta \mu(k) < T_h
\end{cases}, \quad \lambda_1 > \lambda_2
\]

Set upper limit and lower limit of the transition probability $p_{\text{max}}$ and $p_{\text{min}}$. If $p_0(k) > p_{\text{max}}$, then $p_0(k) = p_{\text{max}}$. Similarly, if $p_0(k) < p_{\text{min}}$, then $p_0(k) = p_{\text{min}}$.

The Markov transition probability matrix can be adaptively adjusted according to different characteristics of target motion state and the Markov transition probability matrix can be dynamically regulated between different models according to the change of model probability.

### 4 Simulations and Analysis

The simulation time is 200s. $M_1$ is CV model, $M_2$ is CT model. The state transition matrix

\[
F_1 = \begin{bmatrix} 1 & T & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & T \\
0 & 0 & 0 & 1 \end{bmatrix}
\]

\[
F_2 = \begin{bmatrix} 1 & \sin(\omega T)/\omega & 0 & (\cos(\omega T)-1)/\omega \\
0 & \cos(\omega T) & 0 & \sin(\omega T) \\
0 & \cos(\omega T)-1/\omega & 1 & \sin(\omega T)/\omega \\
0 & \sin(\omega T) & 0 & \cos(\omega T) \end{bmatrix}
\]

Where, $\omega = 2\pi \times (3/360)$.

The initial state $X(0) = [1000 \ 200 \ 1000 \ 200]^T$. The initial state covariance matrix $P(0)$ and the measurement noise covariance matrix $R$ are expressed as

\[
P(0) = \begin{bmatrix} 1000 & 500 & \ & \ \\
\ & 500 & \ & \ \\
\ & \ & 1000 & \ \\
\ & \ & \ & 500 \end{bmatrix}
\]

\[
R = \begin{bmatrix} 200 & 0 \\
0 & 200 \end{bmatrix}
\]

The initial model probability is $\mu(0) = [0.5 \ 0.5]^T$. The initial transition probability matrix $P_0(0)$

\[
P_0(0) = \begin{bmatrix} 0.8 & 0.2 \\
0.2 & 0.8 \end{bmatrix}
\]

Table 1 shows the parameters for the improved IMM algorithm.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_h$</td>
<td>0.3</td>
</tr>
<tr>
<td>$\lambda_1$</td>
<td>0.4</td>
</tr>
<tr>
<td>$\lambda_2$</td>
<td>0.2</td>
</tr>
<tr>
<td>$p_{\text{max}}$</td>
<td>0.95</td>
</tr>
<tr>
<td>$p_{\text{min}}$</td>
<td>0.05</td>
</tr>
</tbody>
</table>

The motion trajectory and the track trajectory are shown in Figure 2. The improved IMM tracking algorithm can steadily track the high-speed maneuvering target.

![Figure 2 The motion trajectory and the track trajectory](image)

Figure 3 The model probability curve of the IMM Algorithm

![Figure 3 The model probability curve of the IMM Algorithm](image)
The improved algorithm avoids transition probability model given by the prior. Judging the trend of the target motion according to changes in the model probability and adjusting the the Markov transition probability matrix.

Table 2. IMM algorithm Position RMS contrast

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Position RMS-X(m)</th>
<th>Position RMS-Y(m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>traditional IMM</td>
<td>8.4390</td>
<td>8.1723</td>
</tr>
<tr>
<td>improved IMM</td>
<td>7.9973</td>
<td>7.7922</td>
</tr>
</tbody>
</table>

From the simulation results we can conclude that the adaptive IMM algorithm in the target linear motion stage or stages of moving in the corners can be accurate and stable tracking maneuvering target, while the method based on the Kalman filter Traditional IMM model can track the target only in the linear motion stage well; when the target turn into corner, the method cannot track the target effectively, and resulting in a larger tracking error the Table 2 shows that the adaptive IMM algorithm of tracking results is superior to the traditional method of IMM.

5 Conclusions

IMM-Kalman filtering algorithm is an effective maneuvering target tracking algorithm, the obvious feature is the finite model estimation by the probability, and the conversion between different models. In traditional IMM algorithm, it is assumed that the traditional Markov transition probability matrix is fixed, which limit the selectivity for maneuvering target motion model. The Markov transition probability matrix can be adaptive adjusted according to different characteristics of target motion state and the Markov transition probability matrix can be dynamically regulated between different models according to the change of model probability. The simulation results show that Adaptive Markov transition probability matrix IMM tracking algorithm can track maneuvering target well, and the algorithm for tracking precision compared to the traditional IMM method has bigger improvement.

Acknowledgments

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References