Using interacting multiple model particle filter to track airborne targets hidden in blind Doppler

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Abstract: In airborne tracking, the blind Doppler makes the target undetectable, resulting in tracking difficulties. In this paper, we studied most possible blind-Doppler cases and summed them up into two types: targets’ intentional tangential flying to radar and unintentional flying with large tangential speed. We proposed an interacting multiple model (IMM) particle filter which combines a constant velocity model and an acceleration model to handle maneuvering motions. We compared the IMM particle filter with a previous particle filter solution. Simulation results showed that the IMM particle filter outperforms the method in previous works in terms of tracking accuracy and continuity.

Key words: Interacting multiple model, Particle filter, Blind Doppler

INTRODUCTION

In airborne radar tracking, when the target flies tangentially with respect to the tracking radar, the reflected Doppler frequency from the target will become indiscriminate to the receiving radar, and the range-rate (or Doppler speed) of that flight may possibly be lower than the blind Doppler limit, i.e., the least range-rate the radar can measure. During the blind Doppler, there is no gated observation from the radar and this could last till the track is lost.

Although no tracking can be executed during the blind Doppler, the blind Doppler cannot always be maintained by the target and it has to reappear finally. Therefore, it is required that tracking should be resumed as soon as the radar detects the target again. The extended Kalman filter (EKF) is a competent technique for tracking with mild nonlinearity (Gordon and Ristic, 2002; Ristic et al., 2004), but this method is incapable of resuming tracking due to the blind Doppler’s great nonlinearity. Preferred means are the particle filter (Arulampalam et al., 2002; Ristic et al., 2004; Zang et al., 2007) and the combined Kalman/particle filter, which can resume tracking very quickly by exploiting the prior knowledge of the blind zone (Gordon and Ristic, 2002; Zaugg et al., 2003).

A major difficulty of using constant velocity (CV) motion model for this issue lies in the target’s maneuverability which specifically refers to the varying extent of the blind Doppler region (existing period and area) and accelerations before the target’s hiding and after its reappearance. The methods in (Gordon and Ristic, 2002; Zaugg et al., 2003) may have difficulties in dealing with such maneuverability. Multiple model method is a main trend of dealing with high maneuver motions. (Li and Jilkov, 2005). Therefore, in this paper, based on previous work in (Gordon and Ristic, 2002), we borrowed the main ideas of the interacting multiple model particle filter proposed by Boers and Driessen (2003) to improve the filtering (Blom and Bar-Shalom, 1988; Boers and Driessen, 2003). Despite the fact that interacting
multiple model method enhances system complexity, it requires fewer particles than single CV model to obtain the same or better performance.

The rest of this paper is organized as follows. Section 2 describes the movement model. Section 3 introduces the generalized types of the blind Doppler. Section 4 describes the algorithm of the interacting multiple model particle filter, and Section 5 presents the simulation results. Finally we conclude the paper.

MOVEMENT MODEL

The movement is described efficiently by two models: CV model and the acceleration model. We do not know the true acceleration beforehand, therefore a specified process noise is added to make the acceleration adjust itself. The detail will be discussed later.

The state dynamics are:

\[ x_{k+1} = F(x_k, T_k, m) + \Gamma(T_k, m)v_k(m), \] (1)

where \( m \in \{1, 2\} \). \( m=1 \) corresponds to the CV model, and \( m=2 \) corresponds to the acceleration model. State evolutions of the two modes are given below:

\[
F(x_k, T_k, 1) = \begin{bmatrix}
1 & T_k & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & T_k \\
0 & 0 & 0 & 1
\end{bmatrix} x_k, \text{ with } x_k = \begin{bmatrix} x_k \\ v_{x_k} \\ y_k \\ v_{y_k} \end{bmatrix},
\]

and \( \Gamma(T_k, 1) = \begin{bmatrix} a_{v_k} T_k^2 / 2 & 0 \\
0 & a_{v_k} T_k \\
0 & 0 & a_{v_k} T_k^2 / 2 \\
0 & 0 & 0 & a_{v_k} \end{bmatrix} \) for mode 1;

\[
F(x_k, T_k, 2) = \begin{bmatrix}
1 & T_k & T_k^2 / 2 & 0 & 0 & 0 \\
0 & 1 & T_k & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & T_k & T_k^2 / 2 \\
0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix} x_k, \text{ with state } x_k = \begin{bmatrix} x_k \\ v_{x_k} \\ a_{x_k} \\ y_k \\ v_{y_k} \\ a_{y_k} \end{bmatrix}^T,
\]

\[
and \quad \Gamma(T_k, 2) = \begin{bmatrix} a_{v_k} T_k^2 / 2 & 0 \\
0 & a_{v_k} T_k \\
0 & 0 & a_{v_k} T_k^2 / 2 \\
0 & 0 & 0 & a_{v_k} \end{bmatrix} \text{ for mode 2.}
\]

The position variances and their cross-covariance are (Mo et al., 1998)

\[ v_k(1) \text{ is a } 2 \times 1 \text{ white Gaussian noise vector with covariance matrix } Q(T_k) = \sigma^2 v_{1,2}. v_k(2) \text{ is } 2 \times 1 \text{ uniformly distributed noise, while } a_{v_k} \text{ and } a_{y_k}
\]

are set to be the maximum acceleration along x-axis and y-axis respectively. This process noise for mode 2 can handle acceleration maneuverability from zero to maximum acceleration, as remarked by Boers and Driessen (2003).

The measurement equation is

\[ z_k = h(x_k) + w_k, \] (2)

where \( z_k = [X_k, Y_k, r_{kk}]^T \) consists of position and range-rate measurements \( X_k, Y_k, r_{kk} \). The unbiased conversions of measurements from polar coordinate to Cartesian coordinate are given by \( X_k = \lambda^{-1} r_k \cos \theta_k, Y_k = \lambda^{-1} r_k \sin \theta_k \) with \( \lambda = \exp(-\sigma^2 \theta^2 / 2) \) being the bias compensation factor (Mo et al., 1998). \( \sigma_r, \sigma_r \) and \( \sigma_\theta \) are the standard deviation for range, range-rate and azimuth respectively.

Measurement noise \( w_k \) is a \( 3 \times 1 \) zero-mean Gaussian vector with covariance matrix

\[ R_k = \begin{bmatrix} \sigma_{X_k}^2 & \sigma_{X_k Y_k} & 0 \\
\sigma_{X_k Y_k} & \sigma_{Y_k}^2 & 0 \\
0 & 0 & \sigma_{r_{kk}}^2 \end{bmatrix}, \] (3)

\( v_k \) and \( w_k \) are assumed to be independent.

The nonlinear function is defined as

\[ h(x_k) = \begin{bmatrix} x_k \\ y_k \\ \frac{x_k v_{x_k} + y_k v_{y_k}}{\sqrt{x_k^2 + y_k^2}} \end{bmatrix}^T. \] (4)

The position variances and their cross-covariance are (Mo et al., 1998)