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A Novel Maneuvering Target Tracking Algorithm for Radar/Infrared Sensors*

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Abstract — In this paper a novel filtering algorithm, called Radar/Infrared(R/IR) converted measurements filter Interacting multiple model (R/IRCMF-IMM), is proposed for tracking a maneuvering target using Radar/Infrared heterogeneous sensors. This filtering algorithm is developed by converting the polar measurements of Radar and Infrared to Cartesian coordinates, and calculating the statistic characteristics of converted measurement errors before filtering, then applying to the IMM technique. Since there are no linearization errors of the measurement model in the process, the new method has better tracking performance than traditional IMM that using Extend Kalman filters (EKFIMM). Additionally, the new method has equal calculation cost with EKFIMM. Finally a simulation example is given and shown that the proposed algorithm achieves significant improvement in the accuracy of tracking estimation comparing with the EKFIMM.

Key words — Maneuvering target tracking, Radar/Infrared, Converted measurement filter, IMM.

I. Introduction

In the recent years, the problem of multi-sensor data fusion in target tracking has attracted general attention. Especially, maneuvering target tracking utilizing R/IR information fusion is a hot research topic. In target tracking, the sensors fusion system is much more favorable than the conventional single sensor in two aspects[1,2]: (1) The radar sensor is an active sensor, which is easy to be interfered by electromagnetic and has bad tracking accuracy when the target is cloaked or extends chaff barrier. The IR sensor is a passive system, which is quite sensitive to atmospheric conditions and has no effect on electromagnetic interference. So R/IR fusion system could improve the anti-interference performance; (2) Taking the high precision of infrared angle measurement and radar range measurement, the R/IR fusion system could improve the tracking accuracy. But there are also some challenges, such as the angle measurement may lead to high nonlinearity of the measurement model, and the target is universal maneuverable. Hence the nonlinear filter for maneuvering target tracking should be researched for radar/IR fusion system.

In practice, the most popular maneuvering target tracking algorithm is IMM that is adaptive for the radar sensor[3,4]. But the IMM technique has large computational cost. In consideration of Real-time, the filtering method of each filter for IMM could not be complex. On the other hand, in view of tracking precision, the filtering method could have high tracking accuracy. In the R/IR fusion tracking system, the dynamic target is usually modeled and tracked in the Cartesian coordinates, whereas the measurements are provided in terms of range and angle with respect to the sensor location in the polar coordinates. This case can be dealt with in two ways. One is performing the state estimation in mixed coordinates, such as the simple filtering method EKF[5]. However, the EKF utilizes the first-order term of a Taylor series expansion for measurement model to get linear approximations. This introduces considerable errors when the model is highly nonlinear, which leads to the divergence of the filtering process and results in low accuracy of the estimation. Whereas the IR angle measurement easily causes high nonlinearity of the measurement model. So the IMM technique with EKF is not so suitable for target tracking in R/IR fusion system. Another way is the CMF, see Refs.[6, 7], that is converting the polar measurements to Cartesian coordinates and then filtering in the Cartesian coordinates. The crucial problem of the CMF is to calculate the statistic characteristics of the converted measurement errors. For this reason, we derive the covariance of the converted measurement errors in the Cartesian coordinates for R/IR fusion tracking system and then develop a new CMF method. We apply this new CMF method into the IMM, forming the R/IRCMF-IMM algorithm, which is used to track maneuvering target. The R/IRCMF-IMM method is insensitive to the nonlinearity of the measurement model. When the calculated statistic characteristics of the converted measurement errors are approach to the real value, the R/IRCMF-IMM could achieve good tracking performance. Meanwhile, the proposed method has the equal calculated amount as the EKFIMM, thus it is suitable for the engineering application.

II. The Sensor Measurement Model[8]

The distance r, azimuth θ of target can be measured by

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radar, the measurement formulas are:

$$\begin{cases} r_R(k) = r(k) + n_{r_R}(k) \\ \theta_R(k) = \theta(k) + n_{\theta_R}(k) \end{cases}$$

where $r(k)$ and $\theta(k)$ are the real value, $\{n_{r_R}(k), k \in \mathbb{N}\}$ and $\{n_{\theta_R}(k), k \in \mathbb{N}\}$ are separately the independent identically distributed (i.i.d) zero-mean Gaussian white noise, with variance $\sigma^2_{r_R}$ and $\sigma^2_{\theta_R}$ respectively. In this paper, we suppose $x(k), y(k), z(k)$ are the position elements of the state vector $\boldsymbol{X}(k)$, so we have the radar measurement model as:

$$\begin{aligned} \boldsymbol{Z}_R(k) =& h(\boldsymbol{X}(k), \boldsymbol{n}(k)) \\ =& \begin{bmatrix} r_R(k) \\ \theta_R(k) \end{bmatrix} \\ =& \begin{bmatrix} \sqrt{x(k)^2 + y(k)^2 + z(k)^2} \\ \arccos \dfrac{x(k)}{\sqrt{x(k)^2 + y(k)^2}} \end{bmatrix} + \begin{bmatrix} n_{r_R}(k) \\ n_{\theta_R}(k) \end{bmatrix} \end{aligned} \tag{1}$$

The observation outputs of infrared sensor are azimuth θ and elevation φ of the target's center. The measurement formulas are:

$$\begin{cases} \theta_I(k) = \theta(k) + n_{\theta_I}(k) \\ \varphi_I(k) = \varphi(k) + n_{\varphi_I}(k) \end{cases}$$

where $\theta(k), \varphi(k)$ are the real value, $\{n_{\theta_I}(k), k \in \mathbb{N}\}$ and $\{n_{\varphi_I}(k), k \in \mathbb{N}\}$ are separately the i.i.d zero-mean Gaussian white noise with variance $\sigma^2_{\theta_I}$ and $\sigma^2_{\varphi_I}$ respectively. We have the IR measurement model as:

$$\begin{aligned} \boldsymbol{Z}_I =& h(\boldsymbol{X}(k), \boldsymbol{n}(k)) \\ =& \begin{bmatrix} \theta_I(k) \\ \varphi_I(k) \end{bmatrix} \\ =& \begin{bmatrix} \arccos \dfrac{x(k)}{\sqrt{x(k)^2 + y(k)^2}} \\ \arcsin \dfrac{z(k)}{\sqrt{x(k)^2 + y(k)^2 + z(k)^2}} \end{bmatrix} + \begin{bmatrix} n_{\theta_I}(k) \\ n_{\varphi_I}(k) \end{bmatrix} \end{aligned} \tag{2}$$

III. The Mathematic Model of the R/IRCMF

For simplicity, there omits the time index k. Considering the location of the radar is $S_R(x_R, y_R, z_R)$, the location of the IR sensor is $S_I(x_I, y_I, z_I)$, the real position of target is $T(x, y, z)$, the radar measurement is (r_R, θ_R), and the observation of IR sensor is (θ_I, φ_I), so the equation set of calculating the target position is as:

$$\begin{cases} r_R = \sqrt{(x - x_R)^2 + (y - y_R)^2 + (z - z_R)^2} \\ \theta_R = \arccos \dfrac{x - x_R}{\sqrt{(x - x_R)^2 + (y - y_R)^2}} \\ \theta_I = \arccos \dfrac{x - x_I}{\sqrt{(x - x_I)^2 + (y - y_I)^2}} \\ \varphi_I = \arcsin \dfrac{z - z_I}{\sqrt{(x - x_I)^2 + (y - y_I)^2 + (z - z_I)^2}} \end{cases} \tag{3}$$

When the locations of radar and IR sensor are different, the last three equations of Eq.(3) can be rewritten as matrix form $\boldsymbol{Ax} = \boldsymbol{B}$, here:

$$\boldsymbol{A} = \begin{bmatrix} \sin\theta_R & -\cos\theta_R & 0 \\ \sin\theta_I & -\cos\theta_I & 0 \\ \sin\varphi_I & 0 & -\cos\theta_I \cos\varphi_I \end{bmatrix},$$

$$\boldsymbol{x} = \begin{bmatrix} x \\ y \\ z \end{bmatrix}, \quad \boldsymbol{B} = \begin{bmatrix} x_R \sin\theta_R - y_R \cos\theta_R \\ x_I \sin\theta_I - y_I \cos\theta_I \\ x_I \sin\varphi_I - z_I \cos\varphi_I \cos\theta_I \end{bmatrix}$$

Using the least-square formula, we can obtain the solution of target position as:

$$\boldsymbol{x} = (\boldsymbol{A}^T \boldsymbol{A})^{-1} \boldsymbol{A}^T \boldsymbol{B}$$

The main idea of the R/IRCMF is to convert the measurements in the polar to the Cartesian coordinate, calculate the statistics of the converted measurement errors, and then utilize the Kalman Filter to estimate the state. This could avoid the linearization process of the measurement model. The key of the R/IRCMF is to obtain the covariance $\boldsymbol{R}$ of the converted measurement errors. Then, we will derive the covariance $\boldsymbol{R}$.

In this paper, we assume $\tilde{\boldsymbol{x}} = [\tilde{x} \quad \tilde{y} \quad \tilde{z}]^T$ is converted measurement error vector. From Eq.(3), we see that $\tilde{x}, \tilde{y}, \tilde{z}$ are not statistically independent because they are related to the measurement $(r_R, \theta_R, \theta_I, \varphi_I)$. The covariance of these errors could be defined as:

$$\boldsymbol{R} = \boldsymbol{E}[\tilde{\boldsymbol{x}} \tilde{\boldsymbol{x}}^T] = \begin{bmatrix} \sigma_x^2 & \sigma_{xy} & \sigma_{xz} \\ \sigma_{yx} & \sigma_y^2 & \sigma_{yz} \\ \sigma_{zx} & \sigma_{zy} & \sigma_z^2 \end{bmatrix}$$

In fact, the covariance $\boldsymbol{R}$ can be calculated by the observation accuracy of radar and IR sensor, that is, $\sigma^2_{r_R}, \sigma^2_{\theta_R}, \sigma^2_{\theta_I}, \sigma^2_{\phi_I}$.

Making use of the calculation equation set of Eq.(3), we get the differential coefficient as:

$$\begin{cases} dr_R = \dfrac{x - x_R}{R_R} dx + \dfrac{y - y_R}{R_R} dy + \dfrac{z - z_R}{R_R} dz \\ d\theta_R = -\dfrac{\sin^2\theta_R}{|y - y_R|} dx + \dfrac{\cos\theta_R \sin\theta_R}{|y - y_R|} dy \\ d\theta_I = -\dfrac{\sin^2\theta_I}{|y - y_I|} dx + \dfrac{\cos\theta_I \sin\theta_I}{|y - y_I|} dy \\ d\varphi_I = -\dfrac{\sin\varphi_I \cos\theta_I}{R_I} dx - \dfrac{\sin\varphi_I \sin\theta_I}{R_I} dy + \dfrac{\cos\varphi_I}{R_I} dz \end{cases} \tag{4}$$

where $R_R = \sqrt{(x - x_R)^2 + (y - y_R)^2 + (z - z_R)^2}$, $R_I = \sqrt{(x - x_I)^2 + (y - y_I)^2 + (z - z_I)^2}$.

To rewrite Eq.(4), we get the matrix form:

$$\boldsymbol{dP} = \boldsymbol{M} \cdot \boldsymbol{dx}$$

where $\boldsymbol{dP} = [dr_R \quad d\theta_R \quad d\theta_I \quad d\phi_I]^T$, $\boldsymbol{dx} = [dx \quad dy \quad dz]^T$, and

$$\boldsymbol{M} = \begin{bmatrix} \dfrac{x - x_R}{R_R} & \dfrac{y - y_R}{R_R} & \dfrac{z - z_R}{R_R} \\ -\dfrac{\sin^2\theta_R}{|y - y_R|} & \dfrac{\cos\theta_R \sin\theta_R}{|y - y_R|} & 0 \\ -\dfrac{\sin^2\theta_I}{|y - y_I|} & \dfrac{\cos\theta_I \sin\theta_I}{|y - y_I|} & 0 \\ -\dfrac{\sin\varphi_I \cos\theta_I}{R_I} & -\dfrac{\sin\varphi_I \sin\theta_I}{R_I} & \dfrac{\cos\varphi_I}{R_I} \end{bmatrix}$$

Based on the least-square formula, we could acquire:

$$\boldsymbol{dx} = (\boldsymbol{M}^T \boldsymbol{M})^{-1} \boldsymbol{M}^T \boldsymbol{dP}$$

Suppose $\boldsymbol{C} = (\boldsymbol{M}^T\boldsymbol{M})^{-1}\boldsymbol{M}^T$, it is easy to obtain the mean of the converted measurement error that is also called the bias:

$$\boldsymbol{\mu} = E[\tilde{\boldsymbol{x}}] = E[\boldsymbol{dx}] = C \cdot E[\boldsymbol{dP}] = 0$$

And it can also get the converted measurement error covariance:

$$\begin{aligned}\boldsymbol{R} =& E[\tilde{\boldsymbol{x}}\tilde{\boldsymbol{x}}^T] \\ =& E[\boldsymbol{dx} \cdot \boldsymbol{dx}^T] \\ =& \boldsymbol{C} \cdot E[\boldsymbol{dP} \cdot \boldsymbol{dP}^T] \cdot \boldsymbol{C}^T \\ =& \boldsymbol{C} \cdot \begin{bmatrix} \sigma_{r_R}^2 & 0 & 0 & 0 \\ 0 & \sigma_{\theta_R}^2 & 0 & 0 \\ 0 & 0 & \sigma_{\theta_I}^2 & 0 \\ 0 & 0 & 0 & \sigma_{\phi_I}^2 \end{bmatrix} \cdot \boldsymbol{C}^T \end{aligned} \quad (5)$$

In this paper, the state model for a discrete system can be expressed as:

$$\boldsymbol{X}(k) = \boldsymbol{F}\boldsymbol{X}(k-1) + \boldsymbol{G}v(k-1) \quad (6)$$

Where $\boldsymbol{F}$ is the transmit matrix, $v(k-1)$ is the i.i.d zero-mean Gaussian white noise with covariance q, G is the noise gain.

The measurement model of converted measurement in Cartesian coordinates is:

$$\boldsymbol{Z}(k) = \boldsymbol{H}\boldsymbol{X}(k-1) + \boldsymbol{W}(k-1) = \boldsymbol{H}\boldsymbol{X}(k-1) + \tilde{\boldsymbol{x}}(k-1) \quad (7)$$

Where $\boldsymbol{Z}(k) = [\,x(k) \quad y(k) \quad z(k)\,]^T$, and $\boldsymbol{H}$ is the measurement matrix.

By now, we get the filtering process of the R/IRCMF method:

(1) Predicting:

$$\hat{\boldsymbol{X}}(k|k-1) = \boldsymbol{F}\hat{\boldsymbol{X}}(k-1) \quad (8)$$

$$\boldsymbol{P}(k|k-1) = \boldsymbol{F}\boldsymbol{P}(k-1)\boldsymbol{F}^T + q\boldsymbol{G}\boldsymbol{G}^T \quad (9)$$

Where $\hat{\boldsymbol{X}}(k-1)$ is the state estimation for the $k-1$ interval, $\hat{\boldsymbol{X}}(k|k-1)$ is the predicted state estimation for the k interval.

(2) Updating:

$$\boldsymbol{K}(k) = \boldsymbol{P}(k|k-1)\boldsymbol{H}^T[\boldsymbol{H}\boldsymbol{P}(k|k-1)\boldsymbol{H}^T + \boldsymbol{R}(k)]^{-1} \quad (10)$$

$$\hat{\boldsymbol{X}}(k) = \hat{\boldsymbol{X}}(k|k-1) + \boldsymbol{K}(k)[\boldsymbol{Z}(k) - \boldsymbol{H}\hat{\boldsymbol{X}}(k|k-1)] \quad (11)$$

$$\boldsymbol{P}(k) = \boldsymbol{P}(k|k-1) - \boldsymbol{K}(k)\boldsymbol{H}\boldsymbol{P}(k|k-1) \quad (12)$$

IV. The R/IRCMF-IMM Algorithm

The IMM technique is developed into a mature and systemic maneuvering target tracking algorithm. This method is decision free, that is, no maneuver detection decision is needed and has adaptive ability. The main drawback of this algorithm is the high computational burden, thus in consideration of Real-time, the filtering methods of every model in the IMM should not be too complex. Here, we apply the simple R/IRCMF to IMM technique.

In this paper, we assume that there aremodels，so the steps of R/IRCMF-IMM are as follows:

(1) Calculating the mixing probabilities:

$$u_{ij}(k-1) = \rho_{ij}u_i(k-1)/\bar{C}_j(k-1), \quad i,j = 1,\cdots,r \quad (13)$$

Where ρ_{ij} is element of mode switching probability matrix, $u_i(k-1)$ is the probability of the ith filter at $k-1$, the normalizing constant is:

$$\bar{C}_j(k-1) = \sum_{i=1}^{r} \rho_{ij}u_i(k-1), \quad j = 1,\cdots,r$$

(2) Computing the mixed initial condition for the r filters with $\{\hat{\boldsymbol{X}}_j(k-1), \boldsymbol{P}_j(k-1)\}_{j=1}^r$, as:

$$\hat{\boldsymbol{X}}_j^0(k-1) = \sum_{i=1}^{r} u_{ij}(k-1)\hat{\boldsymbol{X}}_i(k-1), \quad j = 1,\cdots,r \quad (14)$$

The covariance corresponding to the above is:

$$\begin{aligned}\boldsymbol{P}_i^0(k-1) = \sum_{i=1}^{r} u_{ij}(k-1)[&\boldsymbol{P}_i(k-1) \\ &+ \tilde{\boldsymbol{X}}_{ij}(k-1) \cdot \tilde{\boldsymbol{X}}_{ij}^T(k-1)], \quad j = 1,\cdots,r\end{aligned} \quad (15)$$

Where $\tilde{\boldsymbol{X}}_{ij}(k-1) = \hat{\boldsymbol{X}}_i(k-1) - \hat{\boldsymbol{X}}_j^0(k-1)$.

(3) Mode-matched filtering. The estimation Eq.(14) and covariance Eq.(15) are used as input to filters. By using Eqs.(8)–(12), it could get $\{\hat{\boldsymbol{X}}_j(k)\}_{j=1}^r$ and $\{\boldsymbol{P}_j(k)\}_{j=1}^r$. For simplicity, it just calculates the $\boldsymbol{R}(k)$ one time as it is independent of the filter, which reduces the calculated amount.

(4) Updating mode probability:

$$u_j(k) = \Lambda_j(k)\bar{C}_j(k-1)/C, \quad j = 1,\cdots,r \quad (16)$$

Where the likelihood functions is as:

$$\begin{aligned}\Lambda_j(k) = \boldsymbol{N}\Big[&\boldsymbol{Z}(k); \hat{\boldsymbol{Z}}^j[k|k-1; \hat{\boldsymbol{X}}_j^0(k-1)], \\ &S^j[k; \boldsymbol{P}_j^0(k-1)]\Big], \quad j = 1,\cdots,r\end{aligned}$$

The normalization constant of Eq.(16) is:

$$C = \sum_{j=1}^{r} \Lambda_j(k)\bar{C}_j(k-1)$$

(5) Combinating the state estimate and covariance. The model-conditional estimate and covariance is calculated according to the mix equations:

$$\hat{\boldsymbol{X}}(k) = \sum_{j=1}^{r} \hat{\boldsymbol{X}}_j(k)u_j(k) \quad (17)$$

$$\boldsymbol{P}(k) = \sum_{j=1}^{r} u_j(k)(\boldsymbol{P}_j(k) + [\hat{\boldsymbol{X}}_j(k) - \hat{\boldsymbol{X}}(k)] \cdot [\hat{\boldsymbol{X}}_j(k) - \hat{\boldsymbol{X}}(k)]^T) \quad (18)$$

Note that this combination is only for output purposes, and not part of the algorithm recursions.

The above five steps form one cycle period of the R/IRCMF-IMM algorithm.

V. Simulation

The following example of tracking a highly maneuvering airborne target is considered.

True trajectory The target starts at location (77000, 8000, 8000) in Cartesian coordinates in meters. The initial velocity (in m/s) is $(-426, 0, 0)$, and the sampling period is 1s. Its trajectory is:

a straight line with constant velocity between 0 and 30s;

a fast turn with constant acceleration $(-15, 10, 0)$ (in m/s^2) between 30s and 38s;

a straight line with constant velocity between 38s and 61s;

a slow turn with constant acceleration $(10, -5, 0)$ (in m/s^2) between 61s and 71s;

a straight line with constant velocity between 71s and 100s.

Fig.1 shows the true trajectory of the target.

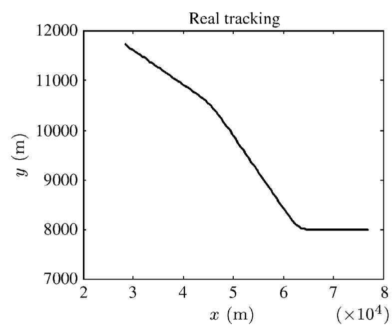

Fig. 1. True trajectory of maneuvering target (position in xy plane)

Target motion models The target dynamics are modeled in Cartesian coordinates as Eq.(4).

Model 1 nearly constant velocity model with zeros mean perturbation in acceleration[9].

The state of the target is position and velocity in each of the 3 Cartesian coordinates (x, y, z), thus $\boldsymbol{X}(k)$ is 6-dimension. The transfer matrix $\boldsymbol{F}$, the noise gain G, and the H are defined as:

$$\boldsymbol{F}_1 = \begin{bmatrix} 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix},$$

$$\boldsymbol{G}_1 = \begin{bmatrix} 0.5 & 0 & 0 \\ 0 & 0.5 & 0 \\ 0 & 0 & 0.5 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix},$$

$$\boldsymbol{H}_1 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

The standard deviation of the process noise is 7.5.

Model 2 nearly constant acceleration model[9].

The state of the target is position, velocity, and acceleration in each of the 3 Cartesian coordinates (x, y, z), thus $\boldsymbol{X}(k)$ is 9-dimension. The transfer matrix $\boldsymbol{F}$ and the noise gain G and the H are defined as:

$$\boldsymbol{F}_2 = \begin{bmatrix} 1 & 0 & 0 & 1 & 0 & 0 & 0.5 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0.5 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0.5 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix},$$

$$\boldsymbol{G}_2 = \begin{bmatrix} 0.5 & 0 & 0 \\ 0 & 0.5 & 0 \\ 0 & 0 & 0.5 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix},$$

$$\boldsymbol{H}_2 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

The standard deviation of the process noise is 10.

The initial model probabilities are $\mu_1(1) = 0.9$, $\mu_2(1) = 0.1$. The mode switching probability matrix is given by:

$$\boldsymbol{\rho} = \begin{bmatrix} \rho_{11} & \rho_{12} \\ \rho_{21} & \rho_{22} \end{bmatrix} = \begin{bmatrix} 0.95 & 0.05 \\ 0.05 & 0.95 \end{bmatrix}$$

Sensors Radar and IR sensors are used to obtain the measurements. Radar is located at (0, 0, 0), the range noise is zero mean white Gaussian with known standard deviation 20m, and the azimuth noise is zero mean white Gaussian with known standard deviation 7mrad. IR sensor is located at (20000, 0, 0) with meters, the azimuth and elevation measurement noises are both zero mean white Gaussian with known standard deviation 2mrad.

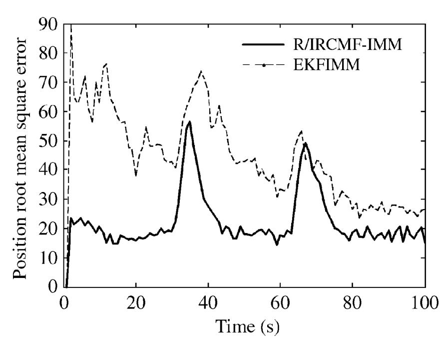

Fig. 2. Position RMSE for different filter algorithms with 50 Monte Carlo runs

Fig.2 shows the RMSE (Root mean square error) in position for the proposed R/IRCMF-IMM and the traditional central EKFIMM based on 50 Monte Carlo runs.

Fig.3 shows the RMSE in velocity for the proposed R/IRCMF-IMM and the traditional central EKFIMM based on 50 Monte Carlo runs.

From Fig.2 and Fig.3, we can see that the proposed approach has outperformed the traditional central EKFIMM. When the target is not maneuvering, the tracking accuracy of the new method is significantly better than EKFIMM. Whereas, the maneuver happens, our method has better capability of maneuver detection, that is, the maneuver detection delay is short.

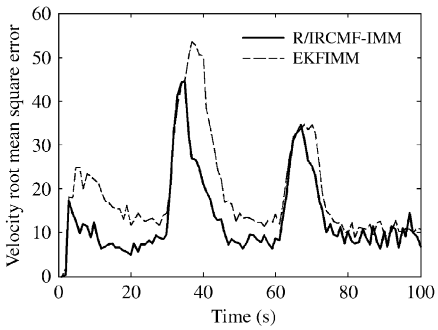

Fig. 3. Velocity RMSE for different filter algorithms with 50 Monte Carlo runs

VI. Conclusion

Taking the high precision of both IR angle measurement and radar distance observation into account, a new maneuvering target tracking algorithm is proposed. Generally, the angle measurement could easily cause high nonlinearity, which may lead the EKF to occur filter divergence. Thereby, this could result in low tracking accuracy. The new method avoids the process of measurement model linearization through converting the polar measurements to Cartesian coordinate. Since no linearization error is introduced in calculating the converted error covariance, the proposed method has better tacking performance than central EKFIMM, which has been proved by the simulation. Furthermore, the new approach is calculated as simply as EKFIMM. In this paper, we evaluate the validity of the new method in one simulation scenarios. In the future research, we will study the scope of application for this proposed method.

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