Oct 2013. Vol. 4, No. 4 ISSN2305-8269
International Journal of Engineering and Applied Sciences

www.eaas-journal.org

TARGET TRACKING FOR MULTISTATIC RARDAR WITH JAMMING UNCERTAINTY

YEE MING CHEN[1] , CHIH-MIN LIN[2] AND CHI-SHUN HSUEH[3]

Dept. of Industrial Engineering and Management, Yuan Ze University , Chung-Li, Tao-Yuan, 320, Taiwan, R.O.C.
[2,3]Dept. of Electrical Engineering, Yuan Ze University , Chung-Li, Tao-Yuan, 320, Taiwan, R.O.C.

E-MAIL: [1] chenyeeming@saturn.yzu.edu.tw, [2]cml@saturn.yzu.edu.tw, [3] s958502@mail.yzu.edu.tw

ABSTRACT:

The multistatic radar sensors offer the system designer new and additional degrees of freedom to reliable solutions to specific applications. The receivers may be passive and hence mainly resistant to jamming. This advantage makes the multistatic radar sensors attractive for a variety of applications, many of which fit well with the needs of homeland security. In this paper the role of active and passive methods as a support to target tracking in homeland security is discovered. A covariance-weighted data fusion (CWDF) tracking algorithm from active and passive radars is introduced to the target tracking system. Based on the proposed algorithm, this paper investigates the problem of 3D maneuvering target tracking in the presence of jamming. The simulation results designate that the proposed algorithm can offer significant tracking and anti-jamming performance. The ideas and methods presented will also bear important significance for developing similar tracking systems in homeland security applications.

Keywords: *Data Fusion ; Tracking; Extended Kalman filter*

1. Introduction

Radar has long been used in a variety of military and civilian applications and has become an vital component of current homeland security systems. Many countries have a network of civil aviation radars that often form a part of a wider air defense capability that is able to guide aircraft. Active and passive radar integrated guidance, as one of multistatic radar sensors composite guidance technologies, is a typical application of information fusion technology in the target tracking field. Target tracking is usually performed by non-homogenous multistatic radar and each radar carries a substantial amount of target state information. In general case, active radar has an ability to obtain range and angle measurements so as to track target precisely, but with poor capabilities to counter jamming. As opposed to active radar, passive radar performs tracking by receiving signals emitted from target and doesn't emit any energy, which make it has the good covertness capability, but estimated error produced by passive radar is often larger than that produced by active radar, but with preferable anti-jamming performance. The complementarities of active and passive radar will significantly improve the multistatic radar sensors operational effectiveness in the electronic countermeasure (ECM) environment. So in many cases, data fusion from active and passive radars is essential to improve tracking performance [1,2]. Such technology is conceived to have a great application prospect in current and future threat offence and homeland security systems. 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 active/passive radars data fusion tracking system.

In practice, the most popular target tracking data fusion algorithm is interacting multiple model (IMM) that is adaptive for the multistatic 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. In the active/passive data fusion tracking system, it can be dealt with in two ways. One is performing the state estimation in mixed coordinates, such as the simple filtering method Extend Kalman filters (EKF)[5]. Another way is the covariance-weighted data fusion, see Refs.[6, 7], that is a covariance-weight state vector data fusion algorithm only considering random errors caused by the distance is discussed instead of traditional invariable-weight method ignoring random errors caused by target distance. The remaining paper is organized as follows. Section 2, describes multistatic radar sensor measurement models. Section 3 states the proposed covariance-weighted data fusion tracking algorithm. In section 4, we present our simulation results and finally in Section 5, the key conclusions and the future works are stated.

2. The Multistatic Radar Sensor Measurement Model

In this section, the movement of a target in a 3-dimensional coordinate system is described by a state-space model. The observation model of the target signal is presented. We consider a single-target scenario for the presentation.

(1) Active radar sensor

As is, usually, the case let the measurements of the target location be made available in spherical form and expressed in the following form. The original measurements from active radar sensor are noise-corrupted range, azimuth and elevation angles of the target in the Spherical Coordinate System. The conventional way to use the linear filter is to transform spherical measurements to pseudo measurements in the Reference Cartesian Coordinate System.

$$\begin{cases} r_m = r + v_r \\ \theta_m = \theta + v_{az} \\ \phi_m = \phi + v_{el} \end{cases} \tag{1}$$

Where r_m range, θ_m azimuth angle, ϕ_m elevation angle denote the radar measurements, respectively. The actual value r, θ and ϕ can be expressed as:

$$\begin{cases} r = \sqrt{x_R^2 + y_R^2 + z_R^2} \\ \theta = \tan^{-1}(y_R / x_R) \\ \phi = \tan^{-1}\left(z_R \big/ \sqrt{x_R^2 + y_R^2}\right) \end{cases} \tag{2}$$

According to equation (1), the measurements corresponding to the N sensors can be modeled by

$$\mathbf{Z}_R^t(k) = \begin{bmatrix} r_R(k) \\ \theta_R(k) \\ \phi_R(k) \end{bmatrix} = \mathbf{H}_R^t[X_R^t(k)] + \mathbf{V}_R^t(k)$$

$$= \begin{bmatrix} \sqrt{x_R^2(k) + y_R^2(k) + z_R^2(k)} \\ \tan^{-1}\left(y_R(k)/x_R(k)\right) \\ \tan^{-1}\left(z_R(k)\big/\sqrt{x_R^2(k) + y_R^2(k)}\right) \end{bmatrix} + \begin{bmatrix} v_r(k) \\ v_{az}(k) \\ v_{el}(k) \end{bmatrix} \tag{3}$$

Where $\mathbf{H}(k)$ is measurement transition matrix, and $\mathbf{V}(k)$ is noise which assumed to be zero-mean white noise.

(2) Passive radar sensor

$$\mathbf{Z}_p^t(k) = [\theta p(k)] = \mathbf{H}_p^t[\mathbf{X}_p^t(k)] + \mathbf{V}_p^t(k)$$
$$= \left[\tan^{-1}[y_p(k)/x_p(k)]\right] + [v_{az}(k)] \tag{4}$$

(3) The Mathematic Model of the Multistatic Radar Sensor

Tracking the trajectory of a target can be viewed as the estimation of the state of a dynamical system from observations. In our case, the dynamic behavior of the state is described by the following model:

The target motion model

$$\tilde{\mathbf{X}}(k+1,k) = \mathbf{X}(k+1) - \hat{\mathbf{X}}(k+1,k) \tag{5}$$

From (3) and (4)，we obtained

$$\hat{\mathbf{Z}}(k+1,k) = \mathbf{H}[\hat{\mathbf{X}}(k+1,k)] \tag{6}$$

then

$$\hat{\mathbf{Z}}(k+1,k) = \mathbf{H}[\mathbf{X}(k+1)] - \left.\frac{\partial h}{\partial X}\right|_{\hat{X}(k+1,k)} \tilde{\mathbf{X}}(k+1,k) \tag{7}$$

and

$$\tilde{\mathbf{Z}}(k+1) = \mathbf{Z}(k+1) - \hat{\mathbf{Z}}(k+1,k)$$
$$= \left.\frac{\partial h}{\partial X}\right|_{\hat{X}(k+1,k)} \tilde{\mathbf{X}}(k+1,k) + \mathbf{v}(k+1) \tag{8}$$

If let $\mathbf{H}(k+1) = \left.\frac{\partial h}{\partial X}\right|_{\hat{X}(k+1,k)}$, then:

$$\tilde{\mathbf{Z}}(k+1) = \mathbf{H}(k+1)\tilde{\mathbf{X}}(k+1,k) + \mathbf{V}(k+1) \tag{9}$$

For active radar sensor:

$$\mathbf{H}^{(R_a)}(k+1) = \left.\frac{\partial h^{(R_a)}}{\partial X^{(R_a)}}\right|_{\hat{X}^{(R_a)}(k+1,k)}$$
$$= \begin{bmatrix} h_{11}^{R_a} & 0 & 0 & h_{14}^{R_a} & 0 & 0 & h_{17}^{R_a} & 0 & 0 \\ h_{21}^{R_a} & 0 & 0 & h_{24}^{R_a} & 0 & 0 & 0 & 0 & 0 \\ h_{31}^{R_a} & 0 & 0 & h_{34}^{R_a} & 0 & 0 & h_{37}^{R_a} & 0 & 0 \end{bmatrix} \tag{10}$$

Where:

$h_{11}^{R_a} = \cos\theta_{Ra} * \cos\phi_{Ra}$, $h_{14}^{R_a} = \sin\theta_{Ra} * \cos\phi_{Ra}$,

$h_{17}^{R_a} = \sin\phi_{Ra}$, $h_{21}^{R_a} = -\sin\theta_{Ra} / r_{Ra} * \cos\phi_{Ra}$,

$h_{24}^{R_a} = \cos\theta_{Ra} / r_{Ra} * \cos\phi_{Ra}$,

$h_{31}^{R_a} = -\sin\phi_{Ra} * \cos\theta_{Ra} / r_{Ra}$,

$h_{34}^{R_a} = -\sin\phi_{Ra} * \sin\theta_{Ra} / r_{Ra}$,

$h_{37}^{R_a} = -\cos\phi_{Ra} / r_{Ra}$

For passive radar sensor:

$$\mathbf{H}^{(R_p)}(k+1) = \left.\frac{\partial h^{(R_p)}}{\partial X^{(R_p)}}\right|_{\hat{X}^{(R_p)}(k+1,k)}$$
$$= \begin{bmatrix} h_{11}^{Rp} & 0 & 0 & h_{14}^{Rp} & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{11}$$

Where:

$h_{11}^{R_p} = -\sin\theta_{Rp} / r_{Rp} * \cos\phi_{Rp}$ 、

Oct 2013. Vol. 4, No. 4 ISSN2305-8269
International Journal of Engineering and Applied Sciences

www.eaas-journal.org

$$h_{14}^{R_p} = \cos\theta_{Rp} / r_{Rp} * \cos\phi_{Rp}$$

3. Proposed covariance-weighted data fusion tracking algorithm

From (10) and (11), we see that the received signal h in a single-target scenario depends only on the current state. In the following, we propose a covariance-weighted data fusion (CWDF) tracking algorithm to estimate target sequentially state. Using this algorithm to track target is discussed in the followings.

Step 1. State variable and its error covariance matrix predictive value calculation

$$\hat{\mathbf{X}}(k+1,k) = \mathbf{F}\left[\hat{\mathbf{X}}(k,k),k\right] + \mathbf{U}(k)\bar{a}$$

Step 2. Calculate predict innovation vector

$$\mathbf{P}(k+1) = \mathbf{F}(k)\mathbf{P}(k,k)\mathbf{F}(k)^T + \mathbf{Q}(k)$$

Step 3. Calculate Kalman gain

$$\mathbf{K}(k) = \mathbf{P}(k+1,k)\mathbf{H}\left(\hat{\mathbf{X}}(k,k-1),k\right)^T$$
$$\left[\mathbf{H}\left(\hat{\mathbf{X}}(k,k-1),k\right)\mathbf{P}(k+1,k)\mathbf{H}\left(\hat{\mathbf{X}}(k,k-1),k\right)^T + \mathbf{R}(k)\right]^{-1}$$

Step 4. Calculate Kalman filter equations

$$\hat{\mathbf{X}}(k+1,k) = \hat{\mathbf{X}}(k+1,k) + \mathbf{K}(k)\tilde{\mathbf{Z}}(k)$$

Step 5. Calculate the covariance matrix

$$\hat{\mathbf{X}}_{CWDF}(k+1,k) = \mathbf{P}(k+1,k)\left(\mathbf{P}_a^{-1}(k+1,k)\hat{\mathbf{X}}_a(k+1,k) + \mathbf{P}_p^{-1}(k+1,k)\hat{\mathbf{X}}_p(k+1,k)\right)$$
$$\mathbf{P}(k+1,k) = \left(\mathbf{P}_a^{-1}(k+1,k) + \mathbf{P}_p^{-1}(k+1,k)\right)$$
$$\mathbf{P}(k+1,k) = \mathbf{P}(k+1,k) - \mathbf{K}(k)[\mathbf{H}(k)\mathbf{P}(k+1,k)\mathbf{H}^T(k) + \mathbf{R}(k)]\mathbf{K}^T(k)$$

Step 6. This procedure is continued for 5-8 scans, depending on target trajectory. At that point, only a few steady tracks should be left to track filtering.

4. CWDF tracking algorithm efficient simulations

For tracking radar, range gate pull-off /in (RGPO/RGPI) is a very effective electronic countermeasures (ECM), which is also referred to range gate walk-off and range gate stealing[8,9]. In the presence of this type of jamming, the jammer senses the pulse radiated by the victim radar and repeats it with a controllable delay. With the high jammer-to-signal ratio (JSR), the false target lures the radar range gate away from the true target. In this section, we consider a type of jamming used against the range tracking radar called RGPO. Jamming the range tracker prevents the multistatic radar sensor from tracking the target and forces it to again search for the target. We used the covariance-weighted data fusion (CWDF) tracking algorithm to determine the level of RGPO jamming.

The following example of tracking a highly maneuvering airborne target is considered. Fig. 1. illustrates the 3D geometrical constellation of the active/passive radars considered in all simulations.

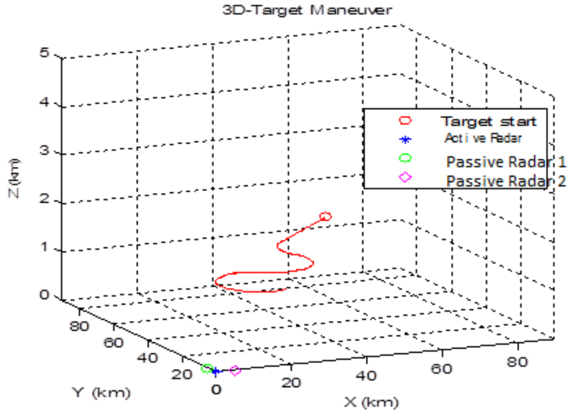

Figure 1. Illustration of the geometrical constellation of the simulated scenario

Figure 2 shows the true track and CWDF tracking algorithm track of air target. Only active radar measurements work without the passive radars measurements, the tracking precision is relatively low. When active and passive radars work together with data fusion, the tracking precision is improved by track correlation.

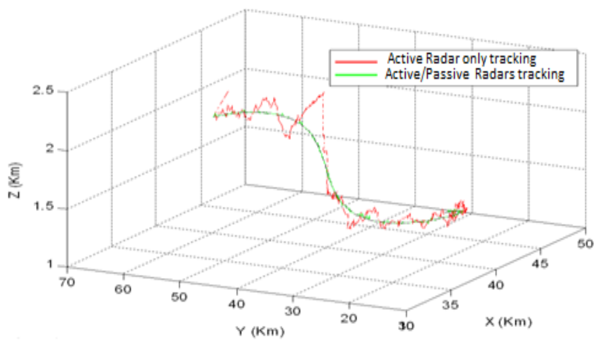

Figure 2. 3D trajectories of the target and multistatic radar sensor formation

Figure 3 shows the CWDF filtering error in RMS position error based on 100 Monte Carlo runs. We can clearly see the improvement of tracking precision.

International Journal of Engineering and Applied Sciences

www.eaas-journal.org

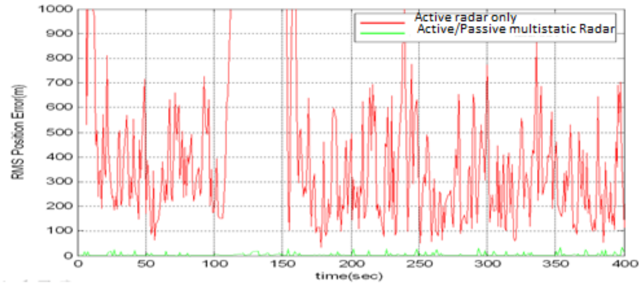

Figure 3. Filtering error for active radar only vs. active/passive data fusion with 100 Monte Carlo runs

The performance assessment of the presented CWDF algorithm can be further indicated in the ECM environment. In this section, the RGPO jamming are taken into account in simulations to evaluate the CWDF efficient. In simulations, a target moves with two deception echo (RGPO) enter the range tracking loop of the victim radar, and the jammer begin to pull the range gate after about 2 s. The RGPO corrupted range measurement is shown in Figure 4. Also shown in Figure 4 were estimated of range produce by EKF and CWDF algorithm. From Figure 4, we can see that the proposed CWDF algorithm has outperformed the traditional EKF.

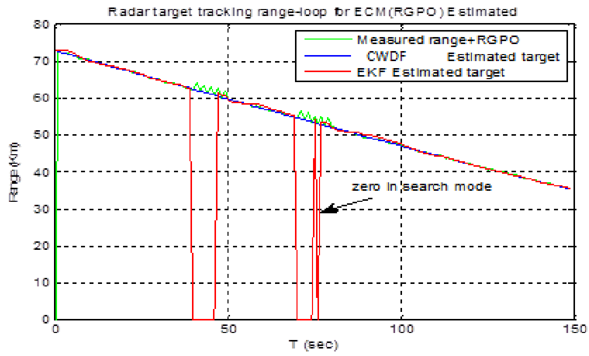

Figure 4. Estimated target trajectories using different tracking algorithms in the RGPO scenario

5. Conclusions

In this paper, a CWDF algorithm which is based on data fusion of active/passive multistatic radar of the range tracking loop is presented to counter against the traditional EKF and RGPO jamming. 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. Taking the precision of both passive radar angle measurement and active radar distance observation into tracking loop, the proposed CWDF algorithm has better tacking performance than traditional EKF, which has been proved by the simulation. In this paper, we evaluate the validity of the CWDF algorithm in one simulation scenarios. In the future research, we will study the scope of application for this proposed method.

Acknowledgments

This research work was sponsored by the National Science Council, R.O.C., under project number NSC102-2623-E-155-002-D.

References

[1] X. R. Li, B. Slocumb, P. West, “Tracking in the Presence of Range Deception ECM and Clutter by Decomposition and Fusion”, Signal and data processing of small targets Conference, pp. 198-210,1999.

[2] F. Neri, Introduction to electronic defense systems (2nd Edition), SciTech Publishing: Raleigh, 2006.

[3] X.R. Li, V.P. Jilkov, “Survey of maneuvering target tracking. Part V. Multiple-model methods”, IEEE Transactions on Aerospace and Electronic Systems, Vol.41, No.4, pp.1255－1321, 2005.

[4] M. Cherniakov (editor), Bistatic Radars: Emerging Technology, Wiley, 2008.

[5] X.R. Li, V.P. Jilkov, “Survey of maneuvering target tracking. Part I. Dynamic models”, IEEE Transactions on Aerospace and Electronic Systems, Vol.39, No.4, pp.1333－1364, 2003.

[6] C. Coleman, H. Yardley, and R. Watson, “A Practical Bistatic Passive Radar System for Use with DAB and DRM Illuminators," Proceedings of the IEEE Radar Conference, , pp. 1514-1519 ,May 2008.

[7] W.H. Zhou, L. Li, G.H. Chen, “An effective algorithm for discriminating RGPO with performance analysis”, Acta Electronica Sinica, 35, pp. 1165-1168, 2007.

[8] M. Greco, F. Gini, A. Farina, Combined effect of phase and RGPO delay quantization on jamming signal spectrum, in: IEEE Int. Radar Conference,pp. 37-42, 2005.

[9] F. Bandiera, A. Farina et al., Detection algorithms to discriminate between radar targets and ECM signals, IEEE Transactions on Signal Processing, 58, pp. 5984-5993, 2010.