

# FUSION USING QUASILINEARIZATION TECHNIQUE FOR THE LIKELIHOOD RATIO BASED T2TA IN MULTI RADAR DATA FUSION

J.VALARMATHI<sup>1</sup> D.S.EMMANUEL<sup>1</sup> S.CHRISTOPHER<sup>2</sup>

<sup>1</sup> School of Electronics Engineering, VIT University, Vellore

<sup>2</sup>PGD (AEW&C) & Director, Centre for Airborne System, Ministry of Defense, Bangalore

E-mail: <sup>1</sup>[jvalarmathi@vit.ac.in](mailto:jvalarmathi@vit.ac.in)

## ABSTRACT

Data fusion techniques combine data from multiple sensors, and related information from associated databases, to achieve improved accuracies and more specific inferences than could be achieved by the use of a single sensor alone. This paper presents the fusion using the generalized quasilinearization technique to obtain a monotone sequence of iterates, converging uniformly for the tracks, obtained after association. Likelihood ratio based cost for association with kinematic information [1] is used for track-to-track association (T2TA). These associated tracks and the fused track are smoothed using Kalman filter (KF). Simulated results through MATLAB are compared with the state vector fusion technique. The main advantage of the proposed method is that fusion follows the actual track where as conventional method results are based on the Kalman estimates.

**Keywords:** *Quasilinearization Technique, Likelihood Ratio, T2TA, Kalman Filter.*

## 1. INTRODUCTION

T2TA problem arises in multisensor systems where each sensor has its own information processing system with its own set of targets in each observation. The problem is, how to decide whether tracks coming from different radar systems represent the same target. This was initially addressed by Singer [26, 5] with independent sequential track correlation technique (ISTCT), in which it is assumed that the estimation error vectors of the same target's state from different radars are uncorrelated. In [5] he employs the correlation gates for correlating the received track information (remote track) with its own store of target tracks (local tracks). This was extended as a computer controlled gating correlation in [26]. All T2TA algorithms by Bar-shalom [1, 10, 11, 22, 25] are referred as dependent sequential track correlation techniques (DSTCT) in which he considered the cross covariance error vector of the same target's state from different radars. The concept of DSTCT was explained in [25] and was optimized through track splitting algorithm in [3] by Gul. [10, 11] provide association decisions based on the attributes/classification information. T2TA with augmented state (combination of kinematic state information and state augmentation information) was explained in [1]. Multidimensional data

association and fusion was dealt in [22]. Mathematical explanation about likelihood ratio test was referred in [7]. Restricted and attenuation memory track correlation algorithms were introduced in Singer's and Bar-shalom's algorithms [6] to get better results in association.

Introduction to multisensor data fusion was explained in [16]. State vector fusion technique was used in [2, 9, 12, 23]. Data fusions of sensors with different accuracies were explained in [2]. Here process noise was assumed to be zero mean Gaussian random process. Cross-covariance computation between the two track estimates from different sensors was explained in [23] for the Bayesian method of fusion. Covariance union, covariance intersection, and use of cross-covariance in the fusion were dealt in [9]. In [12] different algorithms are used for the fusion when the tracking systems were synchronized. Different types of measurement fusion techniques were discussed in [24]. Though, Osborne in [1], used the combination of kinematic state information and state augmentation information in the T2TA all their results show that with only kinematic information T2TA seems acceptable. Thus, in this paper, we used likelihood ratio based cost for association with kinematic information [1, 6, 10] for T2TA. We also proposed to apply the numerical method based fusion technique namely

quasi-linearized iterative method so for not tried in T2TA. This fusion technique had been used to estimate the position and velocity of low earth orbit satellites [17, 18]. This technique gives better approximation of the actual track compared to the state vector fusion. KF is used to smoothen the associated and fused track.

This paper is organized in the follows. System description is given in Section II. In section III, likelihood ratio based cost for association with kinematic information used for T2TA is discussed. In Section IV, data fusion by quasi linearization method and state vector fusion are explained. Also it explains the KF which is used to smoothen the associated and fused track. Simulation results are tabulated and plotted in Section V. Finally, concluding remarks are given in Section VI.

## 2. SYSTEM DESCRIPTION

Let  $R^1(k) = r_k^1 + w_1$  and  $R^2(k) = r_k^2 + w_2$  be the estimated range by radar 1 and 2 at some instant of time  $k$ , with  $r_k^1$  and  $r_k^2$  are the actual range of the targets.  $w_1$  and  $w_2$  are the independent identically distributed noise sequences of zero-mean, white Gaussian process noise with covariance matrix  $Q_1(k)$  and  $Q_2(k)$ . Target position  $(x_k, y_k)$  can be estimated by knowing the radar position and the antenna look angle. Now the challenge is to check whether  $R^1(k)$  and  $R^2(k)$  ranges belong to same target or not. If same, how to combine these measurements? In this paper we propose a numerical fusion technique namely quasilinearized iterative method to obtain a monotone sequence of iterates, converging uniformly for the tracks, which is obtained after association. Likelihood ratio based cost for association with kinematic information is used for T2TA. In this method, association is done for all positions and velocities  $(x, y, \dot{x}, \dot{y})$  individually at every instant. Final decision is made through logical multiplication of these associated positions and the velocities when it has 80% of association with the reference positions and the velocities. KF is used to smoothen the associated and fused track. System description is shown in figure 1.

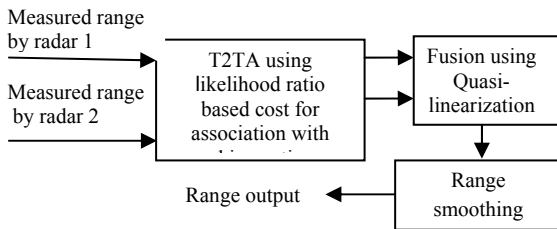


Figure 1. Block diagram of the systems

## 3. TRACK TO TRACK ASSOCIATION

T2TA correctly sorts radar measurements into groups, with each group representing measurements of same target. If an incorrect measurement is associated with a track, the track could divert or cause the other tracks to diverge and thus the tracking could be prematurely terminated. Each radar is assumed to measure individually the range and azimuth angle information of targets in its observation area. The kinematic state will be defined as a target's position and velocity components (in Cartesian coordinates) [1].

In this paper, two radars are assumed to track  $N$  targets. Each radar will individually form kinematic tracks on every target. Each target and radar are assumed to follow a motion and measurement model of the form

$$\mathbf{X}_k = \mathbf{F}_{k-1}\mathbf{X}_{k-1} + \mathbf{W}_{k-1} \quad (1)$$

$$\mathbf{Z}_k = \mathbf{H}_k\mathbf{X}_k + \mathbf{V}_k \quad k=1,2,\dots \quad (2)$$

Where,  $\mathbf{X}_k = (x, y, \dot{x}, \dot{y})^T$ ,  $\mathbf{Z}^k = (z, y)^T$ ,  $\mathbf{F}_{k-1}$  is the state transition matrix and  $\mathbf{W}_{k-1}$  is a zero-mean Gaussian noise process with covariance  $\mathbf{Q}_{k-1}$ .  $\mathbf{H}_k$  is the measurement matrix and  $\mathbf{V}_k$  is a zero-mean Gaussian measurement noise with covariance  $\mathbf{C}_k$ .

The cost of association requires the negative log-likelihood ratio (NLLR)[1]

$$NLLR = -\ln \left\{ \frac{P(z' \text{ common target}')} {P(z' \text{ different target}')} \right\} \\ \triangleq \ln \left( L(\hat{t}_{ij}(k)) \right) = \lambda_{ij}(k)$$

Minimizing the sum of the NLLRs for all the associations will provide the overall T2TA.

Let  $\hat{x}_i^1(k)$  and  $\hat{x}_j^2(k)$  be state estimates of target  $i$  and  $j$  by radars 1 and 2 at time instant  $k$  [1, 6, 10]

$$\hat{t}_{ij}(k) = \hat{x}_i^1(k) - \hat{x}_j^2(k) \quad (3)$$

The estimate errors of the target  $i$  and  $j$  is given by

$$\tilde{x}_i^1(k) = x_i^1(k) - \hat{x}_i^1(k) \quad \text{and}$$

$$\tilde{x}_j^2(k) = x_j^2(k) - \hat{x}_j^2(k)$$

where  $x_i^1$  and  $x_j^2$  are the actual parameter of the target  $i$  and  $j$  by radars 1 and 2. Then the difference in the estimate errors are given by

$$\tilde{t}_{ij}(k) = \tilde{x}_i^1(k) - \tilde{x}_j^2(k) \quad (4)$$

If  $\hat{x}_i^1(k)$  and  $\hat{x}_j^2(k)$  are zero-mean, then  $\hat{t}_{ij}(k)$  will also be zero-mean. The covariance of  $\hat{t}_{ij}(k)$  is

$$C_{ij}(k) = E \left\{ [\hat{x}_i^1(k) - \hat{x}_j^2(k)] [\hat{x}_i^1(k) - \hat{x}_j^2(k)]' \right\} \\ = P^i(k) + P^j(k) - P^{ij}(k) - P^{ji}(k) \quad (5)$$

where  $P^i$  is the covariance of track  $i$  (at radar 1),  $P^j$  is the covariance of track  $j$  (at radar 2), and  $P^{ij} = (P^{ji})'$  is the cross covariance of tracks  $i$  and  $j$  [1, 6].



Under the linear Gaussian and  $H_0$  assumptions, the kinematic state likelihood function will be

$$f_0[\hat{t}_{ij}(k)/H_0] = \left[ (2\pi C_{ij}(k))^{-1} \right] \times e^{\left( -\frac{1}{2} \hat{t}_{ij}(k)' C_{ij}(k) \hat{t}_{ij}(k) \right)} \quad (6)$$

Similarly the joint probability density function (pdf) of  $\hat{t}_{ij}(k)$  under the  $H_1$  is given by  $f_1(\hat{t}_{ij}(k)/H_1)$ , assumed to be uniformly distributed in possible area [1,6]. Then the test based on log-likelihood ratio is given by

$$\ln \left( L(\hat{t}_{ij}(k)) \right) = \ln \left( \frac{f_0(\hat{t}_{ij}(k)/H_0)}{f_1(\hat{t}_{ij}(k)/H_1)} \right) \quad (7)$$

equation (6) may be approximated to

$$\ln \left( L(\hat{t}_{ij}(k)) \right) = -\frac{1}{2} \hat{t}_{ij}(k)' C_{ij}(k) \hat{t}_{ij}(k) + \text{constant} \approx \hat{t}_{ij}(k)' C_{ij}(k) \hat{t}_{ij}(k) \quad (\text{or})$$

$$\ln \left( L(\hat{t}_{ij}(k)) \right) = \lambda_{ij}(k) \cong \text{tijk}' C_{ij} \text{tijk} \quad (8)$$

The track correlation decision is made based on the following hypothesis testing problem

$H_0$ :  $\hat{x}_i^1(k)$  and  $\hat{x}_j^2(k)$  are the estimation of the same target (i.e.) accept  $H_0$  if  $\lambda_{ij}(k) \leq \delta_{ij}(k)$

$H_1$ :  $\hat{x}_i^1(k)$  and  $\hat{x}_j^2(k)$  are the estimation of the different target (i.e.) accept  $H_1$  if  $\lambda_{ij}(k) > \delta_{ij}(k)$

$\delta(k)$  is the threshold at the  $k^{\text{th}}$  observation and is given by

$$\delta_{ij}(k) = \sqrt{-2\sigma^2 \times \ln(P_{fa}(k))} \quad (9)$$

where  $P_{fa}$  is the fixed probability of a false alarm.

#### 4. DATA FUSION

Multi sensor data fusion (MSDF) is the process of combining observations from a number of different radars to provide a robust and complete description of an environment or process of interest. Data fusion techniques combine data from multiple sensors, and related information from associated databases, to achieve improved accuracies and more specific inferences than could be achieved by the use of a single sensor alone [16].

After the track to T2TA, data fusion [16, 18] is achieved by solving the simultaneous equations iteratively through quasi-linearization method [17]. This technique is a successive approximation scheme which has been used to solve nonlinear first

order partial differential equation. Here non linear equation is formed between the radar measured range and the estimated range which is based on the calculation of the distance between the known radars position with the randomly assumed target's position [15, 17, 18].

##### 4.1 Quasi-linearization method

It is a successive approximation scheme which reduces the nonlinear multipoint boundary value problem to a sequence of linear multipoint boundary value problems, whose solutions converge to the solution of the nonlinear problem [17].

Theorem 8.1 in [18] says, 'If  $L$  is a linear operator possessing the positivity property and  $f(u)$  is a strictly convex function of  $u$  for all finite  $u$ , the solution of non linear equations  $L[u] = f(u, x)$  with the boundary condition  $u = 0$  for all  $x \in B$  where  $x$  lies in the domain  $D$  with the boundary of  $B$ , assumed to exist and be unique may be represented in the form  $u = \max_v w[x; v]$  where  $w[x; v]$  is the solution of the associated linear equation  $L[u] = \max_v [f(v) + (u - v)f'(v)]$  which is also assumed to exist and be unique for each admissible function  $v$ '.

Consider the range, estimated based on the calculation of the distance between the known radars position  $S_i = (x_{si}, y_{si})$ ;  $i=1,2,3,\dots,n$ (number of radars) with the randomly assumed target position  $S_{t0} = (x_{t0}, y_{t0})$

$$\hat{R}_{0i} = \sqrt{(x_{si} - x_{t0})^2 + (y_{si} - y_{t0})^2} \quad (10)$$

The non linear relations between radar measured range  $R_{0i}$  and the estimated range  $\hat{R}_{0i}$  is a set of non linear equations added with noise ( $n_i$ ). (i.e)

$$R_{0i} = \hat{R}_{0i} + n_i \quad (11)$$

Assuming equation (11) satisfies the theorem 8.1 of [18]. Thus while applying the quasilinearization technique in equation (11) we get

$$R_{0i} = \hat{R}_{0i} + \frac{\partial \hat{R}_{0i}}{\partial x_{t0}} (x_{t1} - x_{t0}) + \frac{\partial \hat{R}_{0i}}{\partial y_{t0}} (y_{t1} - y_{t0}) \quad (12)$$

These partial derivatives in (12) can be replaced with the forward difference equations as

$$A_i = \frac{\partial \hat{R}_{0i}}{\partial x_{t0}} = \left[ -\frac{(x_{si} - x_{t0})}{\sqrt{(x_{si} - x_{t0})^2 + (y_{si} - y_{t0})^2}} \right]$$

$$B_i = \frac{\partial \hat{R}_{0i}}{\partial y_{t0}} = \left[ -\frac{(y_{si} - y_{t0})}{\sqrt{(x_{si} - x_{t0})^2 + (y_{si} - y_{t0})^2}} \right] \quad (13)$$

$$\text{Let } \begin{bmatrix} x_{t1} - x_{t0} \\ y_{t1} - y_{t0} \end{bmatrix} = \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} = \Delta \mathbf{X} \quad \text{and}$$

$$[R_{0i} - \hat{R}_{0i}] = \Delta \mathbf{Z}_i$$

and for two radar systems ( $i=2$ ) we have the quasi-linearised form as

$$\begin{bmatrix} \Delta z_1 \\ \Delta z_2 \end{bmatrix} = \begin{bmatrix} A_1 & B_1 \\ A_2 & B_2 \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \quad (14)$$

$$\Delta \mathbf{X} = \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} = \begin{bmatrix} A_1 & B_1 \\ A_2 & B_2 \end{bmatrix}^{-1} \begin{bmatrix} \Delta z_1 \\ \Delta z_2 \end{bmatrix} \quad (15)$$

From the known numerical values in (15),  $\Delta x$  and  $\Delta y$  can be found. This  $\Delta x$  and  $\Delta y$  are added to the previous target position to get the updated position  $S_{t_1} = (x_{t_1}, y_{t_1})$ . Now the difference between this new position and the previous position is found using mean square estimation as

$$e = \sqrt{((x_{t_1} - x_{t_0})^2 + (y_{t_1} - y_{t_0})^2)} \quad (16)$$

The above steps from equations (10) to (16) are repeated with the updated target position till the error ( $e$ ) become less than the threshold. This final target position is the optimized fused position from the similar track by two radar systems. If  $(x_{tn}, y_{tn})$  is a sufficiently close approximate of the target position then the linear differential equation (12) is a sufficiently close approximation to the nonlinear differential equation (11).

#### Kalman filter(KF)

Erroneous measurements from radar 1 and 2 are smoothed using KF[19]. In [21], the system is composed of two essential ingredients namely linear dynamic model and linear measurement model given in equations (1) and (2). The state of the target  $\mathbf{X}_k$  with 2D position ( $x_k, y_k$ ) and 2D velocity ( $\dot{x}_k, \dot{y}_k$ ), by considering range alone is given by  $\mathbf{X}_k = (x_k, \dot{x}_k, y_k, \dot{y}_k)$  [14].

Each radar processes its observations locally using a KF [14, 20], to produce the state estimates and associated co variances. The KF algorithm [14] is summarized here for completeness. The predicted state estimate and covariance are given by

$$\begin{aligned} \hat{\mathbf{X}}_{k/k-1} &= \mathbf{F}_{k-1} \hat{\mathbf{X}}_{k-1/k-1}; \\ \mathbf{P}_{k/k-1} &= \mathbf{F}_{k-1} \mathbf{P}_{k-1/k-1} \mathbf{F}_{k-1}^T + \mathbf{Q}_{k-1} \end{aligned} \quad (17)$$

The optimized state estimate and covariance are given by

$$\begin{aligned} \hat{\mathbf{X}}_{k/k} &= \hat{\mathbf{X}}_{k/k-1} + \mathbf{K}_k (\mathbf{Z}_k - \mathbf{H}_k \hat{\mathbf{X}}_{k/k-1}) \\ \mathbf{P}_{k/k} &= \mathbf{P}_{k/k-1} - \mathbf{K}_k \mathbf{S}_k \mathbf{K}_k^T \end{aligned} \quad (18)$$

where  $\mathbf{K}_k$  and  $\mathbf{S}_k$  are the Kalman gain and innovation covariance, respectively,

$$\begin{aligned} \mathbf{S}_k &= (\mathbf{H}_k \mathbf{P}_{k/k-1} \mathbf{H}_k^T) + \mathbf{C}_k \\ \mathbf{K}_k &= \mathbf{P}_{k/k-1} \mathbf{H}_k^T \mathbf{S}_k^{-1} \end{aligned} \quad (19)$$

#### 4.1.2 State vector fusion algorithm (dependent sequential track correlation technique [6,25])

Let  $\hat{\mathbf{X}}_i^1(k/k)$ ,  $\hat{\mathbf{X}}_j^2(k/k)$ ,  $\mathbf{P}_1(k/k)$  and  $\mathbf{P}_2(k/k)$  be the associated state estimates and the covariance of target  $i$  and  $j$  by radars 1 and 2 at time instant  $k$ . Then the fused state estimate and covariance using state vector fusion technique is given by[23]

$$\begin{aligned} \hat{\mathbf{X}}_c(k/k) &= \hat{\mathbf{X}}_i^1(k/k) + [\mathbf{P}_1(k/k) - \mathbf{P}_{12}(k/k)] \\ &\times [\mathbf{P}_1(k/k) + \mathbf{P}_2(k/k) - \mathbf{P}_{21}(k/k) - \\ &\mathbf{P}_{12}(k/k) - \mathbf{P}_{21}(k/k)]^{-1} \end{aligned} \quad (20)$$

$$\begin{aligned} \mathbf{P}_c(k/k) &= \mathbf{P}_1(k/k) - [\mathbf{P}_1(k/k) - \mathbf{P}_{12}(k/k)] \\ &\times [\mathbf{P}_1(k/k) + \mathbf{P}_2(k/k) \\ &- \mathbf{P}_{21}(k/k) - \mathbf{P}_{12}(k/k)]^{-1} \\ &\times [\mathbf{P}_1(k/k) - \mathbf{P}_{12}(k/k)] \end{aligned} \quad (21)$$

Where

$$\begin{aligned} \mathbf{P}_{12}(k/k) &= \mathbf{P}_{21}(k/k)' \\ &= Cov(\hat{\mathbf{X}}_i^1(k/k), \hat{\mathbf{X}}_j^2(k/k)) \end{aligned}$$

## 5. COMPUTER SIMULATION RESULTS

### 5.1 Initial assumption

Here two similar radars are considered in the simulations. Radar 1 identified 4 targets and radar 2 identified 5 targets in which 2 are common by both radars. The initial positions of these targets are normally distributed in the observation region [14]. Constant velocity and azimuth angle is assumed for each track which are all uniformly distributed in 10-150 m/s and 30° respectively. The initial ranges of the above tracks are shown in table-1&2. Results are simulated using MATLAB. Initial assumptions are

- Total number of samples = 500
- Incremental rate = 0.1 sec
- Azimuth angle = 30°
- Expected processing time is 500 × 0.1 = 50 sec

Table 1 Initial values of tracks by Radar-1

Parameters	Radar-1			
	T1	T2	T3	T4
X-postion(km)	136.78	99.31	148.96	120.01
X-Velocity(m/s)	69.28	11.54	17.32	86.60
Y-postion(km)	78.77	57.33	86.00	69.16
Y-Velocity(m/s)	40	6.66	10	50
Range(km)	<b>157.84</b>	114.67	172.01	<b>138.51</b>
Velocity(m/s)	<b>80</b>	13.3	20	<b>100</b>

Table 2 Initial values of tracks by Radar-2

Parameters	Radar-2				
	T1	T2	T3	T4	T5
X (km)	39.27	143.12	136.7	286.24	120.02
Ẋ (m/s)	34.61	40.41	69.28	51.96	86.61



Y(km)	22.67	82.63	78.78	165.26	69.18	2.4249	0.00304	0.0049	0.0086	0.0123
$\dot{Y}$ (m/s)	20	23.33	40	30	50	4.1044	0.0028	0.009	0.0023	0.0218
Range (km)	45.34	165.26	157.8	330.52	138.52	5.7184	0.0018	0.0043	0.0033	0.0052
Velocity(m/s)	40	46.7	80	60	100	7.8993	0.0012	0.0023	0.01	0.0092

5.2 T2T Association

These parameters are then considered to decide whether two tracks coming from different radars represent the same target. Equations (3 to 9) are used to find the associated parameters by both the radars. In this simulation, equations (8 and 9) are used for finding the threshold by fixing the probability of false alarm  $P_{fa} = 10^{-4}$  and probability of detection = 0.9 [4]

Table 3 Matching % of Radar -1 and Radar-2 data at constant SNR=18dB for and measurement error ( $\sigma_v$ ) = 0.7681 for track 1&2

R-2 \ R-1	X-Position					Y-Position				
	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5
T1	1	1	427	1	1	1	1	500	1	1
T2	1	1	1	1	1	1	1	1	1	1
T3	1	1	1	1	1	1	1	1	1	1
T4	1	1	1	1	500	1	1	1	1	460
R-2 \ R-1	X-Velocity					Y-velocity				
	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5
T1	1	1	500	1	1	1	1	500	1	1
T2	1	500	1	1	1	1	500	1	1	1
T3	1	1	1	1	1	1	1	1	1	1
T4	500	1	1	500	500	500	1	1	500	500

Overall Association		Conclusion		
T1	T2	T3	T4	T5
0	0	1	0	0
0	0	0	0	0
0	0	0	0	0
0	0	0	0	1

Common tracks are  
**T1 of R-1 & T3 of R-2**  
**T4 of R-1 & T5 of R-2**  
 T-target, R-Radar

- QLT with KF(T1)<sup>1</sup> - Track-1 estimation error in fusion using quasi-linearization technique with Kalman smoothing
- SVF with KF(T1)<sup>2</sup> - Track-1 estimation error in fusion using state vector fusion with Kalman smoothing
- QLT with KF(T2)<sup>3</sup> - Track-2 estimation error in fusion using quasi-linearization technique with Kalman smoothing
- SVF with KF(T2)<sup>4</sup> - Track-1 estimation error in fusion using state vector fusion with Kalman smoothing

Table 4 Measurement error analysis of different fusion technique at constant SNR=18dB for different measurement error ( $\sigma_v$ ) for track 1

measur error ( $\sigma_v$ )	Track 1		Track 2	
	QLT with KF(T1) <sup>1</sup>	SVF with KF(T1) <sup>2</sup>	QLT with KF(T2) <sup>3</sup>	SVF with KF(T2) <sup>4</sup>
0.7681	0.0038	0.0059	0.0062	0.0211

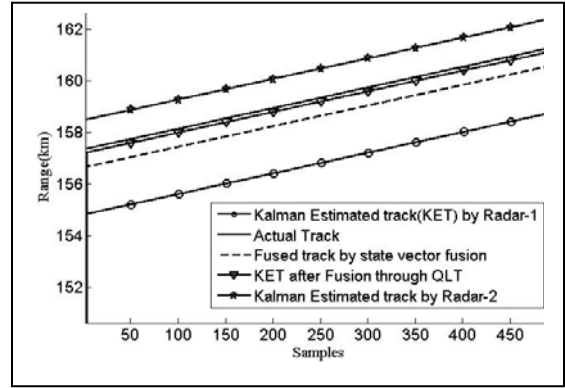


Figure.2 Fused track (Track-1 of radar-1 and track-3 of radar-2)

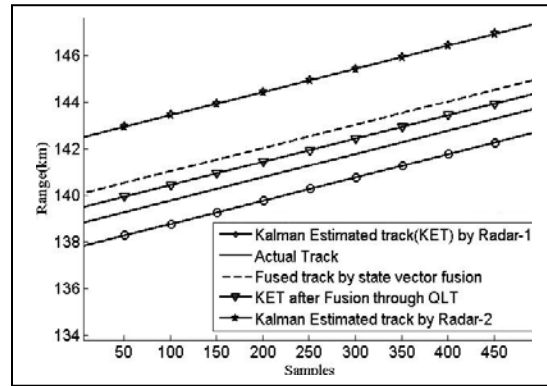


Figure.3 Fused track (Track-4 of radar-1 and track-5 of radar-2)

For lesser number of target scenario, association is better with low SNR and high additive noise as shown in Table 4. As the number of targets increased from 4 to 40, due to the range resolution between two tracks, more false association occurred. However it did not affect the conclusion. But, in the case of two sensors of different increment rates due to the need of interpolation, proper association is possible only at low noise level. From figure (2) and (3), fused track using quasi-linear technique is following approximately the actual track, irrespective of the individual radar track estimation. But fused track, using state vector fusion technique will appear approximately in the middle of the individual radars track estimation.

6. CONCLUSION

From the simulated results it is observed that depending upon the measurement error ( $\sigma_v$ ), error in



fusion using quasilinearization technique varies. *i.e* when  $\sigma_v$  increase the error in fusion increases. But after using Kalman smoothing this error remain almost constant. Hence the performance of the QLT with Kalman filter works well compare to other technique. In the case of state vector fusion (SVF), fused track will be always like an average of the individual Kalman estimated tracks. If the Kalman estimated tracks are closer to the actual, then SVF gives very good results. Otherwise there is more error in the fused track. Since Kalman smoothing depends on the initial value, error in the initial value reflects in the final results. Thus track initialization may be the key to get better result. But validation of the algorithms can be done only with the real data.

#### REFERENCES:

- [1] Osborne,R.W., Bar-Shalom, Y., Willett,P., 'Track-to-track association with augmented state', *FUSION, 2011 Proceedings of the 14th International Conference*, 1-8
- [2] Haimovich, A.M., et al., 'Fusion of sensors with dissimilar measurement/tracking accuracies', *IEEE Transactions on Aerospace and Electronic Systems*, 29, 1 (1993), 245—249.
- [3] Gul, E., 'On the track similarity tests in track splitting algorithm', *IEEE Transactions on Aerospace and Electronic Systems*, 30, 2 (1994), 604—606.
- [4] Merrill L. Skolnik, 'Introduction to radar systems', 2<sup>nd</sup> edition, McGraw-Hill, 1981.
- [5] Kanyuck, A. J., Singer .R. A., 'Correlation of Multiple-Site Track Data', *IEEE Transactions on Aerospace and Electronic system* Vol. AES-6, NO. 2, 180-187.
- [6] You and Jingwei, 'New track correlation algorithms in a multisensor data fusion system', *IEEE Transactions on Aerospace and Electronic systems* Vol.42, No. 4, October 2006, 1359-1371
- [7] Erich L. Lehmann,'On likelihood ratio tests', *Lecture notes, Institute of Mathematical Statistics*, University of California at Berkeley.
- [8] Kaplan,L.M., Dale.W.B and Bar-ShalomY., 'Simulations Studies of Multisensor Track Association and Fusion Methods', *Proc. IEEE Aerospace Conf Paper 1597*, Version 3, Updated 4 Jan 2006, 1-16
- [9] Matzka and Altendorfer, 'A Comparison of Track-to-Track Fusion Algorithms for
- [23] Using Multidimensional Data Association',*IEEE Trans. on Aerospace and Automotive Sensor Fusion,' Proce. Of IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems, Seoul, Korea, August 20 - 22, 2008, 189-194.*
- [10] Bar-Shalom,Y., Chen,H., 'Track-to-Track Association Using Attributes', *Journal of Advances in Information Fusion* Vol. 2, No. 1 June 2007,49-59.
- [11] Bar-Shalom, Y., Li, X. R., and Kirubarajan,T., 'Estimation with Applications to Tracking and Navigation: Algorithms and Software for Information Extraction', New York: Wiley, 2001.
- [12] Xin Tian and Bar-Shalom, Y., 'Track to Track fusion configuration and association in a sliding window', *Journal of advances in information fusion*, Vol.4, No.2, December 2009, 146-164.
- [13] Florian Folster and Hermann Rohling, 'Data Association and Tracking for Automotive Radar Networks', *IEEE Transactions on Intelligent Transportation Systems*, Vol.6, No.4, December 2005.pp 370-377.
- [14] Ramachandra, K.V., 'Kalman filtering techniques for radar tracking', *Marcel Dekker, Inc*, 2000.
- [15] Griffiths, D.V. and Smith, I.M., 'Numerical methods for Engineers-A programming approach', CRC Press, 1991.
- [16] David L. Hall and James Linas, 'Hand book on multi sensor data fusion', *Boca Raton, FL, CRC Press*, 2001
- [17] Ohap, R., Stubberud, A., 'A Technique for estimating the state of a Nonlinear System', *IEEE transaction on Automatic control*, vol.10, Issue 2, 1965, pp 150-155
- [18] Kalaba, R., 'On nonlinear differential equation, the maximum operation and monotone convergence', *J.Math. Mech.*, vol 8, 1959, 519-574.
- [19] McGee, L. A. and Schmidt.S.F., 'Discovery of the Kalman Filter as a Practical Tool for Aerospace and Industry', *NASA Technical Memorandum 86847* November 1985, 1-21
- [20] Schmidt, S. F., 'The Kalman filter, 'its recognition and development for aerospace Applications', *AIAA J. Guidance Control*, vol. 4, no. I, Jan.-Feb. 1981, 4-7.
- [21] Kalman, R. E., 'A new approach to linear filtering and prediction problems', *Trans. ASME, Set. D, J. Basic Eng.*, vol. 82, Mar. 1960, 35-45.
- [22] R., 'Efficient Multisensor Fusion *Electronic Systems*, Apr 2001, Vol. 37, Issue 2, 386– 400



- [24] Chang, K. C., Saha, R. K., Bar-shalom, Y., 'On optimal track-to-track fusion', *IEEE Trans. on Aerospace and Electronic Systems*, vol. 33, no. 4 October 1997,1271-1275
- [25] Qiang gan and Chris j. Harris,' Comparison of two measurement fusion methods for Kalman-filter-based multisensor data fusion', *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 37, No. 1 January 2001,Pp 273-280
- [26] Bar-Shalom, Y., 'On the track-to-track correlation problem', *IEEE Trans. on Automatic control*, Vol.26, Issue2, 1981, 571-572
- [27] Singer, R. A., Kanyuck, A. T., 'Computer Control of Multiple Site Track Correlation', *Automatica*, 7, 3(1971), 455-463.