A Real Time 3D Multi Target Data Fusion for Multistatic Radar Network Tracking

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Abstract— The paper is devoted to propose a data fusion algorithms into multistatic radar network to improve its tracking capability. The proposed data fusion algorithm is based on using common measurement architecture gives state estimates with relatively low and medium uncertainty followed by cumulative measurement fusion (CMF) or cumulative state vector fusion (CSVF) algorithm which is very simple, easy to implement and can be used in real time. Extended Kalman Filter (EKF) is used as a non-linear tracking and predictor algorithm. The system is simulated using Matlab program to compare the performance of the estimation routines of both fusion algorithms and the targets scenario is simulated using Monte Carlo simulation. Simulation results have shown that these cumulative fusion algorithms improve the multistatic radar network tracking capability and produce a significant reduction in the root sum square error (RSSE), absolute error, and root sum square variance (RSSV) than achieved from monostatic radar.

1. INTRODUCTION

In a multistatic-multi-target environment, where each radar processes its own observations and sends the resulting tracks to a data fusion center, the first step is to determine whether or not two or more tracks, coming from different radar systems with different accuracies, represent the same target (track-to-track association). The next step is to combine the radar tracks when it is determined that they indeed represent the same target (track fusion). Both problems arise when several radars carry out surveillance over a common volume (overlapping sensor coverage). A survey of the current research in this area has been presented in [1–8]. Furthermore, the goal of data fusion is to operate on a combination of radar sensor measurements, features, track states, and object type and identification likelihoods to produce a single integrated air picture of the air space to a high degree of accuracy. Technologies that enable this synergistic fusion and interpretation of data at several levels from disparate, distributed radars and other sensors should enhance system acquisition, tracking and discrimination of threat objects in a cluttered environment and provide enhanced battle space awareness. There are two approaches for fusion of multiple radar data: measurement fusion and state vector fusion. In the first approach, the radar measurements are combined and an optimal estimate of the target state vector is obtained. State vector fusion is preferable for implementation in a variety of practical systems. In this approach, each radar employs an estimator to extract a target track state vector and its associated covariance matrix from its respective sensor measurement, that are then transmitted over a data link to a fusion center. At the fusion center, track-to-track correlation and state vector fusion are performed to obtain a composite target state vector [9].

The proposed method uses current radars data for track-to-track association using cumulative measurement fusion, and cumulative state vector fusion in order to produce an accurate target estimation and prediction with the multistatic radar network. Results based on Monte Carlo simulations are presented. The proposed method is able to perform track correlation and fusion with low root sum square error (RSSE), absolute error, and root sum square variance (RSSV) than achieved from monostatic radar. The remainder of this paper is organized as follows. Section 2 describes the target tracking algorithms and the extended Kalman filter. Section 3 presents a brief overview of data association and fusion methods in the tracking systems. In Section 4 present the proposed comulative track-to- track association and track fusion. Simulation results and discussion are presented in Section 5. Finally, Section 6 concludes the paper.

2. THEORITICAL DESCRIPTION OF EKF

A general motion model used in discrete extended Kalman filter for target tracking is [10].

$$x(k) = FX(k-1) + Gw(k-1) \tag{1}$$

$$z(k) = h(X(k)) + v(k) \tag{2}$$

where $X(k)$ is the state vector, F is the state transition matrix and G is the process noise gain matrix. The process noise $w(k)$ and the measurement noise $v(k)$ are zeromean, mutually indepencent, white, Gaussian with covariance Q and R respectively. $z(k)$ is the measurement vector at time k and $h(X(k))$ is a nonlinear function of the states computed at time k.

3. FUSION ALGORITHMS

3.1. Measurement Fusion (MF)

In this architecture (Fig. 1), the measurement vector consists of fused azimuth, fused elevation and range. Similarly, the measurement covariances for azimuth and elevation measurement noise covariance for range is taken from radars. Instead of fusing the measurement in the use of EKF, the measurements from radars are merged into an augmented measurement vector and measurement noise variances from radars also concatenated to produce the same results [13, 14].

State Prediction: (Eq. (4)).

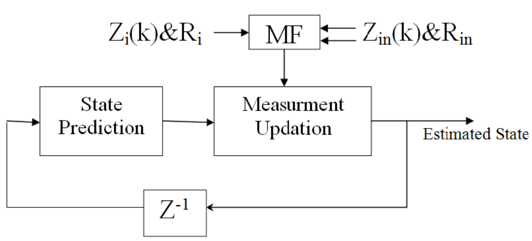

Figure 1: Information flow diagram of CMF algorithm.

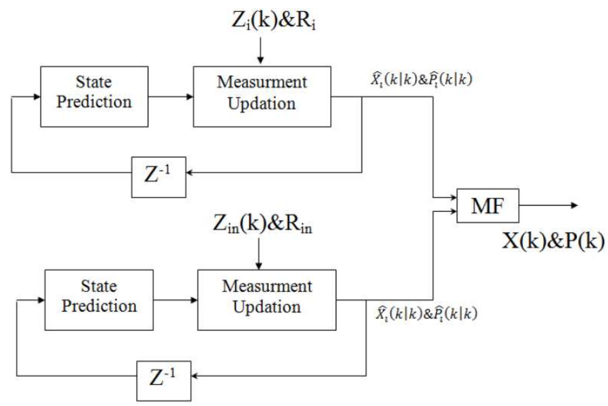

Figure 2: Information flow diagram of CSVF algorithm.

Fusion:

$$Z_d(k) = \begin{bmatrix} \theta_{ri} & \varphi_{ri} & r_{ri} \end{bmatrix}^T \tag{3}$$

$$R_d(k) = \begin{bmatrix} \sigma_{r\theta} & 0 & 0 \\ 0 & \sigma_{r\varphi} & 0 \\ 0 & 0 & \sigma_{rr} \end{bmatrix} \tag{4}$$

$$Z_f = Z_i(k) + Z_i(k)\left[R_i + R_{i+1}\right]^{-1}\left(Z_{i+1}(k) - Z_i(k)\right) \tag{5}$$

$$R_f = R_i + R_i\left[R_i + R_{i+1}\right]^{-1} R_i \tag{6}$$

3.2. State Vector Fusion (SVF)

In this architecture (Fig. 2), tracks are found by radars measurements separately and the resultant state vectors (tracks) are fused to get final target state estimations. Similarly, the state error covariances of the individual tracks are fused to get the final state error covariance matrix.

$$\tilde{X}_i(k|k-1) = F\hat{X}_i(k-1|k-1) \tag{7}$$

$$\tilde{P}_i(k|k-1) = F\hat{P}_i(k-1|k-1)F^T + GQG^T \tag{8}$$

Measurement updation:

$$H_i = h\left(\tilde{X}_i(k|k-1)\right) \tag{9}$$

$$e_i = z_i - \tilde{z}_i(k|k-1) \tag{10}$$

$$S_i = H_i P_i(k|k-1) H_i^T + R_i \tag{11}$$

$$K_i = \tilde{P}_i(k|k-1) H_i^T + S_i^{-1} \tag{12}$$

$$\hat{X}_i(k|k) = \tilde{X}_i(k|k-1) + k_i e_i \tag{13}$$

$$\hat{P}_i(k|k) = \left[I - K_i H_i\right]\tilde{P}_i(k|k-1) \tag{14}$$

Fusion:

$$\hat{X}_f(k|k) = \hat{X}_i(k|k) + \hat{P}_i(k|k)\left[\hat{P}_{i+1}(k|k) + \hat{P}_i(k|k)\right]^{-1}\left(\hat{X}_{i+1}(k|k) - \hat{X}_i(k|k)\right) \tag{15}$$

$$\hat{P}_f(k|k) = \hat{P}_i(k|k) + \hat{P}_i(k|k)\left[\hat{P}_{i+1}(k|k) + \hat{P}_i(k|k)\right]^{-1}\hat{P}_i^T(k|k) \tag{16}$$

4. SIMULATION RESULTS

The 3DOF kinematic model, with position, velocity and acceleration components in each of the three Cartesian coordinates x, y and z has the following transition and process noise gain matrices.

$$F = \mathrm{diag}\left[\ \varphi \quad \varphi \quad \varphi\ \right] \tag{17}$$

$$G = \mathrm{diag}\left[\ \eta \quad \eta \quad \eta\ \right] \tag{18}$$

where φ is

$$\varphi = \begin{bmatrix} 1 & T & T^2/2 \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix} \tag{19}$$

$$\eta = \left[\ T^3/6 \quad T^2/2 \quad T\ \right] \tag{20}$$

where T is the sampling interval, F is the state transition matrix and G is the process noise gain matrix.

The percentage fit error (PFE) in x, y and z positions:

$$\mathrm{PFEx} = 100 * \frac{\mathrm{norm}(x - \hat{x})}{\mathrm{norm}(x)} \tag{21}$$

similarly for y and z positions.

Root mean square error in position:

$$\mathrm{RMSPE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\frac{(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 + (z_i - \hat{z}_i)^2}{3}} \tag{22}$$

Root sum square error in position:

$$\mathrm{RSSPE} = \sqrt{(x - \hat{x})^2 + (y - \hat{y})^2 + (z - \hat{z})^2} \tag{23}$$

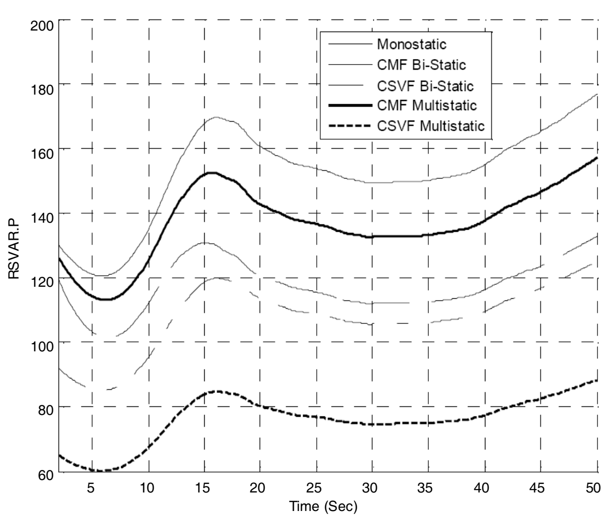

Figure 3: Root sum variance in position.

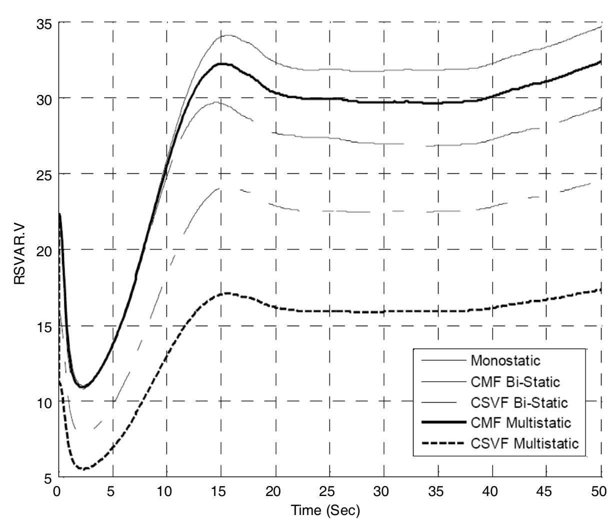

Figure 4: Root sum variance in velocity.

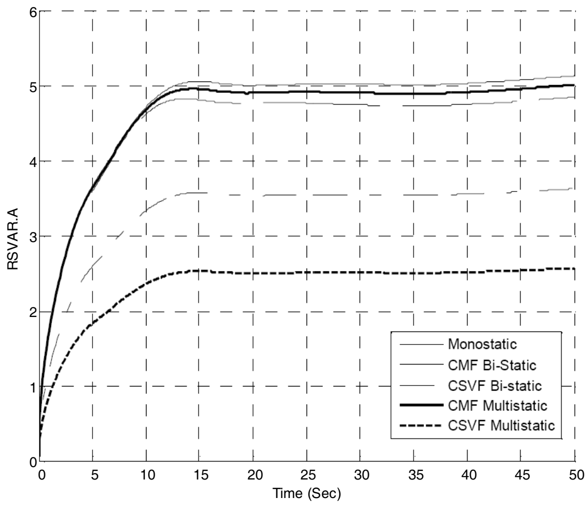

Figure 5: Root sum variance in acceleration.

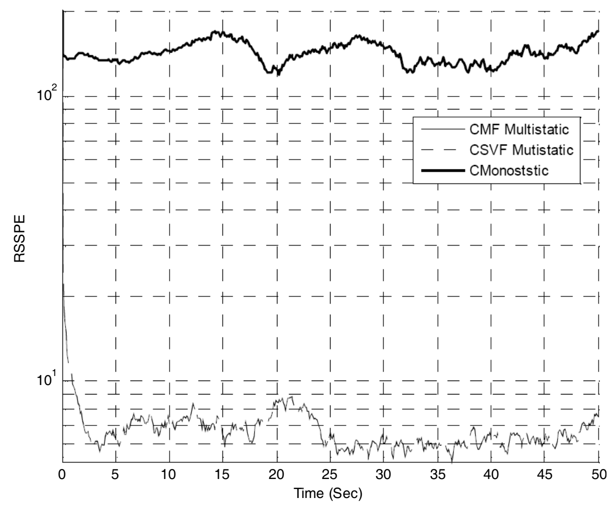

Figure 6: Root sum square error in position.

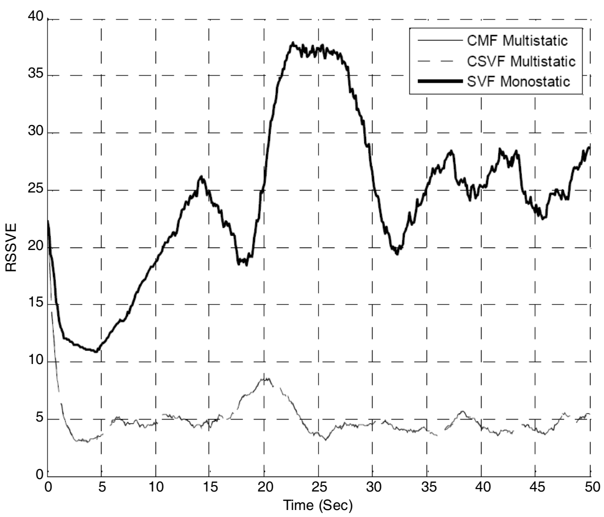

Figure 7: Root sum square error in velocity.

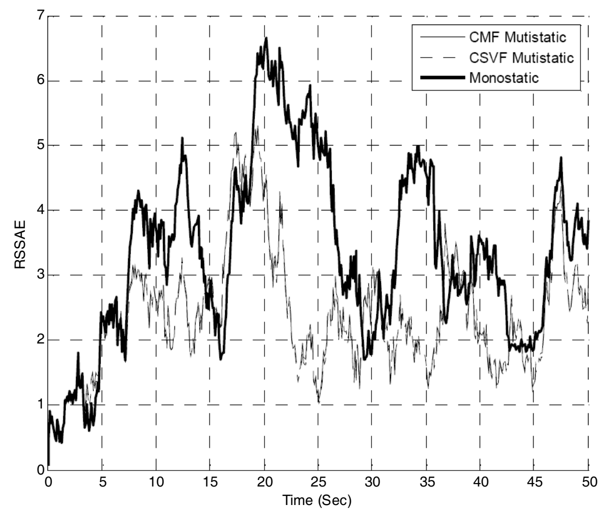

Figure 8: Root sum square error in acceleration.

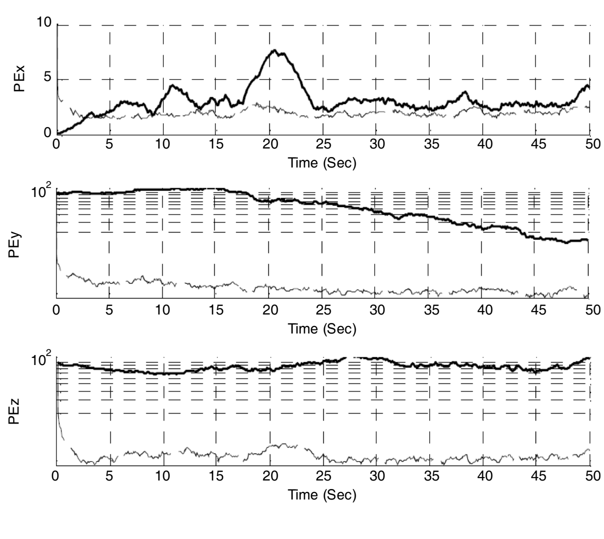

Figure 9: Absolute error in positions.

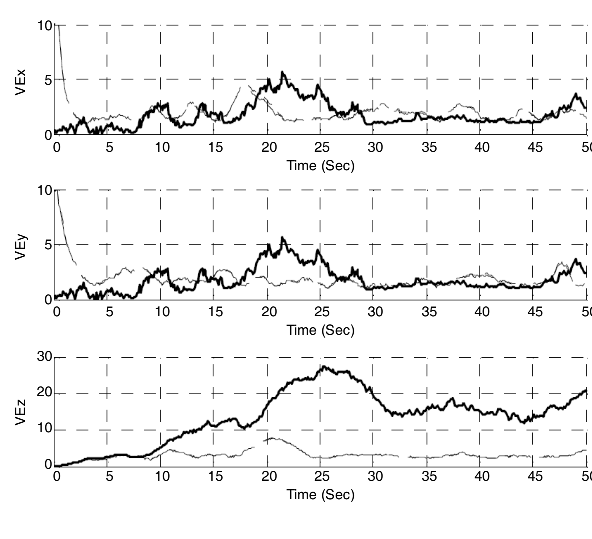

Figure 10: Absolute error in velocities.

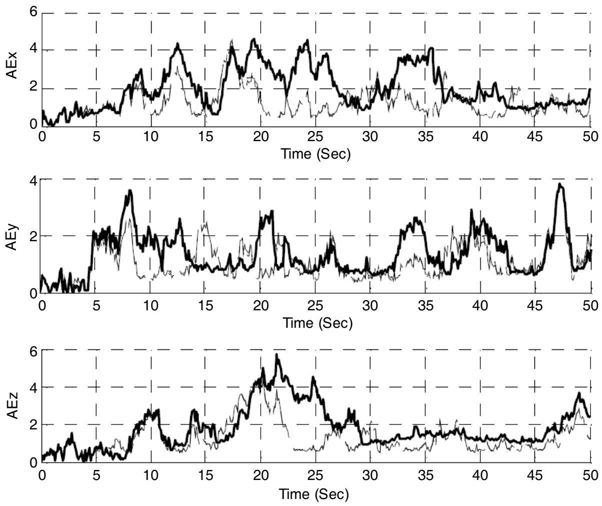

Figure 11: Absolute error in accelerations.

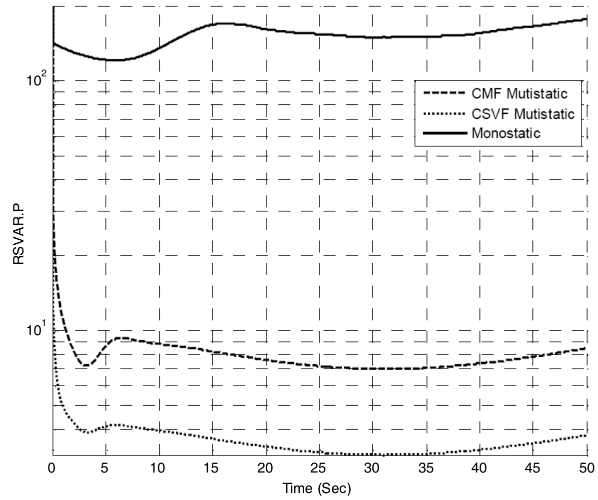

Figure 12: Root sum variance in position.

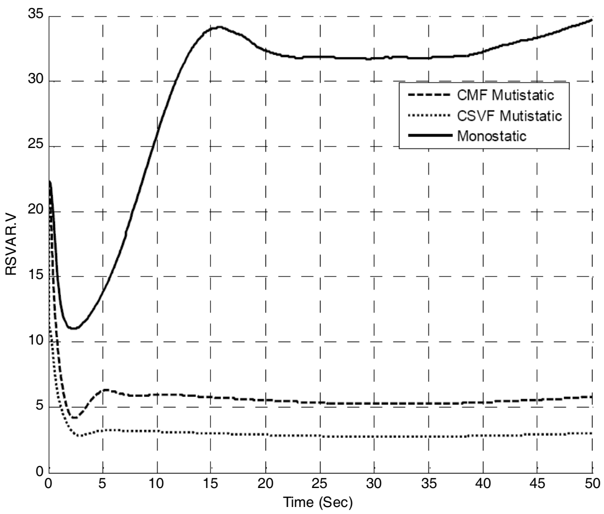

Figure 13: Root sum variance in velocity.

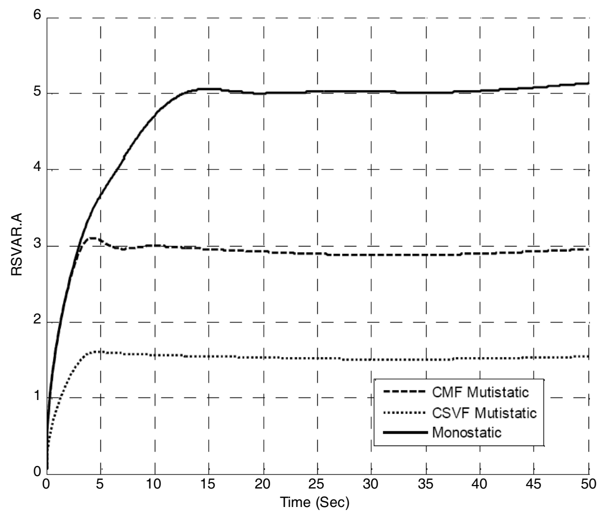

Figure 14: Root sum variance in acceleration.

Absolute error in (AE) x, y and z positions

$$AE_x(i) = |x(i) - \hat{x}(i)| \quad i = 1, 2, 3, \ldots, N, \tag{24}$$

similarly for y and z positions.

The simulation taken first with two cases; the first Bistatic radar with the assumption of identical noise covariance matrix for the two radar information; the second multistatic radar also with identical noise covariance matrix for the four radar information. The two cases compared with monostatic radar information with CMF and CSVF algorithms. Figs. 3–5 show a comparison of root sum variance of the position, velocity, and acceleration with the two test cases with respect to monostatic radar. It is clear that multistatic radar with CSVF improves significantly the root sum variance of the position, velocity, and acceleration respectively. Figs. 6–8 demonstrate the root sum square error in position, velocity, and acceleration respectively for the multistatic radar compared with monostatic radar with both CMF and CSVF. These figures conclude the significant degradation in the RSSE for both fusion algorithms which reflects the great enhancement of the fusion algorithms with the multistatic radar network. The absolute errors in position, velocity, and acceleration are improved also with multistatic radar an shown in Figs. 9–11. The root sum variance comparison illustrated in Figs. 12–14, and clarify the strength of the fusion algorithms with the multistatic radar network.

5. CONCLUSION

The paper proposes a data fusion algorithms into multistatic radar network to improve its tracking capability. It uses current radars data for track-to-track association using cumulative measurement fusion, and cumulative state vector fusion in order to produce an accurate target estimation and prediction with the multistatic radar network. The system is simulated using Matlab program to compare the performance of the estimation routines of both fusion algorithms and the targets scenario is simulated using Monte Carlo simulation. Simulation results have shown that these cumulative fusion algorithms improve the multistatic radar network tracking capability and produce a significant reduction in the root sum square error (RSSE), absolute error, and root sum variance (RSSV) than achieved from monostatic radar.

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