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An Innovative Asynchronous, Multi-rate, Multi-sensor State Vector Fusion Algorithm for Air Defence Applications

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Abstract: This paper presents an innovative approach for data fusion of asynchronous, multi-rate, multi-sensor data in real time. This technique is based on state vector data fusion. For air defence applications, the target information from multi sensors is sent to a central control centre to create a complete threat scenario which would be used for taking appropriate decision. This target data needs to be sent in real time, hence there is a need for low bandwidth consuming data fusion algorithms but at the same time there should be minimal degradation in data accuracy. The optimal fusion algorithm requires the entire state covariance information matrix to be transmitted to the data fusion centre, however this requires huge bandwidth for transmission of data. To avoid this generally, only diagonal elements are transmitted at the cost of considerable degradation in performance. The authors present an innovative approach by considering the only covariance of position, velocity and acceleration but by neglecting the cross covariance terms among position, velocity and acceleration. The accuracy of this proposed algorithm is about 95% of that of optimal method but the reduction in bandwidth requirement is of the order of 60%.

Keywords: Data fusion, Kalman Filter

1. INTRODUCTION

The objective of data fusion algorithm is to derive more information from various sensors, through combining, than is present in any individual element of input data. Data fusion process reduces the ambiguity in measured information, expand the spatial and temporal coverage, and improve the robust operational performance, operational reliability of a system and provides an efficient approach for the exploration of unknown environments. Data fusion is extensively used in military fields such as command, control, communication, and intelligence missions and detection, tracking and identification, and many nonmilitary fields such as remote sensing, weather prediction, air traffic control, medical treatment, and navigation. State estimation forms the key component in data fusion, which determines an estimate of the state (e.g., position, velocity) of a static or dynamic target based on measurements related to the state. There are mainly four modes in multi-sensor state estimations, namely, centralized, distributed, composed, and multilevel modes [1].

This paper is organized as follows. The section 2 provides different fusion architectures used for fusing multi-sensor data. The fusion algorithms are discussed in section 3. Section 4 presents the detailed results and section 5 concludes the paper

2. KALMAN FILTER BASED FUSION METHODS

Among different approaches for Kalman Filter-based sensor fusion, two commonly employed techniques are (i) state-vector fusion and (ii) measurement fusion [2]. The state-vector fusion method uses state covariance of the filtered output of individual noisy sensor data to obtain an improved joint state estimate. On the other hand, the measurement fusion method directly fuses the sensor measurements to obtain a weighted or combined measurement and then uses a single Kalman Filter to obtain the final state estimate based on the fused measurement. The two philosophies are depicted in figure 1. However, both the systems have their own merits and demerits. The measurement fusion method, which combines multi-sensor data using minimum mean square error estimate, requires that the sensors should have identical measurement matrices. Although the measurement fusion method provides better overall estimation performance, state-vector fusion has lower computational cost and possesses the advantage of parallel implementation and fault tolerance. Judicious trade-off between computational time and numerical accuracy has to be made for selection of algorithm for real time application.

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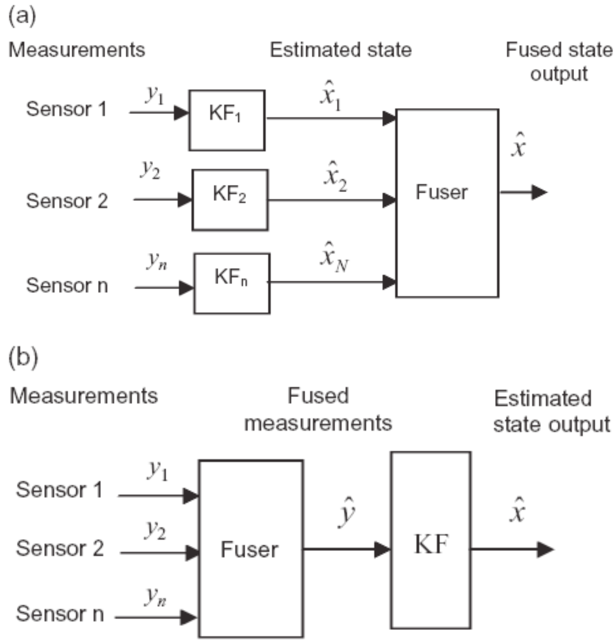

Figure 1

3. DATA FUSION ALGORITHMS

Method I:

The Kalman filters running at respective radar sites gives the state and its covariance matrix. The optimal method of fusing the two state vectors is by considering all the terms in the covariance matrix. The drawback of this method is that it demands huge communication bandwidth.

The fusion algorithm for state and covariance is given as follows.

$$X_k = X_k^1 + P_k^1\left(P_k^1 + P_k^2\right)^{-1}\left(X_k^2 - X_k^1\right) \qquad (1)$$

$$P_k = P_k^1 - P_k^1\left(P_k^1 + P_k^2\right)^{-1}P_k^1 \qquad (2)$$

$i = 1,2$

X_k^1, X_k^2 are track data from sensor I and sensor II respectively.

P_k^1, P_k^2 are covariance matrix of target states from sensor I and sensor II respectively

$$X_k^i = \begin{bmatrix} x_i & y_i & z_i & vx_i & vy_i & vz_i & ax_i & ay_i & az_i \end{bmatrix}^T \qquad (3)$$

$$P_k^i = \begin{bmatrix} P^i_{xx} & P^i_{xy} & P^i_{xz} & P^i_{xv_x} & P^i_{xv_y} & P^i_{xv_z} & P^i_{xa_x} & P^i_{xa_y} & P^i_{xa_z} \\ P^i_{yx} & P^i_{yy} & P^i_{yz} & P^i_{yv_x} & P^i_{yv_y} & P^i_{yv_z} & P^i_{ya_x} & P^i_{ya_y} & P^i_{ya_z} \\ P^i_{zx} & P^i_{zy} & P^i_{zz} & P^i_{zv_x} & P^i_{zv_y} & P^i_{zv_z} & P^i_{za_x} & P^i_{za_y} & P^i_{za_z} \\ P^i_{v_xx} & P^i_{v_xy} & P^i_{v_xz} & P^i_{v_xv_x} & P^i_{v_xv_y} & P_{v_xv_z} & P^i_{v_xa_x} & P^i_{v_xa_y} & P^i_{v_xa_z} \\ P^i_{v_yx} & P^i_{v_yy} & P^i_{v_yz} & P^i_{v_yv_x} & P^i_{v_yv_y} & P_{v_yv_z} & P^i_{v_ya_x} & P^i_{v_ya_y} & P^i_{v_ya_z} \\ P^i_{v_zx} & P^i_{v_zy} & P^i_{v_zz} & P^i_{v_zv_x} & P^i_{v_zv_y} & P^i_{v_zv_z} & P^i_{v_za_x} & P^i_{v_za_y} & P^i_{v_za_z} \\ P^i_{a_xx} & P^i_{a_xy} & P^i_{a_xz} & P^i_{a_xv_x} & P^i_{a_xv_y} & P^i_{a_xv_z} & P^i_{a_xa_x} & P^i_{a_xa_y} & P^i_{a_xa_z} \\ P^i_{a_yx} & P^i_{a_yy} & P^i_{a_yz} & P^i_{a_yv_x} & P^i_{a_yv_y} & P^i_{a_yv_z} & P^i_{a_ya_x} & P^i_{a_ya_y} & P^i_{a_ya_z} \\ P^i_{a_zx} & P^i_{a_zy} & P^i_{a_zz} & P^i_{a_zv_x} & P^i_{a_zv_y} & P^i_{a_zv_z} & P^i_{a_za_x} & P^i_{a_za_y} & P^i_{a_za_z} \end{bmatrix} \qquad (4)$$

METHOD II:

The communication bandwidth requirement of Method I can be reduced by neglecting the cross-covariance between the state variables. This method is generally used in real time fusion implementation, but it leads to degradation in accuracy of the fused data.

$$X_k = X_k^1 + P_k^1\left(P_k^1 + P_k^2\right)^{-1}\left(X_k^2 - X_k^1\right) \qquad (5)$$

$$P_k = P_k^1 - P_k^1\left(P_k^1 + P_k^2\right)^{-1}P_k^1 \qquad (6)$$

$$X_k^i = \begin{bmatrix} x_i & y_i & z_i & vx_i & vy_i & vz_i & ax_i & ay_i & az_i \end{bmatrix}^T \qquad (7)$$

$$P_k^i = \begin{bmatrix} P^i_{xx} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & P^i_{yy} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & P^i_{zz} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & P^i_{v_xv_x} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & P^i_{v_yv_y} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & P^i_{v_zv_z} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & P^i_{a_xa_x} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & P^i_{a_ya_y} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & P^i_{a_za_z} \end{bmatrix} \qquad (8)$$

METHOD III (Proposed Method):

The drawback in the method II i.e. degradation in the performance of data fusion is overcome by this method. In this method, instead of considering all the cross-covariance terms, we consider along with self variances the cross-covariance terms corresponding to only position, only velocity and only acceleration. It is to be noted that it uses only two Kalman filters running at Radar site, however for clarity the equations are presented separately.

The fused state and its associated covariance matrix is as follows:

$$X_k^{POS} = X_k^{POS1} + P_k^{POS1}\left(P_k^{POS1} + P_k^{POS2}\right)^{-1}\left(X_k^{POS2} - X_k^{POS1}\right) \qquad (9)$$

$$P_k^{POS} = P_k^{POS1} - P_k^{POS1}\left(P_k^{POS1} + P_k^{POS2}\right)^{-1}P_k^{POS1} \qquad (10)$$

X_k^{POS1}, X_k^{POS2} are position of target from Radar I and Radar II respectively.

P_k^{POS1}, P_k^{POS2} are covariance matrix of target states from Radar I and Radar II respectively.

$$X_k^{POSi} = \begin{bmatrix} x^i & y^i & z^i \end{bmatrix}^T$$

$$P_k^{POSi} = \begin{bmatrix} P^i_{xx} & P^i_{xy} & P^i_{xz} \\ P^i_{yx} & P^i_{yy} & P^i_{yz} \\ P^i_{zx} & P^i_{zy} & P^i_{zz} \end{bmatrix} \qquad (11)\ \&\ (12)$$

i = 1, 2