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Unified Framework of Modeling and Simulations for Multi-platforms Multi-sensors Multi-objects Source Information Fusion (M3SIF) System

Wenlong Cai, Shaobo Guo, Shuo Zhang and Jinyong Lin

National Key Laboratory of Science and Technology on Aerospace Intelligence Control
Beijing Aerospace Automatic Control Institute Beijing
Beijing, P.R.China
bitguoshaobo@163.com;caiwenlon@buaa.edu.cn;gcshuo@163.com;ljiny3771@sina.com

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Abstract. *In this paper, we present a unified framework of modeling and simulations for Multi-platforms Multi-sensors Multi-objects Source Information Fusion (M^3SIF) system. The space-time registration and target tracking of multi-sensor measurement data are studied explicitly. The registration algorithm takes the influence of the random noise measured by the sensors into account. Compared with the traditional algorithm, the accuracy of registration is improved when applying our proposed algorithm. The extended state Kalman filter (EKF) is utilized to estimate the system state and registration error simultaneously. The simulation results show that the accuracy of the sensor registration error after the least-squares time registration is significantly better than that of the non-time-registered registration error estimate. Besides, the convergence speed is faster than the registration error estimation without time registration, which verifies the effectiveness of the proposed algorithm.*
Keywords: Multi-sensor system, Modeling and simulations, Extended Kalman filter, Space-time registration

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1. **Introduction.** In recent years, a variety of military or civil multi-sensor information systems have emerged for complex application background. The combination of multi sensors leads to the diversity of information forms, the increase of data and the speed of data processing, which greatly exceeds the ability of information processing in human brain. Therefore, data fusion has become a research hotspot, and the theory and technology of data fusion have been paid more and more attention [1-3].

In the design of every kind of tracking system, the original information by using the information fusion technology integrated from multiple sensors, to obtain good tracking performance, can reduce the false alarm rate and improve the target detection and recognition and tracking ability and enhance the advantages of system fault tolerance and reconstruction ability etc [4]. In the fusion process, data from multiple sensors are usually transformed into the same spatio-temporal reference frame. If the sensor data is fused directly, the tracking results will deteriorate due to the presence of registration errors [5].

Sensor registration includes time registration and spatial registration. Document [6, 7] gives the time registration and fusion method based on the least square method for the non-synchronous information, and designs the tracking filter, but does not consider the measurement of the system error contained by the sensor. The space registration problem of fixed radar network is studied in document [8, 10]. [8] proposed a maximum likelihood

(EML) registration algorithm, and pointed out that the traditional registration algorithm of the sensor measurement error is attributed to the registration error, ignoring the impact of random error. [9] uses two level extended Kalman filter to complete the target tracking problem, which makes the algorithm reduce the requirements of computing resources such as time and storage space. [10] applies registration algorithm to maneuvering target tracking problem. [11] proposed a novel two-stage nonlinear least square (LS) optimization approach to the multi-sensor registration problem with the assumption that the target moves in a straight line with unknown constant velocity. [12] presented a method for sensor registration that overcomes the shortage of standard marker or artificial-feature-based approaches by utilizing the geometric structure of the terrain surrounding the sensor platform.

In the air ground integrated system for air combat platform, more is the tracking problem of mobile platform. In this paper, the time and space data registration and target tracking of Multi-sensor Based on extended Kalman filter and multiple aerial mobile platforms are studied. Monte-Carlo simulation shows that the proposed method can effectively estimate the target motion state and sensor registration error. Compared with the traditional registration method, the proposed method has faster convergence speed and higher accuracy.

2. **Framework.** A multi-sensor system consisting of multiple surface radars, satellites, airborne early warning aircraft and fighter jets is a typical Multi-sensors (Multi-sensors, Multi objects Source Information Fusion) system. Its information processing using centralized distributed structure (Figure 1). Its integration process is the first to be remotely monitored by airborne early-warning aircraft and long-range surveillance radars, and its data is transmitted either directly or through communications satellites to the fusion center. The Fusion Center's decision is sent back to these sensors and decides whether to start a new sensor for monitoring and whether to intercept the attack. As can be seen from Fig. 1, each sensor has multiple sources of information, the entire system includes multiple platforms, all of the platform data through the communication data link. So the whole system integration can be divided into two levels. Each subsystem constitutes a platform-level integration of the platform and system-level integration of the entire system. Airborne early warning aircraft, various ground-based radars and aircraft each form a different sensor platform. Each platform is responsible for integrating data from all information sources in the platform and transmitting the results of the fusion to the fusion center in a report format. All the reports and self- System-level integration of the database to determine the goal of the only track.

Fig. 2 shows the fusion of the entire system block diagram, which gives the fusion function model of each sensor or platform in the system. In the whole system research, the sensors (belonging to the same platform or different platforms) work independently and asynchronously, and their sampling rates are not all the same. The primary fusion (preprocessing) of the platforms is carried out in their own reference frame (for example, the reference frame of the aircraft can take the frame of the loader). Moreover, each platform asynchronously provides a report to the Fusion Center. So in the fusion before the need for time and space alignment, in order to form a unified observation point of time and space.

The task of time alignment is to synchronize the measurement information that is asynchronous to each sensor of the same target to the same reference standard. Since the measurement of targets is done independently of each other for different sensors and on different platforms, the time they report to the fusion center is mutually exclusive and the time it takes to transmit information between platforms and fusion centers varies,

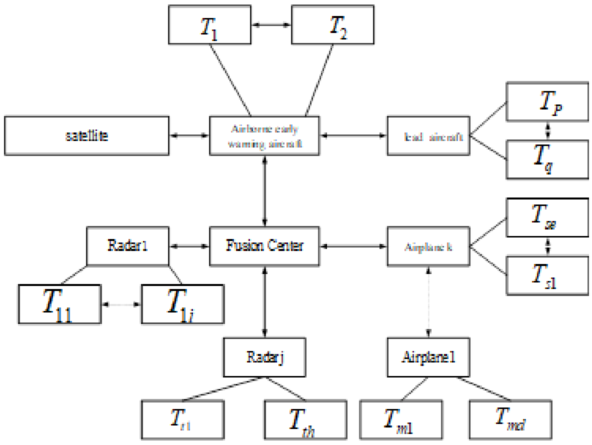

FIGURE 1. Typical Information Processing Centralized Distribution Structure.

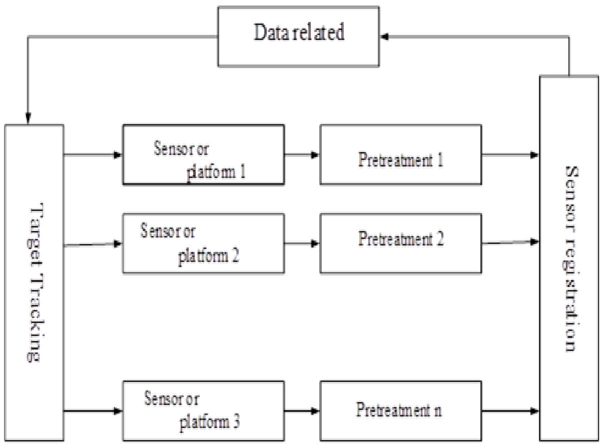

FIGURE 2. System integration diagram.

so There may be a time difference between each sensor report. Therefore, before the integration of information should be out of sync at the merging moment of the message.

The task of spatial alignment is to coordinate the space target. For the measurement of each sensor with different coordinate system in the same platform, the platform must be converted into the data in the same coordinate system when it is fused. For different platforms, the coordinate system is different. Therefore, before merging the information of all platforms, it is necessary to convert them into the unified observation coordinate system. After merging, the fusion result needs to be transformed back to the coordinate data of different platforms. Posted to each platform. Therefore, data alignment can be divided into: platform-level alignment and system-level alignment.

2.1. **Coordinate Transformation of Multiple Platforms and Sensors.** Considering two airborne mobile platforms, sensors A and B are located on different platforms. Without losing generality, it is assumed that the sensor A is located at the origin of the coordinate (in absolute coordinates, the position of A is always changing, i.e. the position of the coordinate origin is always changing), and the position of the sensor B relative to the sensor A is [u(k),v(k)]. The target is T_k, as shown in Fig. 3.

The distances and azimuths of target T_k measured by sensors A and B in the figure are $[r_A(k), \theta_A(k)]$ and $[r_B(k), \theta_B(k)]$, $\eta_A = [\Delta\theta_A, \Delta r_A]$ and$\eta_B = [\Delta\theta_B, \Delta r_B$ respectively.

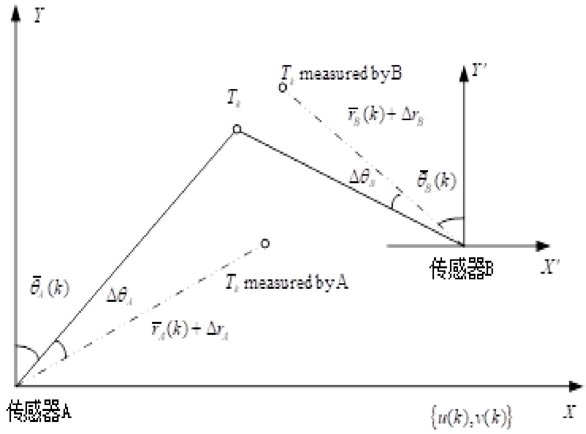

FIGURE 3. The geometric relationship of registration error.

Define $[r_A\bar(k), \theta_A\bar(k)][r_B\bar(k), \theta_B\bar(k)]$, $[x_A(k), y_A(k)]$ and $[x_B(k), y_B(k)]$ for the sensors A and B and $[x\bar{k}, y\bar{k}]$ is the true Cartesian coordinate of the target relative to sensor A.

2.2. **Target's motion model.** In the Cartesian inertial coordinate system, the trajectory of the target can be accurately described by polynomial , but for polynomials with too high order, the calculation is too large and the tracking filter is not easy to adjust. In order to simplify the analysis we can assume that in a small time interval , the target sits in an accelerating linear motion in three-dimensional space with initial velocity at , acceleration , azimuth , and elevation angle (As shown in Fig. 4), the polynomial can be simplified to:

$$x_{m2} = x_{m1} + (vt + \frac{1}{2}at^2)\sin\alpha\sin\beta + \omega_1(t) \tag{1}$$

$$\mathrm{y_{m2} = y_{m1} + (vt + \frac{1}{2}at^2)} \cos\alpha\sin\beta + \omega_1(\mathrm{t}) \tag{2}$$

$$\mathrm{z_{m2} = z_{m1} + (vt + \frac{1}{2}at^2)} \cos\beta + \omega_3(\mathrm{t}) \tag{3}$$

Assuming that the true coordinates of target T_k are $[x\bar{k}, y\bar{k}]$ and the true velocity of the target is $[x\bar{k}, y\bar{k}]$, the state vector of the target is denoted by $\xi(k) = [x\bar{k}, x\bar{k}, y\bar{k}, y\bar{k}]$. The dynamic model of the target movement is

$$\xi(k+1) = \Phi_\xi(k) + \Gamma_\omega(k) \tag{4}$$

$$\Phi = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & T \\ 1 & 0 & 0 & 1 \end{bmatrix}, \Gamma = \begin{bmatrix} \frac{T^2}{2} \\ T \\ \frac{T^2}{2} \\ T \end{bmatrix} \tag{5}$$

3. **Time and space alignment algorithm.** Time alignment, whether platform-level or system-level, synchronizes measurement information that is not synchronized to sensors of the same target to the same benchmark. Under normal circumstances the sensor data will be unified to scan a longer period of a sensor data. The following two different methods can be used according to the sensor data when registering: (1) least squares rule registration method; (2) interpolation extrapolation.

Due to the close placement of sensors inside the platform and the alignment of data from different sensors inside the platform, the origins of different coordinate systems can be considered as common points. Therefore, the spatial alignment is to rotate their coordinate system to a coordinate system parallel to the selected coordinate system of the fusion center. Let OX'Y'Z' be the coordinate system corresponding to the fusion center coordinate system, θ', η', Is the azimuth and elevation angle of the target M in the OX'Y'Z' coordinate system; is the sensor coordinate system to be converted, θ' and η' are the azimuth and elevation angle of the target M in the coordinate system, respectively. It is assumed that the coordinate system is obtained by rotating the OX'Y'Z' coordinate system angle counterclockwise about the three axes X,Y,Z respectively. Because the target M point before and after the coordinate system transformation of its radial distance from O unchanged, so the reference given by the literature3 can be obtained before and after the rotation angle relationship. Under normal circumstances, the coordinate system OXYZ coordinate system is only rotated around the Z axis (that is: the Z axis of different coordinate system is parallel, the aircraft level flight), so $\alpha = \delta = 0$, then $\eta = \eta'$, $\theta = \theta' - \beta$, if the coordinates of M point in OX'Y'Z' coordinate system are (x'_M, y'_M, z'_M) Then the coordinate converted to OXYZ coordinate system is (x_M, y_M, z_M), Then:

$$x_M = x'_M \cos\beta + y'_M \sin\beta + n_1(t) \tag{6}$$
$$y_M = -x'_M \sin\beta + y'_M \cos\beta + n_2(t) \tag{7}$$
$$z_M = z'_M \cos\beta + n_3(t) \tag{8}$$

where $n_i(t), (i = 1, 2, 3, ...)$ is the measurement noise.

After platform level alignment, system level alignment is possible. Under normal circumstances, the target position coordinatesy (x_M, y_M, z_M) obtained by platform-level fusion can be translated to the fusion center coordinate system to obtain the position coordinates of the target M point in the fusion center coordinate system. But this method needs to be the sensor to get the radial distance, azimuth, elevation angle into (x'_M, y'_M, z'_M) , And in the conversion process will bring the calculation error. The following describes a two platform sensor direct alignment algorithm.

Suppose the sensor A is at the origin O of the coordinate system O_A, X_A, Y_A, Z_A of the platform A, and the slope, azimuth and elevation angles of the k_{th} target are respectively r_A, θ_A, η_A; the sensor deviation is $\Delta r_M, \Delta\theta_M, \Delta\eta_M$. The sensor B is located at u, v, ω of the coordinate system $O_A X_A Y_A Z_A$ at the origin O_B, O_B of the coordinate system $O_A X_A Y_A Z_A$ of the platform B. The sensor B measures the slope distance, azimuth, High and low angle measurements were r_B, θ_B, η_B (Fig. 4); sensor bias $\Delta r_B, \Delta\theta_B, \Delta\eta_B$. The target M is represented by $r'_A(k), \theta'_A(k), \eta_A(k)$ and $r'_B(k), \theta'_B(k), \eta_B(k)$ True Slope, Azimuth and Elevation to Sensor A and B.

And assuming that the measurement noise is subject to a normal distribution with variance σ_n^2 and independent of each other, for small deviation systems, the first-order approximation to Eqs. (10) and (11) is simplified and expressed in matrix form as:

$$X(k) = A(k)^o\eta + B(k) + n(k) \tag{9}$$

where $X(k) = (x_A(k), y_A(k), z_A(k), x_B(k), y_B(k), z_B(k))$ is a target measurement vector. $n(k) = (n_1(k), n_2(k), n_3(k), n_4(k), n_5(k), n_6(k))_T$is the target random measurement error vector, whose variance matrix is $\sigma_n^2 I.\eta = (\Delta r_A, \Delta\theta_A, \Delta\eta_B, \Delta l_B, \Delta\theta_B, \Delta\eta_B)$ is the system deviation vector. $B(k) = (x'(k), y'(k), z'(k), x'(k), y'(k), z'(k))^T$ is a target real position vector.$A(k) = diag(A11(k), A22(k))$ is a diagonal matrix, where

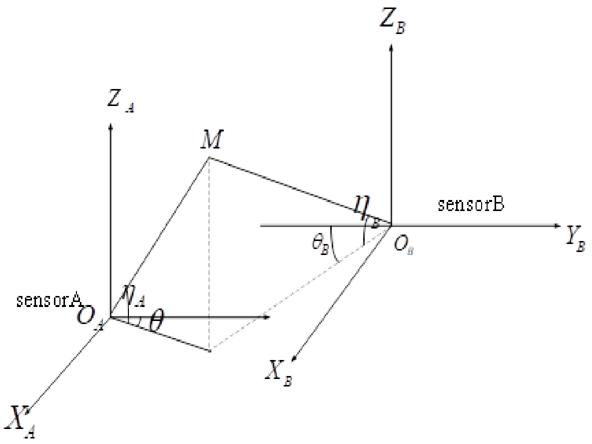

FIGURE 4. Rectangular coordinate system sensor registration relationship.

$$A_{11}(k) = \begin{bmatrix} \frac{x'(k)}{r'_A(k)} & y'(k) & z'(k)^o \sin\theta'_A(k) \\ \frac{y'(k)}{r'_A(k)} & -x'(k) & -z'(k)^o \cos\theta'_A(k) \\ \frac{y'(k)}{r'_A(k)} & 0 & r'(k)^o \cos\eta'_A(k) \end{bmatrix} \tag{10}$$

$$A_{22}(k) = \begin{bmatrix} \frac{x'(k)-u}{r'_B(k)} & y'(k)-v & -(z'(k)-\omega)^o \sin\theta'_B(k) \\ \frac{y'(k)-v}{r'_B(k)} & -(x'(k)-u) & -(z'(k)^o-\omega)\cos\theta'_B(k) \\ \frac{z'(k)^o}{r'_B(k)} & 0 & r'_B(k)^o \cos\eta'_B(k) \end{bmatrix} \tag{11}$$

It can be seen that both A(k) and B(k) are independent of system deviation and relate only to the actual position of the target in the system.

4. **Simulation results.** Fig. 5 shows the simulation results of the estimation of the registration error of the distance and angle measurement of the sensor A. Among them, the dotted line indicates the true value of the registration error, the solid line indicates the registration error estimate without time registration, and the dotted line indicates the registration error estimate value after using the time registration method in this paper.

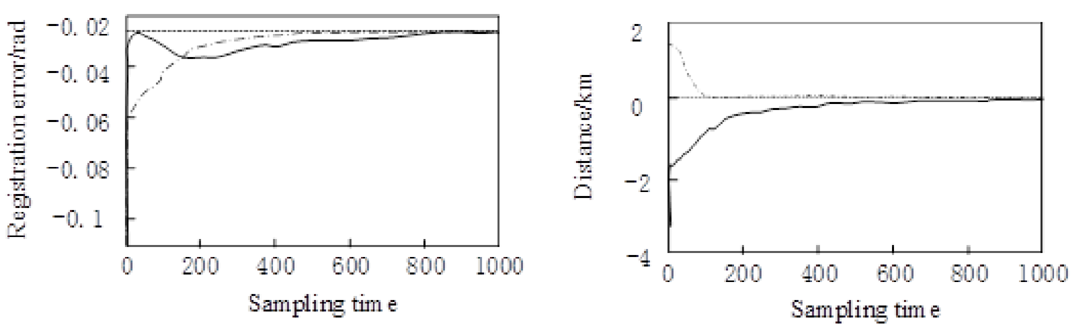

FIGURE 5. Estimation of registration error.

As can be seen from the figure, compared with the estimation of the registration error of the sensor without the time registration by the least square method, the convergence precision is high and the convergence speed is fast. This is because the least-squares method filters the noise while registering the sensor time, reducing the impact of noise on the registration error.

Figure3 shows the estimation of the target state variables, including the target bits.Set and speed. Due to space limitations, only the status of the abscissa direction is given.

The simulation results show that the algorithm can estimate the registration error and state simultaneously, and the results of the registration of multi-sensor data of air mobile platform after the time registration in this paper are better than the results of non-time registration. Supposed that the basic deviations of each sensor are $\Delta r = 1km, \Delta\theta = 0.0087radand\Delta\eta = 0.0175$rad. Sensor A is at the origin and sensor B is at the point u,v,w in the coordinate system, as shown in Fig. 6. The simulation results of the registration bias of sensor A and sensor B at different sets of K are shown in Table 1 respectively. Clearly, the Sensor B performs better than the sensor A at each threshold of K with lower registration bias.

Based on the deviations given in Table 1, $\zeta(k) = (x'(k), y'(k), z'(k))$when $u = 100km, v = 20km$, values shown in Fig. 7 (next to two is the A, B sensor measured measurement trajectory, the middle one is the registration of the trajectory). Suppose the number of measurements and the noise deviation from 0 to 2 km. A similar result to Table 1 is obtained when $u = 50km, v = 10km, w = 0km$.

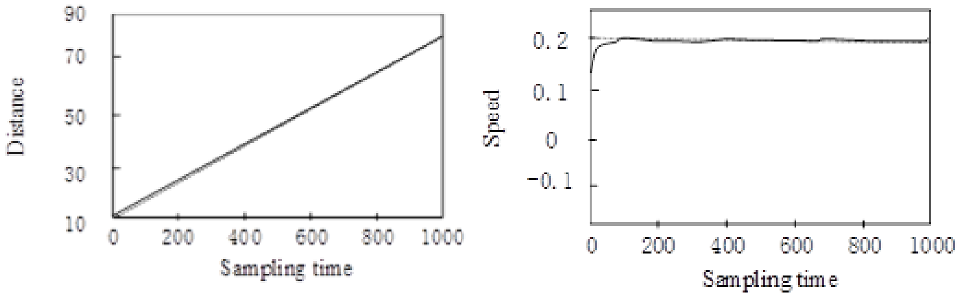

FIGURE 6. Estimate of target state variables.

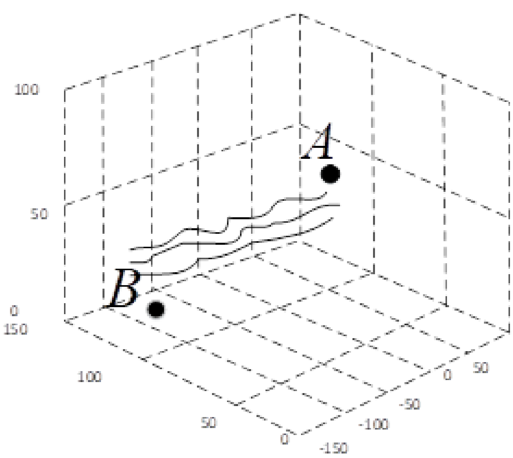

FIGURE 7. After registration and A, B track the relationship between the trajectory.

5. **Conclusion.** In this paper, the space-time registration and target tracking of multi-sensor measurement data are studied. The registration algorithm takes into account the influence of the random noise measured by the sensor. Compared with the traditional registration algorithm, the accuracy is improved. The extended state Kalman filter is

TABLE 1. Different kernel function classification results.

K	Sensor A			Sensor B		
	Δr	$\Delta\theta$	$\Delta\eta$	Δr	$\Delta\theta$	$\Delta\eta$
10	1.1542	0.0094	0.0199	-0.2934	0.0072	0.0183
20	1.2234	0.0088	0.0199	-0.2245	0.0073	0.0185
30	1.1636	0.0089	0.0176	-0.1549	0.0076	0.0184
40	1.0925	0.0092	0.0185	-0.0996	0.0074	0 .0178
50	1.1039	0.0087	0.0187	-0.1227	0.0081	0 .0174
60	1.0799	0.0087	0.0176	-0.0678	0.0081	0 .0172
70	1.0232	0.0078	0.0167	-0.0282	0.0082	0 .0173
80	0.9876	0.0078	0.0175	0.0269	0.0082	0 .0172
90	1.0054	0.0087	0.0179	-0.0112	0.0084	0 .0170
100	1.0187	0.0089	0.0176	0.0476	0.0082	0 .0172

used to estimate the system state and registration error simultaneously. The simulation results show that the accuracy of the sensor registration error after the least-squares time registration is significantly better than that of the non-time-registered registration error estimate, And the convergence speed is faster than the registration error estimation without time registration, which verifies the effectiveness of the proposed algorithm.

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