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An Asynchronous Data Fusion Algorithm for Target Detection Based on Multi-Sensor Networks

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ABSTRACT The time interval of the observational data changes irregularly because of the difference of sensors' sampling rate, the communication delay and the target leaving observation region of the sensor sometimes. These problems of asynchronous observation data greatly reduce the tracking accuracy of the multi-sensors system. Therefore, asynchronous data fusion system is more practical than synchronous data fusion system, and worthier of study. By establishing an asynchronous track fusion model with irregular time interval of observation data and combining with the Track Quality with Multiple Model (TQMM), an asynchronous track fusion algorithm with information feedback is proposed, and the TQMM is used for weight allocation to improve the performance of the asynchronous multi-sensor fusion system. The simulation result shows that the algorithm has better tracking performance compared with other algorithms, so that this kind of problem of track-to-track fusion for asynchronous sensors is solved effectively.

INDEX TERMS Asynchronous fusion, multi sensors, track fusion, track quality with multiple model.

I. INTRODUCTION

The technology multi-sensor fusion tracking [1], [2], which applies the data fusion [3], [4] to the target tracking, solved some tracking accuracy problems in many situations, and has a broad application prospect and great scientific value. Further, distributed data fusion algorithms are very important for target detection based on multi-sensors networks. The time interval of the observational data changes irregularly because of the difference of sensors' the communication delay, sampling rate and the target leaving observation region of the sensor sometimes, so, the synchronous observation data is always in ideal condition. As we know, such problems of asynchronous observational data from sensors greatly reduce the tracking accuracy of the multi-sensors system. Therefore, the problem of asynchronous data fusion is more practical and difficult than synchronous data fusion. Asynchronous track fusion is often mainly divided into two categories. One is that different kinds of detection sensors have different and fixed sampling periods and the other one is the time interval of target information provided by detection sensors has no rule, meaning detection sensors have no fixed sampling interval. The first category can also be divided into two parts according to the starting time of different sampling periods. In both categories, asynchronous information from multi- sensor systems can be synchronized by track pretreatment [5] – [7], and then be tracked by traditional synchronous track fusion system. However, these pretreatment process schemes will cause some errors increasing and reduce the reliability of data fusion system.

Therefore, some researchers proposed a series of asynchronous track fusion methods, algorithms and systems. These studies have made a good contribution to the research of asynchronous fusion technology. Some asynchronous fusion algorithms introduce some traditional data registration methods to the fusion systems for realizing the synchronization of asynchronous data before fusion process, such as the interpolation, extrapolation, least squares method and so on. Some fusion algorithms deal with asynchronous data on the basis of its receiving time, then select a proper fusion method for this asynchronous data fusion, such as asynchronous fusion algorithms based on information matrix [8], [9],

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asynchronous track fusion algorithm under the principle of minimum error covariance matrix trace [10] – [12], time-varying bias estimation for asynchronous multi-sensor multi-target tracking systems [13], distributed weighted fusion estimators with random delays [14] and Step by Step Prediction Fusion based on Asynchronous Multi-sensor System (SSPFA) [15], [16], etc. The SSPFA algorithm mainly uses the multi-sensor's measurement information in a data fusion cycle to get the filtering estimation, to obtain the local state estimation and the corresponding error covariance of each sensor at the last moment of data fusion cycle. Then, after the state prediction of fusion time, SSPFA operates the order weighting of the sensor prediction information based on the obtaining order of sensor predictive values and the principle of minimum error covariance matrix. Finally, the multi-sensor asynchronous fusion is achieved.

In addition, there are some researches on asynchronous fusion algorithms, such as [17], it proposed a novel asynchronous multi-sonar data integration approach, in which the Gaussian Mixture Probability Hypothesis Density (GMPHD) filter is used to filter clutter for local sonar sensor. Lu K *et al.* develop an exact fusion algorithm to solve track-to-track fusion problem [18], under the condition that at each time step only parts of the sensors send their local estimation tracks to the fusion center. Formulas are derived to obtain the exact cross-covariances between the local tracks by taking into consideration the impact of the potential feedback from the fusion center. In [19], it proposes a time registration method based on state extrapolation to solve data synchronization problem in multi-target tracking. In [20], oriented on asynchronous data in multi-sensor data fusion system, a real-time fusion architecture is put forward, which is in unbiased minimum variance sense. The proposed asynchronous fusion algorithm can solve the measurements sequentially that does not need to preset fusion periods for fusion center to synchronize asynchronous data transmitted from multi sensors. In [21], a sequential processing simultaneous spatiotemporal bias and state estimation algorithm for asynchronous multi-sensor system is proposed. The spatiotemporal bias is combined with target state to obtain an augmented state vector, and the augmented state model is formulated. For asynchronous multi-sensor with known but different sampling periods, a sequential processing method is proposed to handle the multiple measurements. The relationship of sensor measurements, target state and spatiotemporal bias is analyzed, and the corresponding measurement model is formulated. An algorithm is used to handle the nonlinearity between the augmented measurement and state vectors, is proposed to jointly estimate the spatiotemporal bias and target state.

With these novel algorithms, the first kind of asynchronous problem could be basically solved; while, the second problem could not be solved well.

According to the filtering predictive thought of the SSPFA, an algorithm named TFASP (Track - to - Track Fusion for Asynchronous Multi-sensor based on Step by Step Prediction) was proposed [16], [27]. By the local state estimation of multi-sensor fusion, the algorithm predicts the sampling values in a fusion cycle. After weight fusion of the same sensor's predictive value at fusion moment, this algorithm regards the fusion value as sensor's equivalent observation information at data fusion moment and achieves the global fusion of asynchronous multi-sensors by the step-by-step filter fusion finally. As the input value of the step-by-step filter data fusion, local sensor's weight fusion decides the tracking performance of the algorithm. However, determined by the observation precision and sensors' prediction error, the weight of local sensor's weight fusion has no direct relation with the difftime between the sampling time and fusion time. Therefore, the large error of local sensor's state estimation will reduce the tracking accuracy of the whole system. Besides, there is no feedback mechanism [22], [23] in the entire system. These problems cause some shortcoming in this algorithm.

The motivation of this paper is how to better solve the above problems in asynchronous data fusion based on multi-sensor networks. In summary, the main contributions of this paper can be listed as follows:

(1) Using the track quality of Kalman filtering [24] – [26], combined with our proposed TQMM (the Track Quality with Multiple Model) [27], a novel asynchronous multi-sensor track fusion algorithm is proposed, named AFTQMM (Asynchronous Fusion based on Track Quality with Multiple Model).

(2) We introduced a feedback mechanism; the algorithm feeds back one-step prediction of the global state estimation to each local sensor, and then after getting the track quality with multiple model of all sampling points based on the feedback information, each local sensor can be assign weights according to the TQMM of each sampling point, which improves the accuracy of equivalent observation of each local sensor at the fusion moment, as well as improves the performance of global state estimation.

The paper is organized as below sections: Section II demonstrates the concept of TQMM and local tracking. In Section III, the definitions of asynchronous fusion algorithm based on TQMM are given, then discusses the implementation details and advantages of AFTQMM. In Section IV, the simulation results show that the algorithm has better performance compared with other algorithms, and then Section V concludes whole paper.

II. TRACK QUALITY WITH MULTIPLE MODEL AND LOCAL TRACKING

A. TRACK QUALITY WITH MULTIPLE MODEL

In a distributed system, several networked sensors track the target to form a local track and transmit it to the fusion center for data registration, association and fusion. Distributed structure is widely used by engineers because of its good real-time and fusion performance. TQMM is based on a distributed fusion structure.

If the dynamic equation and measurement equation of multi-sensor networks system are:

$$X^l(k+1) = F^l(k) X^l(k) + w^l(k) \tag{1}$$

$$Z^l(k) = H^l(k) X^l(k) + V^l(k), \quad l = 1, 2, \cdots, NUM \tag{2}$$

In (1), $X^l(k)$ stands for the state vector of model l in k moment, and $X^l(k+1)$ stands for the state vector of model l in $k+1$ moment. $F^l(k)$ represents the one-step state transition matrix from moment k to $k+1$ under model l, and the system process noise $w^l(k)$ is gaussian white noise sequence. In (2), NUM is the amount of the filter models. $Z^l(k)$ represents the sensor's observed values of target state under model l. $H^l(k)$ is measurement matrix, and measurement noise $V^l(k)$ stands for gaussian white noise sequence.

Besides,

$$E\left[w^l(k)\right] = 0 \tag{3}$$

$$Cov\left(w^l(k), w^l(\tau)\right) = E\left[w^l(k) w^{l^T}(\tau)\right] = Q^l(k)\delta_{k\tau} \tag{4}$$

In (4), $Q^l(k)$ is a nonnegative definite matrix. Besides,

$$E\left[v^l(k)\right] = 0 \tag{5}$$

$$Cov\left(v^l(k), v^l(\tau)\right) = E\left[v^l(k) v^{l^T}(\tau)\right] = R^l(k)\delta_{k\tau} \tag{6}$$

In (6), $R^l(k)$ is the positive definite matrix.

System process noise and measurement noise are independent of each other, that is, to meet

$$Cov\left(w^l(k), v^l(\tau)\right) = 0 \quad \tau = 1, 2, \cdots, k, \cdots \tag{7}$$

Local track quality is very important, it determines the track quality of whole system, which means the final track quality of system after fusion will not be too high if the local track quality is poor [19].

Assuming that the one-step prediction and its covariance of the state of model $l(l = 1, 2, \cdots, NUM)$ in time k are $X^l(k+1|k)$ and $P^l(k+1|k)$ respectively, then the state's one-step prediction and covariance of model $l(l = 1, 2, \cdots, NUM)$ of sensor $i(i = 1, 2, \cdots, N)$ in $k+1$ time based on model l $(l = 1, 2, \cdots, NUM)$ state in the k time are

$$v^l(k+1) = Z(k+1) - H^l(k+1)\hat{X}^l(k+1|k) \tag{8}$$

$$S^l(k+1) = H^l(k+1) P^l(k+1|k) H^l(k+1)^T + R^l(k) \tag{9}$$

To describe our track quality, a standardized distance equation [17] could be defined as follow.

$$d^l(k+1) = v^l(k+1)^T S^l(k+1)^{-1} v^l(k+1) \tag{10}$$

The track quality of model l in time $k+1$ is

$$U^l(k+1) = \alpha U^l(k) + (1-\alpha) d^l(k+1) \tag{11}$$

In equations, the value of U represents our track quality. Obviously, the smaller U is, the better track quality is. Here, α is a historical power factor with the range from 0 to 1, and $\alpha = 1/5$ in follow simulation.

When $k+1 = 4$, the track quality of sensor i in model l is

$$U^l(4) = d^l(4) \tag{12}$$

Therefore, TQMM of sensor i in time $k+1$ is

$$U(k+1) = \sum_{j=1}^{N} U^l(k+1) u_{k+1}(l) \tag{13}$$

B. LOCAL TRACKING

To meet the target mobility and obtain more precise local estimate information, IMM (Interacting Multiple Model) filtering algorithm [27] can be adopted for the local tracking of multi-sensors. For reducing the computational complexity and improving the real-time performance of information processing, only three kinds of IMM filtering algorithms are applied. In this function, the system state vector $X = [x \;\; \dot{x} \;\; \ddot{x} \;\; y\dot{y} \;\; \ddot{y} \;\; z \;\; \dot{z} \;\; \ddot{z}]^T$, and the model prior probability $U = [1 \;\; 0 \;\; 0]$. The total output of the IMM filters is the weighted average [28] of the filtering results of multiple filters, and the weight is the model probability. Which model plays a leading role has a high probability, ranging from 0.9 to 1, while the other models have a low probability, less than 0.1 and close to 0. Besides, the transition probability of Markov model is

$$P_{ij} = \begin{bmatrix} 0.95 & 0.025 & 0.025 \\ 0.025 & 0.95 & 0.025 \\ 0.025 & 0.025 & 0.95 \end{bmatrix} \tag{14}$$

III. ASYNCHRONOUS FUSION ALGORITHM BASED ON TQMM

A. MAIN IDEA AND BASIC FLOW

The main idea of the AFTQMM algorithm includes: the observed filter prediction at the fusion moment is gotten from each sensors' local state estimated information, and obtained the predicted value of the fusion moment observation; then, using the weight fusion on same sensor's several prediction values to obtain each sensors' observed information at the fusion moment; finally, global fusion estimation output of asynchronous multi-sensor is achieved based on step by step filtering fusion process. The basic implementation process of the algorithm is shown in Figure 1.

B. ASYNCHRONOUS FUSION MODEL

According to the basic process in Figure 1, and if the data fusion period is T, the number of sensors used in this period is N. The basic fusion model of this asynchronous fusion algorithm can be given as shown in Figure 2.

C. STEPS OF ALGORITHM

As shown in Figure 1 and Figure 2, the algorithm AFTQMM includes four functional units: multi-model prediction, feedback function, weights fusion of each local sensor unit and step by step filtering fusion. The process of the algorithm can be shown below.

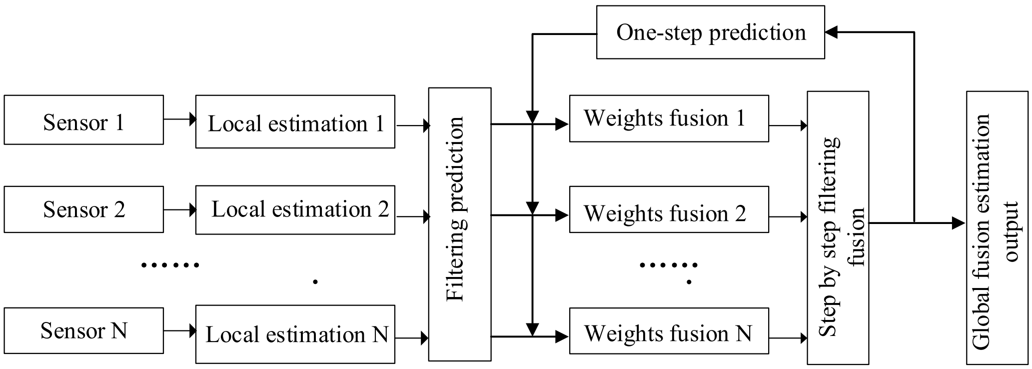

FIGURE 1. The basic process of asynchronous fusion algorithm based on TQMM.

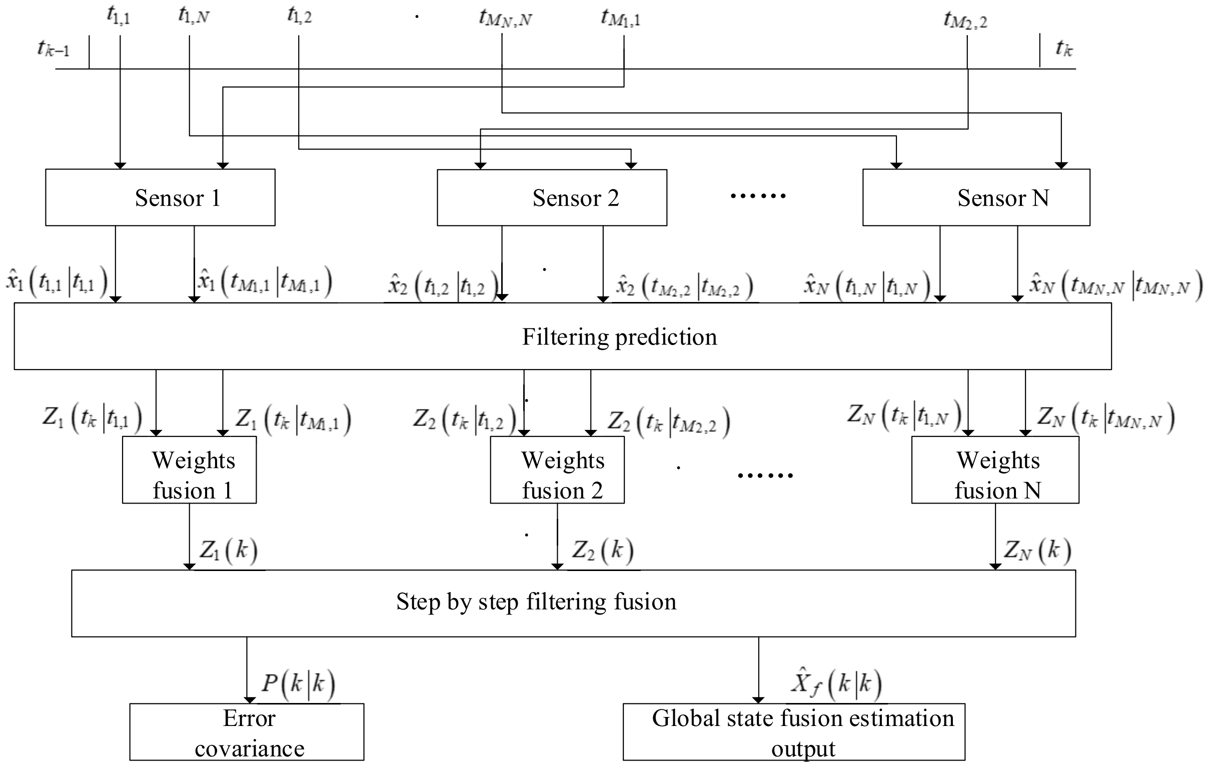

FIGURE 2. Asynchronous fusion model of AFTQMM.

Assuming the global state fusion estimation and the corresponding error covariance of the system are $X_f(k-1|k-1)$ and $P(k-1|k-1)$ in the fusion time moment t_{k-1} respectively. $N(N \geq 0)$ is the number of sensors with observed information in fusion period, and the observation value of each sensor $i\,(i = 1, 2, \cdots, N)$ is $M_i\,(M_i \geq 0)$. In Figure 2, the fusion model is established on the basis that each sensor has at least 2 sampling points in the fusion cycle, which means $M_i \geq 2$. However, due to the randomness of data provided by multiple sensors, various situations will occur in the fusion cycle $(t_{k-1}, t_k]$, which are mainly divided into two categories. One is $N = 0$, that is, the fusion center cannot obtain the continuous target information within a certain interval. The other is $N > 0$, according to the number of observations, M_i is divided into two parts, one is $M_i = 1$, the other is $M_i \geq 2$. There are different ways to optimize the fusion process for different situations.

When $N = 0$, one step prediction is made based on the state estimate value of the previous fusion time to obtain the state estimate of the current fusion time. However, in the case of $N = 0$ continuous existence, the information obtained by this method will reduce the effectiveness of the fusion algorithm due to the accumulation of prediction errors. With the improvement of sensor performance, sensors are usually used effectively to detect and track the target in an all-round way, to avoid the continuous occurrence in the fusion center $N = 0$ as far as possible. When $N > 0$, if $M_i = 1$, the weighted fusion process can be eliminated, directly predict and participate in step by step filtering fusion. While, if $M_i \geq 2$, the algorithm can operate according to the asynchronous fusion model described in figure 2. In addition, when some sensors have observation information at the time of fusion, the observation information can be directly used to participate in the step by step filtering fusion.

The number of multi sensors with observation information and the number of observations in fusion cycle $(t_{k-1}, t_k]$ are defined as N and $M_i (i = 1, 2, \cdots, N)$ respectively. In addition, the target state estimation and the corresponding covariance error of sensor i in observed time $t_{j,i} (j = 1, 2, \cdots, M_i)$ can be defined as $\hat{x}_i \left(t_{j,i}|t_{j,i}\right)$ and $p_i \left(t_{j,i}|t_{j,i}\right)$. The following is the detailed introduction to the process of obtaining the state estimation $\hat{X}_f (k|k)$ and error covariance $P (k|k)$ of the system track at the time t_k of fusion center.

1) MULTI-MODEL PREDICTION

Check for N. When $N \neq 0$, all sampling points $\left[t_{1,i}, t_{2,i}, \cdots, t_{M_i,i}\right]$ of the sensor i in fusion circle are searched, and then one step prediction is made based on three models to predict the information of each sampling pinot to the fusion time t_k. The process is as is described as follows. Calculate the time difference, that is

$$\Delta t_{j,i} = t_k - t_{j,i}, \quad j = 1, 2, \cdots, M_i \tag{15}$$

In (15), the local state estimation and the error covariance of each sensor in time $t_{j,i}$ are $\hat{x}_i \left(t_{j,i}|t_{j,i}\right)$ and $p_i \left(t_{j,i}|t_{j,i}\right)$. For time difference, the corresponding state transition matrix $F^l_{j,i} \left(t_{j,i}\right) (l = 1, 2, 3)$ could be gotten by the IMM filtering, and then the predictive value of observation could be got.

$$Z^l_i \left(t_k|t_{j,i}\right) = H^l_i (k) \cdot F^l_{j,i} \left(t_{j,i}\right) \cdot \hat{x}_i \left(t_{j,i}|t_{j,i}\right), \quad l = 1, 2, 3 \tag{16}$$

In (16), $H^l_i (k)$ is the observation matrix of sensor i's model l. The multi-model prediction could be got based on the observed prediction $Z^l_i \left(t_k|t_{j,i}\right)$ of model l

$$Z_i \left(t_k|t_{j,i}\right) = \sum\nolimits_{i=1}^{3} Z^l_i \left(t_k|t_{j,i}\right) \cdot u^i_l(k) \tag{17}$$

In (17), $u^i_l(k)$ is defined as the probability of sensor i's model l at time t_k.

2) FEEDBACK ELEMENT

Operate one step prediction for the system state estimation at time t_{k-1}. The state vector and its covariance are shown as follow equations respectively.

$$\hat{X}_f (k|k-1) = \sum\nolimits_{l=1}^{3} \hat{X}^l_f (k|k-1) \cdot u^l (k) \tag{18}$$

$$\begin{aligned} P (k|k-1) = \sum\nolimits_{l=1}^{3} u^l (k) \cdot \Big\{ & P^l (k|k-1) \\ & + \left[\hat{X}^l_f (k|k-1) - \hat{X}_f (k|k-1)\right] \\ & \times \Big[\hat{X}^l_f (k|k-1) \\ & - \hat{X}_f (k|k-1)\Big]' \Big\} \end{aligned} \tag{19}$$

In (18) and (19), $u_l(k)$ represents the probability of the system's model l at time t_k. $\hat{X}^l_f (k|k-1)$ and $P^l (k|k-1)$ represent the one step prediction and error covariance of system track at time t_{k-1} based on model l respectively. The expression is as follows.

$$\hat{X}^l_f (k|k-1) = F^l(k-1)\hat{X}^l_f (k-1|k-1) \tag{20}$$

$$\begin{aligned} P^l (k|k-1) = {} & F^l (k-1) P^l (k-1|k-1) F^l (k-1)^T \\ & + Q^l(k-1) \end{aligned} \tag{21}$$

In equations, the $F^l (k-1)$, $X^l_f (k-1|k-1)$ and $P^l (k-1|k-1)$ represent the state transition matrix, state estimation and error covariance of system track's model l at time t_{k-1} respectively, and $Q^l (k-1)$ is a nonnegative definite matrix.

3) WEIGHTs FUSION OF LOCAL SENSORS

In the feedback function, the state at the previous moment of the fusion center can got one step prediction and fed back to each local sensor. The predicted value of local sensor state can be obtained. Based on the TQMM of the predicted state value of the system, the weight of each predicted state is further determined to realize the weights fusion. The process of determining the weight factor is shown in figure 3.

In the fusion cycle $(t_{k-1}, t_k]$, the innovation and covariance of sensor $i\,(i = 1, 2, \cdots, N)$'s observation based on system track one step prediction from the time $t_{j,i}\,(j = 1, 2, \cdots, M_i)$ to the fusion time t_k are as follows.

$$v^l_{i,j} (k) = z_i(t_k|t_{j,i}) - H^l_i (k)\, \hat{X}_f (k\,|k-1) \tag{22}$$

$$S^l_{i,j} (k) = H^l (k)\, P (k\,|k-1)\, H^l_i (k)^T + R^l (k-1) \tag{23}$$

According to the principle in section II, the TQMM of each sensor i's sampling point j be defined as $U_{i,j} (k)$.The measurement degree of TQMM of the sensor i's sampling point j could be obtained.

$$h^j_i (k) = \exp\{-U_{i,j} (k)\} \tag{24}$$

The corresponding weight is

$$\omega^i_j (k) = h^j_i (k) \Big/ \sum_{j}^{M_i} h^j_i (k) \tag{25}$$

Finally, by weights fusion, the equivalent observation data of the sensor i at time t_k are obtained as follows.

$$Z_i(k) = \sum_{j=1}^{M_i} w^j_i (k)\, Z_i(t_k|t_{j,i}) \tag{26}$$

4) STEP BY STEP FILTERING FUSION

Through the above steps, we can get the observation information $Z_1 (k), Z_2 (k), \cdots, Z_N(k)$ of N sensors in fusion time t_k. Using the idea of step by step filtering fusion from document [15], the global state fusion estimation and the

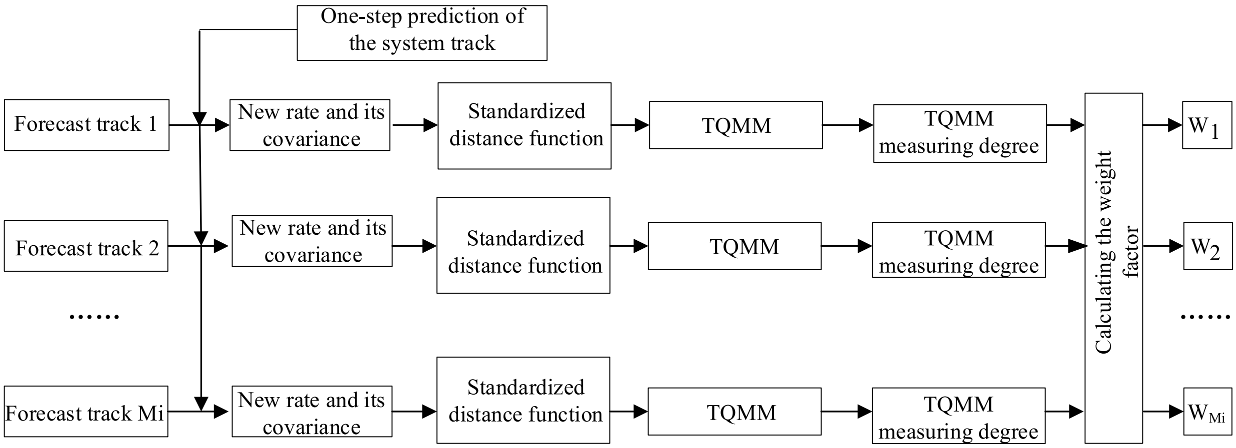

FIGURE 3. The process of determining the weight factor.

corresponding error covariance at the fusion time can be obtained.

$$\begin{cases} \hat{X}_f(k|k) = \hat{X}_N(k|k) \\ P(k|k) = P_N(k|k) \end{cases} \tag{27}$$

Known, the equations $\hat{X}_f(k|k-1) = F(k-1)\hat{X}_f(k-1|k-1)$ and $P(k|k-1) = F(k-1)P(k-1|k-1)F(k-1)^T + GQG^T$ are true, the specific expression of (27) is as follows. When $N = 1$, let's make $\hat{X}_1(k|k-1) = \hat{X}_f(k|k-1)$ and $P_1(k|k-1) = P(k|k-1)$, then

$$\hat{X}_1(k|k) = F(k-1)\hat{X}_f(k-1|k-1) + K_1(k)\left[Z_1(k) - H\hat{X}_1(k|k-1)\right] \tag{28}$$

$$P_1(k|k) = [I - K_1(k)H(k)]P_1(k|k-1) \tag{29}$$

When $N \geq 2$,

$$\hat{X}_N(k|k) = F(k-1)\hat{X}_f(k-1|k-1) + \times \sum_{i=1}^{N}\left\{K_i(k)\left[Z_i(k) - H(k)\hat{X}_i(k|k-1)\right]\right\} \tag{30}$$

$$P_N(k|k) = \left\{\prod_{i=1}^{N}[I - K_i(k)H(k)]\right\}P_1(k|k-1) \tag{31}$$

In above equations, $K_i(k)$ is the filtering gain matrix of sensor i $(i = 1, 2, \cdots, N)$, and its calculating formula is as follows:

$$K_i(k) = P_i(k|k-1)H(k)^T \times \left[H(k)P_i(k|k-1)H(k)^T + R_i(k)\right]^{-1} \tag{32}$$

When $i = 2, \cdots, N$, we can get $\hat{X}_i(k|k-1) = \hat{X}_{i-1}(k|k)$ and $P_i(k|k-1) = P_{i-1}(k|k)$.

IV. SIMULATION EXPERIMENT

A. SIMULATION ENVIRONMENT

In the simulation verification, Root Mean Square Error (RMSE) and Trace of Error Covariance Matrix (TECM) [16], [23], [27] were selected as target tracking performance indicators for comparative analysis. Assuming that six sensors fixed on the same platform make asynchronous observation on the same target, due to the limitations of the sensors themselves and the communication delay between local nodes and the fusion center, the sampling time of the track data obtained by the fusion center may deviate from the fixed sampling period.

Therefore, the offset Δt with respect to the fixed sampling period in the actual sampling period of the sensor should be considered. Moreover, at some sampling moments, there is no sampling information because the target escapes from the tracking area of the corresponding sensor. In this scenario, the track fusion problem is a typical asynchronous fusion problem of the second kind. Each sensor associates the observed data, forms the target track, and reports the resulting track and the associated observed value to the fusion center. However, because the measurement errors and observation coordinates of each sensor are not uniform, data from each sensor needs to be preprocessed before fusion, which usually includes data space alignment, gross error rejection and so on. 600 monte carlo simulation experiments were conducted ($M = 600$). The expressions of RMSE and TECM are as follows.

$$RMSE = \sqrt{\frac{\sum_{n=1}^{M}\left((x-\hat{x}^n)^2 + (y-\hat{y}^n)^2 + (z-\hat{z}^n)^2\right)}{M}} \tag{33}$$

$$TECM = \frac{\left(\sum_{n=1}^{M} trace(P^n)\right)}{M} \tag{34}$$

In (33) and (34), $\hat{x}^n$, $\hat{y}^n$, $\hat{z}^n$ are the position information of the n^{th} simulation fusion track, and P^n is the error covariant matrix of the n^{th} simulation tracking.

B. RESULTS AND ANALYSIS

The algorithm performance is considered from three aspects: first, examining influence of the number of sensors on AFTQMM's track performance; then, checking influence of

TABLE 1. Parameter setting of example 1.

Sensors	Sampling period		0.2s, 0.5s, 0.8s, 1.0s, 1.2s, 1.5s
	Observation precisions (x, y, z)		50.23m, 51.15m, 55.57m, 50.28m, 57.69m, 51.59m
	Positions		(2800m, 0m, 0m), (0m, 500m, 260m), (0m, 100m, 1800m), (50m, 100m, 500m), (50m, 100m, 2800m), (100m, 500m, 800m)
Target	Initial position		(-6700m，3900m，-5800m)
	Initial speed		-545m/s
	Motion state	0-120s	acceleration of 0.7m /s^2 in the X-axis and 1.1m /s^2 in the Y-axis
	Total time		120s

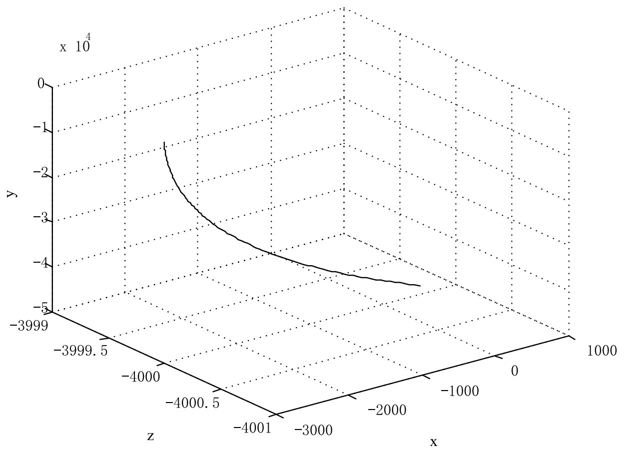

FIGURE 4. The flight path of the maneuvering target.

fusion cycle on AFTQMM's performance; finally, proving the limitation of SSPFA, applicability of TFASP and the optimal solution of AFTQMM on second problem of asynchronous fusion by the appropriate sampling period and the number of sensors.

The performance of AFTQMM is tested in three aspects. First, the effect of sensor number on tracking performance of AFTQMM is tested. Secondly, the influence of fusion period on the performance of AFTQMM is examined. Finally, it proves the applicability of TFASP to these problems and the optimization of AFTQMM to solve these problems.

1) EXAMPLE 1

The sampling periods of six target detection sensors are 0.2s, 0.5s, 0.8s, 1.0s, 1.2s and 1.5s. The offset of the fixed sampling period Δt obeys the uniform distribution on [0, 1/1000]. The parameter setting of Example 1 is shown in Table 1, and the flight path diagram is shown in Figure 4.

a) A system with three, four, five and six sensors were used to track the maneuvering target at same time. The fusion period of the four systems (the fusion period of four systems is 1.0s) was used to examine the influence of the number of sensors on the tracking performance of AFTQMM algorithm

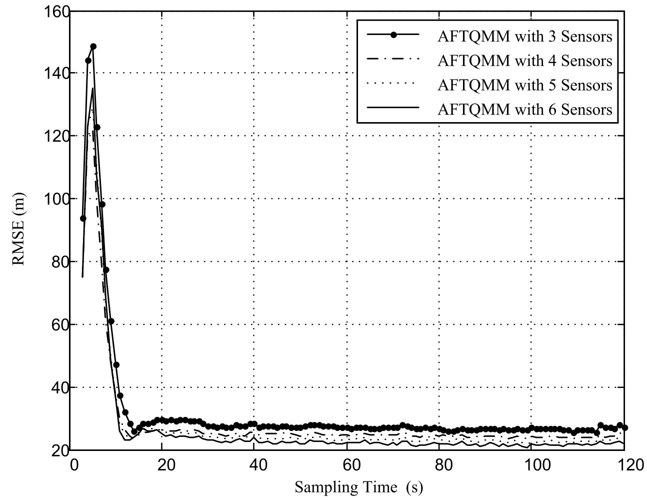

FIGURE 5. RMSE versus sampling time for different sensor number.

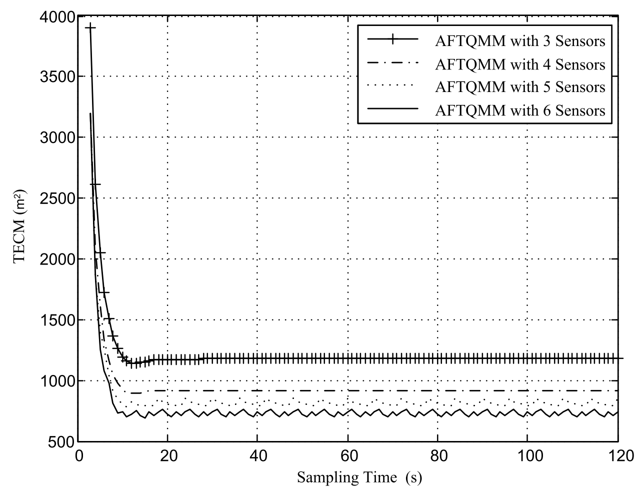

FIGURE 6. TECM versus sampling time for different sensor number.

The Figure 5, Figure 6 and Table 2 prove that with the increasing of the number of sensors, the RMSE and TECM curves of AFTQMM algorithm decrease, and the tracking performance of the system gradually improves. The number of sensors has a great influence on the tracking accuracy of the system. The more sensors in the system, the better the performance. But as the number of sensors increased further, the improvement became smaller and smaller.

b) Examine the influence of fusion cycle on algorithm performance. We track the maneuvering target by systems with fusion periods T of 0.5, 1.0, 1.5, 2.0 and 2.5 simultaneously (five systems are all six-sensors system).

When tracking the maneuvering target, with the increasing of fusion cycle, the RMSE (in Figure 7 and table 3) and TECM (in Figure 8 and table 3) curves keep rising, and the track performance of the system reduces gradually. However, after the fusion period increases to $T = 1.5$s, the system fusion accuracy doesn't decrease obviously.

c) Based on the conclusion of experiments above, with consideration of the systematic complexity, the operating rate and

TABLE 2. The relationship between RMSE, TECM average value and the number of sensors.

	Local track	AFTQMM (3 Sensors)	AFTQMM (4 Sensors)	AFTQMM (5 Sensors)	AFTQMM (6 Sensors)
RMSE average value (m)	52.06	32.25	28.51	27.75	26.76
TECM average value (m^2)	4146	1227	960	852	769

TABLE 3. The relationship between RMSE, TECM average value and the fusion period.

	Local track	AFTQMM (T=0.5)	AFTQMM (T=1.0)	AFTQMM (T=1.5)	AFTQMM (T=2.0)	AFTQMM (T=2.5)
RMSE average value(m)	52.03	25.62	29.66	33.61	34.84	35.65
TECM average value(m^2)	4158	777	829	923	1039	1126

TABLE 4. The comparison of RMSE, TECM average values of three fusion algorithms.

	Local track	SSPFA	TFASP	AFTQMM
RMSE average value (m)	52.05	34.02	30.93	27.75
TECM average value (m^2)	4146	2989	3107	852

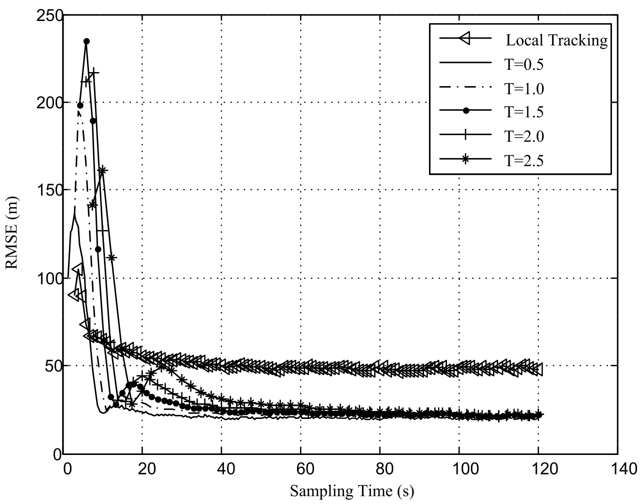

FIGURE 7. RMSE versus sampling time for different fusion period.

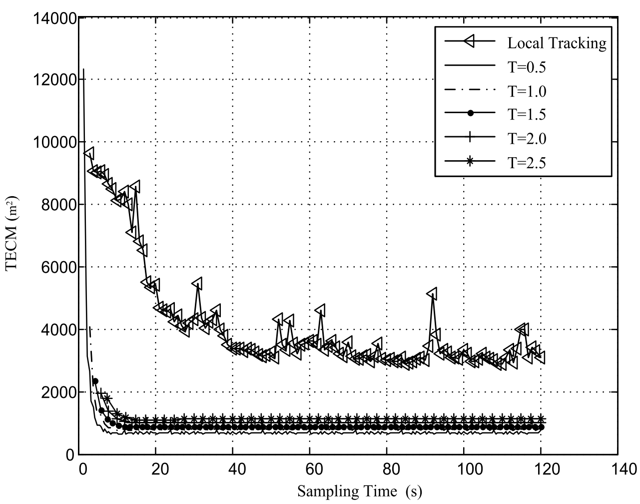

FIGURE 8. TECM versus sampling time for different fusion period.

the track performance, five-sensor system with fusion period $T = 1.0$s is applied to track the maneuvering target and verify the performance of SSPFA, TFASP and AFTQMM.

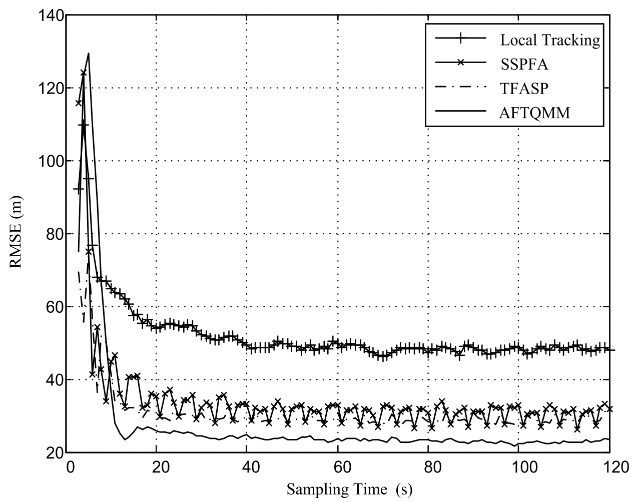

FIGURE 9. The comparison of RMSE of three fusion algorithms.

Based on Figure 9 and Table 4, RMSE curve of SSPFA algorithm is below the local track RMSE curve when five-sensor system tracks the maneuvering target. From the whole tracking, the track accuracy of SSPFA is higher than that of the local track based on RMSE average characterization; while, the RMSE curve of the former fluctuates, and the algorithm does not converge. Besides, the RMSE curves of AFTQMM and TFASP are both lower than that of local track and SSPFA. Compared with the local track, the track accuracies of AFTQMM and TFASP are increase by 46.69% and 40.58%. And the track accuracy of AFTQMM is obviously higher than that of TFASP algorithm, with the track accuracy increasing by 10.28%.

Figure 10 and Table 4 show, when tracking the maneuvering target, the TECM curve of SSPFA algorithm fluctuates up and down with local tracking TECM curve as the center and does not converge. Except for the initial tracking time, the TECM curve of TFASP algorithm almost coincides with the TECM curve of local tracking, and the tracking accuracy is not significantly improved. But the TECM curves of

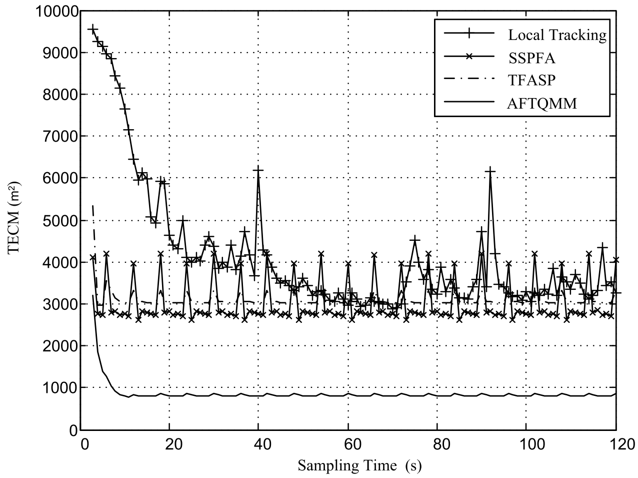

FIGURE 10. The comparison of TECM of three fusion algorithms.

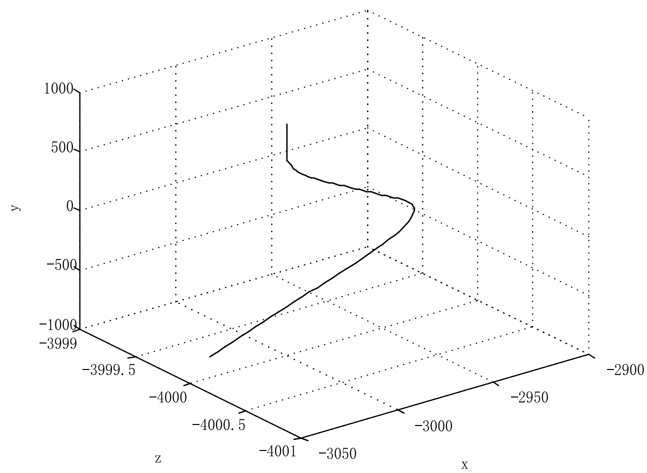

FIGURE 11. The flight path of the maneuvering target.

TABLE 5. Parameter setting of Example 2.

Sensors	Sampling period		0.2s, 0.5s, 0.8s, 1.0s, 1.2s, 1.5s
	Observation precisions (x, y, z)		50.23m, 51.15m, 55.57m, 50.28m, 57.69m, 51.59m
	Positions		(2800m, 0m, 0m), (0m, 500m, 0m), (0m, 0m, 1800m), (50m, 100m, 500m), (50m, 100m, 2800m), (100m, 500m, 800m)
Target	Initial position		(-3000m，1000m，-4000m)
	Initial speed		100m/s
	Motion state	0-20s	100m/s
		20-40s	at a turn rate of 0.157rad/s
		40-60s	constant speed
		60-80s	at a turn rate of -0.157rad/s
		80-120s	constant speed
	Total time		120s

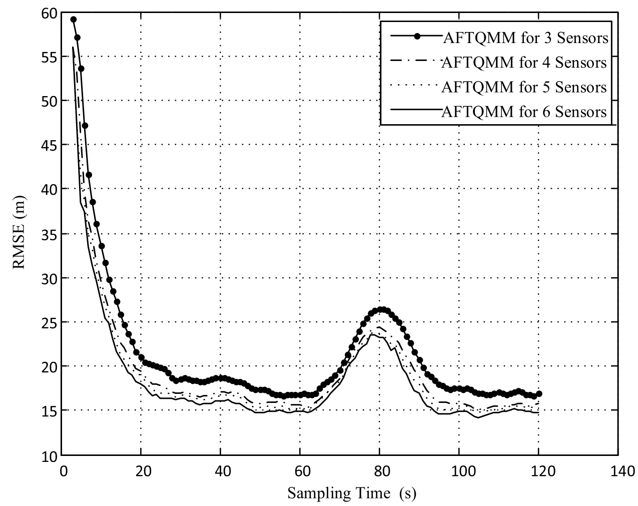

FIGURE 12. RMSE versus sampling time for different sensor number.

AFTQMM are completely below that of local track, SSPFA and TFASP, which can improve the track accuracy.

2) EXAMPLE 2

The scenario setup of Example 2 is similar to Example 1, its parameter setting is shown in Table 5. The target flies a constant speed in 0-20s, performs a turn maneuver at a turn rate of 0.157rad/s in 20-40s, then flies at a constant speed in 40-60s, performs a turn maneuver at a turn rate of -0.157rad/s in 60-80s, and performs a constant speed in 80-120s. The total flight time of the target is 120s. The flight path diagram is shown in Figure 11.

a) A system with three, four, five and six sensors were used to track the maneuvering target at same time. The fusion period of the four systems (the fusion period of four systems is 1.0s) was used to examine the influence of the number of sensors on the tracking performance of AFTQMM algorithm.

The Figure 12, Figure 13 and Table 2 prove that with the increasing of the number of sensors, the RMSE and TECM curves of AFTQMM algorithm decrease, and the tracking performance of the system gradually improves. However, after the number of sensors is greater than 5, the fusion of the system is not significantly improved. In the engineering application, the relationship between tracking performance and system complexity should be considered comprehensively, and an appropriate number of sensors should be selected to achieve high tracking accuracy, enable real-time processing of the fusion center, and reduce the engineering cost as far as possible.

b) Examine the influence of fusion cycle on algorithm performance. We track the maneuvering target by systems with fusion periods T of 0.5, 1.0, 1.5, 2.0 and 2.5 simultaneously (five systems are all six-sensors system).

When tracking the maneuvering target, with the increasing of fusion cycle, the RMSE (in Figure 14 and Table 7) and TECM (in Figure 15 and Table 7) curves keep rising, and the track performance of the system reduces gradually.

However, after the fusion period increases to $T = 1.5$s, the system fusion accuracy doesn't decrease obviously. In engineering application, with consideration of the relationship between the track performance and the computation speed, the appropriate number of sensors can achieve the

TABLE 6. The relationship between RMSE, TECM average value and the number of sensors.

	Local track	AFTQMM (3 Sensors)	AFTQMM (4 Sensors)	AFTQMM (5 Sensors)	AFTQMM (6 Sensors)
RMSE average value (m)	51.08	21.49	19.57	18.94	18.34
TECM average value (m^2)	4631	691	535	478	436

TABLE 7. The relationship between RMSE average value and the fusion period in AFTQMM.

	Local track	AFTQMM (T=0.5)	AFTQMM (T=1.0)	AFTQMM (T=1.5)	AFTQMM (T=2.0)	AFTQMM (T=2.5)
RMSE average value(m)	51.09	17.14	18.59	19.43	19.44	19.18
TECM average value(m^2)	4695	484	502	562	652	725

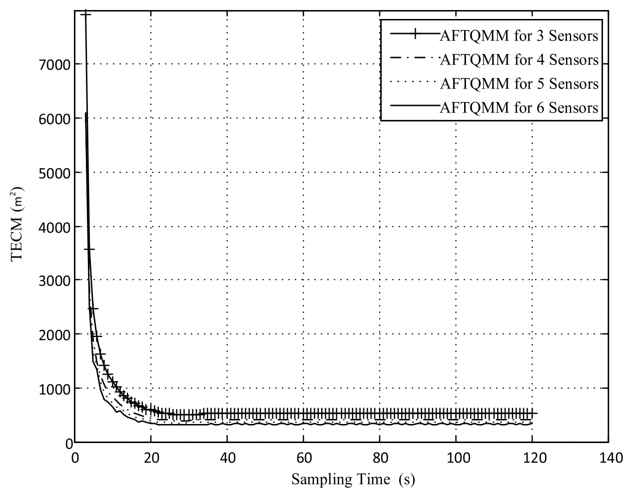

FIGURE 13. TECM versus sampling time for different sensor number.

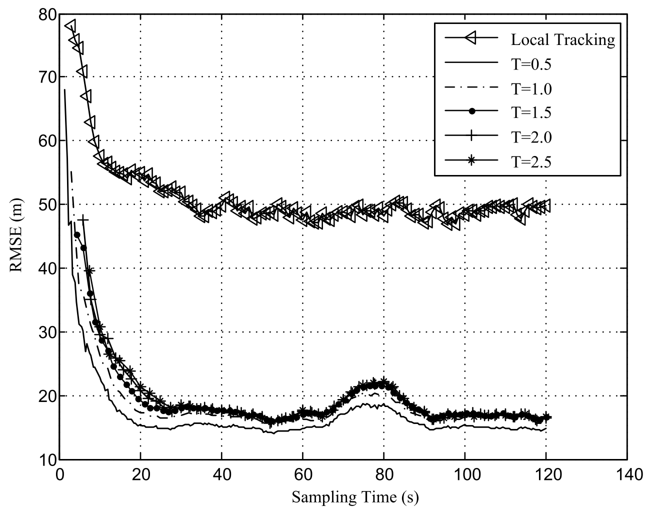

FIGURE 14. RMSE versus sampling time for different fusion period.

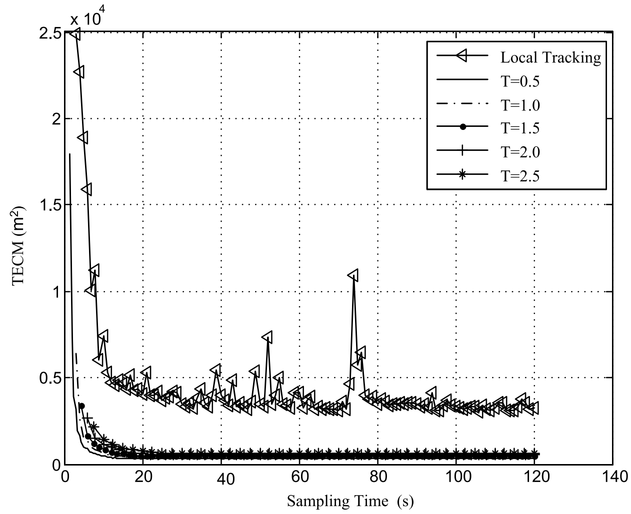

FIGURE 15. TECM versus sampling time for different fusion period.

better track accuracy without influencing the system real-time capability. c) Based on the conclusion of experiments above, with consideration of the systematic complexity, the operating rate and the track performance, five-sensor system with fusion period $T = 1.0$s is applied to track the maneuvering target and verify the performance of SSPFA, TFASP and AFTQMM.

Based on Figure 16 and Table 8, RMSE curve of SSPFA algorithm is below the local track RMSE curve when five-sensor system tracks the maneuvering target. From the whole tracking, the track accuracy of SSPFA is higher than that of the local track based on RMSE average characterization; while, the RMSE curve of the former fluctuates, and the algorithm does not converge. Besides, the RMSE curves of AFTQMM and TFASP are both lower than that of local track and SSPFA. Compared with the local track, the track accuracies of AFTQMM and TFASP are increase by 62.92% and 57.01%. And the track accuracy of AFTQMM is obviously higher than that of TFASP algorithm, with the track accuracy increasing by 13.76%.

Figure 12 shows that when the target starts the second maneuver, the RMSE curve of ATFQMM will fluctuate within a narrow range, also, the same fluctuation can be seen in figure 14 and figure 16. And then, the RMSE curve will come back to the steady state following the continuous

TABLE 8. The comparison of the RMSE average values of three fusion algorithms.

	Local track	SSPFA	TFASP	AFTQMM
RMSE average value (m)	51.08	32.24	21.96	18.94
TECM average value (m^2)	4631	6024	608	478

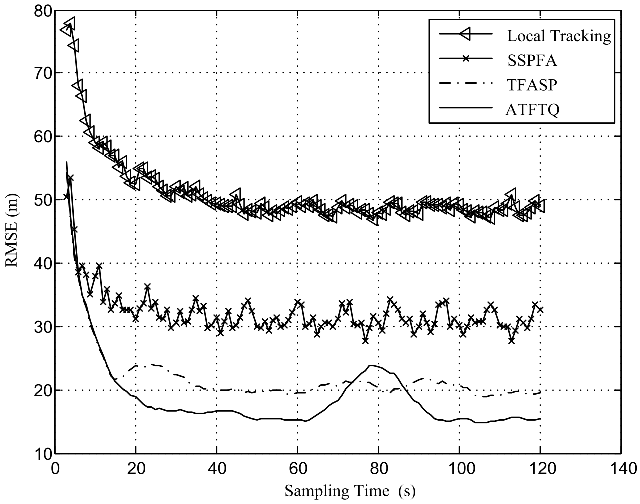

FIGURE 16. The comparison of the RMSE of three fusion algorithms.

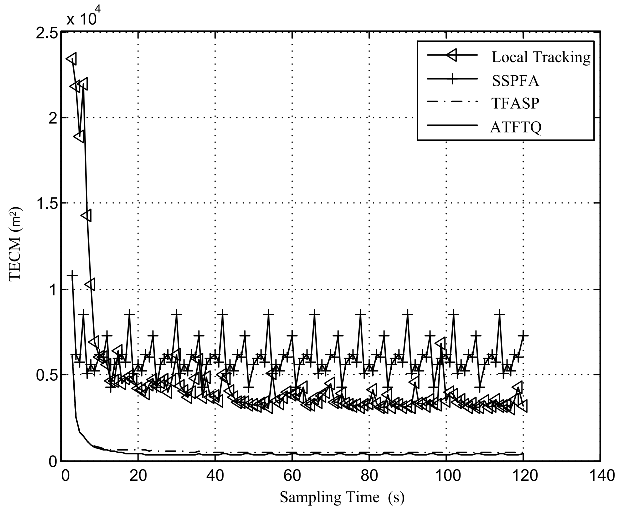

FIGURE 17. The comparison of the TECM of three fusion algorithms.

maneuvering. Researches show that the curve's fluctuation is resulted from the prediction error increasing of target maneuvering. The error of one-step prediction is decided by approximation level of the state transition matrix to the actual motion. The weighted array of multi models can approach to the state transition matrix of any maneuvering target, to get the smaller prediction error. But, in order to adapt to the target maneuver, the probability of each model needs a short time for corresponding adjustment. Firstly, when using IMM filtering algorithm for local nodes tracking, three models need a short adjustment for the target maneuvering. Secondly, the probabilities of the three motion nodes, which still need an adjustment. Thirdly, for adapting the target maneuvering, feedback element also needs a short adjustment in the multi-model prediction for system state estimation. The model probability adjustment will be performed at each sampling point, and the RMSE curve can be stable over several sampling periods. Besides, the model probability adjustment is determined by the model possibility, and the model possibility is determined by the one-step prediction error and its covariance. The whole multi-model system is a negative feedback system. When the prediction error increases, the system will adjust the model possibility by predicting error and its covariance, then adjust the model's probability to help the state transition matrix (after the weighted array) approach to the maneuvering state. Therefore, the next-time forecast error will decrease. So, Fig. 9 shows that the amplitude and duration of RMSE curve jitter have little influence on the performance of the algorithm.

Figure 17 and TABLE 8 show, when tracking the maneuvering target, the TECM curve of SSPFA is almost completely above the TECM curve of local track. The phenomenon further proves the drawbacks of SSPFA in solving the second kind of asynchronous fusion. But the TECM curves of AFTQMM and TFASP are completely below that of local track, which can improve the track accuracy.

The experiment above examines the relationship among the AFTQMM performance, fusion cycle and the number of sensors. Besides, it also proves two things. Firstly, AFTQMM and TFASP can solve the second kind of asynchronous fusion which cannot be solved by SSPFA. Secondly, the performance of AFTQMM is better than that of TFASP. Reasons are as follows:

First, in fusion period, equivalent observation values are obtained in different ways. The difficulty of asynchronous fusion lies in how to get the high-precision equivalent observation of fusion moment based on the sampling points of non-fusion moment in fusion cycle. The accuracy of equivalent observations is determined by the accuracy of the the most of the sensor's observation, SSPFA only adopts the observation's error of the local sensors at fusion moment increases, then, the track accuracy of the whole system decreases.

But, ATFTQMM assigns weight through TQMM, which is synthetically decided by sampling accuracy and prediction error. In this way, the whole system forms a negative feedback mechanism, so high precision sampling point achieves bigger weight, and vice versa. Therefore, this algorithm possesses higher fusion accuracy.

Second, the data processing methods of the fusion center are different. SSPFA performs the weight fusion of the two predictions at fusion time accordingly under the condition of minimum trace of the error covariance matrix. The sequential approach of SSPFA causes root-mean-square error fluctuating on local estimated error curves of each sensor.

While, TFASP updates state estimation ways for step by step filtering fusion, by the information obtained by weighted combination of each sensor. And, AFTQMM also gets the global estimation by step by step filtering fusion. However, AFTQMM increases the feedback mechanism of local nodes in the fusion center, assists local nodes for weight assignment, gets more accurate equivalent observations, and then improves the fusion effect.

V. CONCLUSION

This paper studies the problems of the asynchronous track fusion under the condition of irregular sampling interval based on multi-sensor networks. It sets a model for this kind of asynchronous track fusion and puts forward a distributed asynchronous track fusion algorithm with information feedback. To improve the stability of the system and the accuracy of equivalent observations, this paper introduces the feedback mechanism from fusion center to local nodes, which effectively upgrades the system performance.

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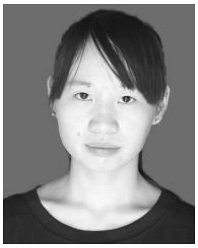

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