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Asynchronous Data Fusion With Parallel Filtering Frame

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***Abstract*—This paper studies the design of data fusion algorithm for asynchronous system with integer times sampling. Firstly, the multisensor asynchronous samplings is mapped to the basic axis, accordingly a sampling sequence of single sensor can be taken. Secondly, aiming at the sensor with the densest sampling points, the modified parallel filtering is given. Afterwards, the sequential filtering fusion method is introduced to deal with the case that there are multiple mapped measurements at some sampling point. Finally, a novel parallel filtering fusion algorithm for asynchronous system with integer times sampling is proposed. Besides, a judgment scheme to distinguish measurement number at every sampling point in the fusion period is also designed. One simple computer numerical value simulation is demonstrated to validate the effectiveness of the judgment scheme and the proposed asynchronous fusion algorithm.**

***Index Terms*—data fusion; asynchronous system; integer times sampling; parallel filtering; sequential filtering**

I. INTRODUCTION

In recent years, multisensor data fusion technology is paid great attention in many military and civil fields, and is extensively applied. At present, a lot of data fusion algorithms to different application backgrounds and constraints are presented [1-11]. For the research of classical data fusion, the synchronous multisensor system, in which every sensor has common sampling rate and sampling time is uniform, is none of main objects. But, in the practical system, these sensors in the multisensor system have often different sampling rates and sampling points because of different task requirement and different kinds of sensors. As a result, it is interesting to study asynchronous data fusion with different sampling rates, and has important theoretical sense and extensive application scene.

Up to now, some useful data fusion algorithms for asynchronous system under the centralized frame have been presented [2,6,7,8,10,11]. The work in [2] is to firstly discretize the continuous system, secondly establish the relative measurement to current state by use of the relation between the states of local points and the fusion center, and afterwards use the centralized fusion to estimate the state of the target. But, this algorithm only adapts the case that every sensor only has one measurement in the fusion period, and the more complex case cannot be dealt with. An interesting work is also done in [6] by combing wavelet with Kalman filter. It can treat with the noise-reduction effectively but the multisensor case cannot be solved. In [7], the multisensor multiscale fusion was considered; nevertheless the given algorithm is complex. In addition, the design of data fusion algorithm for multirate sampling system were researched in [10,11]. Basically, they both adopt the re-modeling idea to the state of sampling points in the fusion period. Thereby, these two algorithms are suboptimal in the sensor of linear minimum mean square error (LMMSE).

Aiming at the above-mentioned problems, this paper takes a kind of multisensor dynamic system with different sampling rates, and introduces the parallel filtering and sequential filtering to solve asynchronous data fusion with integer times sampling. Accordingly, a novel optimal asynchronous data fusion algorithm is proposed and the running steps are listed in this paper. Its main structure includes four aspects such as measurement mapping, parallel filtering, judgment of measurement number, and sequential filtering.

The rest of this paper is organized as follows. In Section II, it describes the multisensor system with integer times sampling and problem formulation. Section III proposes a novel parallel filtering fusion algorithm. Computer simulation is done in Section IV. Finally, we conclude in Section V.

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II. PROBLEM FORMULATION

A. System Description

A kind of multisensor system which is composed of N sensors is considered. Every sensor observes the target state with different sampling rate, and the measurement is

$$z_i(k_i+1)=\boldsymbol{H}_i(k_i+1)\boldsymbol{x}(k_i+1)+\boldsymbol{v}_i(k_i+1) \quad (1)$$

where $i=1,2\cdots,N$, $\boldsymbol{H}_i(k_i+1)$ is the measurement matrix. The corresponding state equation of i sensor is

$$\boldsymbol{x}(k_i+1)=\boldsymbol{\Phi}(k_i+1,k_i)\boldsymbol{x}(k_i)+\boldsymbol{w}(k_i) \quad (2)$$

where the sampling period of i sensor is T_i which a is an integer, and

$$T_j / T_{j+1} = L, \quad j=1,2,\cdots,N-1; \ L=1,2,\cdots \quad (3)$$

where L is also an integer. Suppose that the sampling period for which the sampling period is the biggest among them is the fusion period, then

$$T=T_1 \quad (4)$$

So, there are M_i measurements for sensor i in a fusion period, then

$$T=M_iT_i \quad (5)$$

It easily knows that the sampling periods for all of sensors have the integer L times relation from Eq. (3) and Eq. (4).

Figure.1 shows the multisensor system with $L=2$. $kM_i+l_i \quad (i=1,2,\cdots,N;\ l_i=1,2,\cdots,M_i)$ is l_i th sampling time of sensor i in $(k+1)$ th fusion period, and

$$M_i=L^{i-1}, \quad (i=1,2,\cdots,N) \quad (6)$$

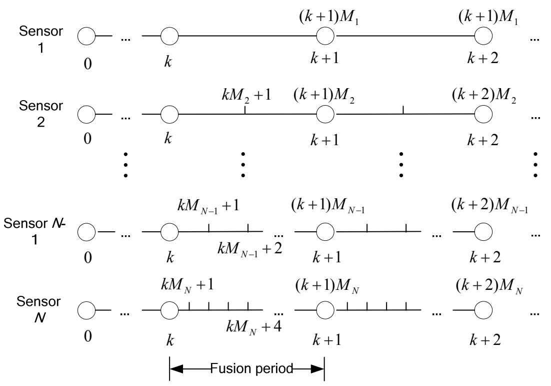

Figure.1 The sampling of multisensor system with $L=2$

Then, the dynamic given by Eq.(1) and (2) can be

$$\boldsymbol{z}_i(kM_i+l_i)=\boldsymbol{H}_i(kM_i+l_i)\boldsymbol{x}(kM_i+l_i)+\boldsymbol{v}_i(kM_i+l_i) \quad (7)$$

$$\boldsymbol{x}(kM_i+l_i)=\boldsymbol{\Phi}_i(kM_i+l_i,kM_i+l_i-1)\boldsymbol{x}(kM_i+l_i-1)+\boldsymbol{w}(kM_i+l_i-1) \quad (8)$$

where $i=1,2,\cdots,N; l_i=1,2,\cdots,M_i$,and $k\geq 0$ is a dis crete time variable. $\boldsymbol{x}(kM_i+l_i)\in R^{n\times 1}$ is state vector, $\boldsymbol{\Phi}_i(kM_i+l_i,kM_i+l_i-1)\in R^{n\times n}$ is state transfer mat rix of sensor i . Process noise $\boldsymbol{w}(kM_i+l_i-1)\in R^{n\times 1}$ is a Gaussian white noise sequence, and satisfies

$$\begin{cases} E\{\boldsymbol{w}(kM_i+l_i-1)\}=\boldsymbol{0} \\ E\{(\boldsymbol{w}(kM_i+l_i-1))(\boldsymbol{w}(jM_i+l_i-1))^T\} \\ \quad =\boldsymbol{Q}(kM_i+l_i-1)\delta_{kj} \end{cases} \quad (9)$$

where $k,j\geq 0;\ 0\leq l_i\leq M_i$.

$\boldsymbol{z}_i(kM_i+l_i)\in R^{p_i\times 1}$ is the measurement of sensor i to $\boldsymbol{x}_i(kM_i+l_i)$ at kM_i+l_i , $\boldsymbol{H}_i(kM_i+l_i)\in R^{p_i\times n}$ is the measurement matrix. Measurement noise $\boldsymbol{v}_i(kM_i+l_i)\in R^{p_i\times 1}$ is also a Gaussian white noise and its statistical property is

$$\begin{cases} E\{\boldsymbol{v}_i(kM_i+l_i)\}=0 \\ E\{\boldsymbol{v}_i(kM_i+l_i)\boldsymbol{v}_j^T(jM_j+l_i)\}=\boldsymbol{R}_i(kM_i+l_i)\delta_{ij} \end{cases} \quad (10)$$

where $k,\ j\geq 0; 0\leq l_i\leq M_i$. $\boldsymbol{R}_i(kM_i+l_i)$ is a positive matrix, and there are correlative between process noise and measurement noises, namely

$$E\{(\boldsymbol{w}(kM_i+l_i-1))(\boldsymbol{v}_i(jM_i+l_i-1))\} = \boldsymbol{S}_i(kM_i+l_i-1)\delta_{kj} \quad (11)$$

where $k,\ j\geq 0;\ 0\leq l_i\leq M_i$. The original state $\boldsymbol{x}(0)$ is a random vector and satisfies

$$E\{\boldsymbol{x}(0)\}=\boldsymbol{x}_0 \quad (12)$$

$$E\{[\boldsymbol{x}(0)-\boldsymbol{x}_0][\boldsymbol{x}(0)-\boldsymbol{x}_0]^T\}=\boldsymbol{P}_0 \quad (13)$$

B. Problem Formulation

In order to conveniently describe the proposed algorithm, it is necessary to transform the above-mentioned multisensor dynamic system to a single one. Based on the sampling time of fusion center, the sampling points of all of sensors can be mapped to this reference axis, see Figure.2. we easily know: firstly, there is one measurement at least at the sampling point in a fusion period after they are mapped. And, the measurement number at every sampling point is different basically. Secondly, in a fusion period there are all measurements from sensor N at every sampling point.

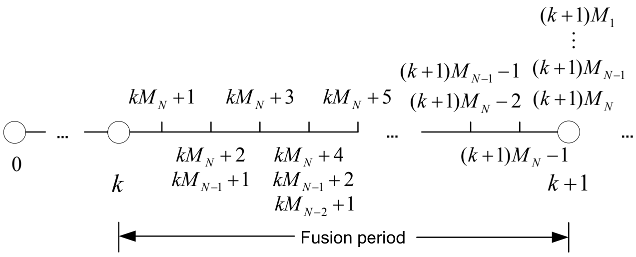

Figure.2 The mapped multisensory dynamic sampling system

Then, the basic idea of parallel filtering fusion algorithm with integer times sampling is as follows: the sampling points of all of sensors are mapped to the reference axis on the basis of sampling time of fusion center. Afterwards, the time axis of sensor N can be taken as basis and the parallel filtering algorithm can be performed. Especially, when the sampling point has multiple measurements, the sequential filtering fusion in [9] can be used. Finally, we can get the fusion estimate based on the global information for every sampling point $kM_N + l_N$ in the fusion period. In order to realize above-mentioned idea, the following problems must be solved: i) One is how to perform the parallel filtering algorithm based on sensor N . ii) The other is how to distinguish which sensor measurements every sampling time has in a fusion period. Next, the fusion algorithm is established in terms of solving above-mentioned two problems.

III. PARALLEL FITERING FUSION ALGORITHM WITH INTEGER TIMES SAMPLING

A. Parallel Filtering Fusion Algorithm

By considering i) this subsection presents the parallel filtering fusion algorithm in the case that there is only one measurement at every sampling point, namely only consider the measurement of sensor N .

From Eq.(7) and Eq.(8), state equation and measurement equation of sensor N are as follows:

$$\boldsymbol{x}(kM_N+l_N)=\boldsymbol{\Phi}_N\boldsymbol{x}(kM_N+l_N-1)+\boldsymbol{w}\ (kM_N+l_N-1) \tag{14}$$

$$\begin{aligned}\boldsymbol{z}_N(kM_N+l_N)=\boldsymbol{H}_N(kM_N+l_N)\boldsymbol{x}(kM_N+l_N)\\+\boldsymbol{v}_N(kM_N+l_N)\end{aligned} \tag{15}$$

So, one has the following theorem.

Theorem 1 According to (14) and (15), one can get the following new multisensor system

$$\boldsymbol{x}\big((k+1)M_N+l_N\big)=\boldsymbol{\Phi}_N^M\boldsymbol{x}(kM_N+l_N)+\boldsymbol{w}^*(kM_N+l_N) \tag{16}$$

$$\boldsymbol{z}_N(kM_N+l_N)=\boldsymbol{H}_N\boldsymbol{x}(kM_N+l_N)+\boldsymbol{v}_N(kM_N+l_N) \tag{17}$$

where

$$\boldsymbol{w}^*(kM_N+l_N)=\sum_{l=0}^{M-1}\boldsymbol{\Phi}_N^l\boldsymbol{w}\big[(k+1)M_N+l_N-l-1\big] \tag{18}$$

$$E\left\{\begin{pmatrix}\boldsymbol{w}^*(kM_N+l_N)\\ \boldsymbol{v}_N(kM_N+l_N)\end{pmatrix}\begin{pmatrix}\boldsymbol{w}^{*T}(jM_N+l_N),\boldsymbol{v}_N^T(jM_N+l_N)\end{pmatrix}\right\}=\begin{pmatrix}\boldsymbol{Q}_N^* & \boldsymbol{S}_N\\ \boldsymbol{S}_N^T & \boldsymbol{R}_N\end{pmatrix}\delta_{kj} \tag{19}$$

$$\boldsymbol{Q}_N^*=\sum_{l=0}^{M-1}\boldsymbol{\Phi}_N^l\boldsymbol{Q}_N\left(\boldsymbol{\Phi}_N^l\right)^T \tag{20}$$

and

$$\begin{cases}\boldsymbol{\Phi}_N=\boldsymbol{\Phi}_N(kM_N+l_N,kM_N+l_N-1)\\ \boldsymbol{H}_N=\boldsymbol{H}_N(kM_N+l_N)\end{cases} \tag{21}$$

$$\begin{cases}\boldsymbol{Q}_N=\boldsymbol{Q}(kM_N+l_N-1)\\ \boldsymbol{R}_N=\boldsymbol{R}_N(kM_N+l_N),\boldsymbol{S}_N=\boldsymbol{S}_N(kM_N+l_N)\end{cases} \tag{22}$$

■

Proof. The derivations of Eq. (16) to Eq. (22) can be finished easily.

In terms of (14), we have

$$\begin{aligned}
&\boldsymbol{x}\big((k+1)M_N+l_N\big)\\
&=\boldsymbol{\Phi}_N\cdot\boldsymbol{x}_N\big((k+1)M_N+l_N-1\big)+\boldsymbol{w}_N\big((k+1)M_N+l_N-1\big)\\
&=\boldsymbol{\Phi}_N\big\{\boldsymbol{\Phi}_N\cdot\boldsymbol{x}_N\big((k+1)M_N+\big)l_N-2\\
&\qquad+\boldsymbol{w}_N\big((k+1)M_N+l_N-2\big)\big\}+\boldsymbol{w}_N\big((k+1)M_N+l_N-1\big)\\
&=\boldsymbol{\Phi}_N^2\cdot\boldsymbol{x}_N\big((k+1)M+i-2\big)+\boldsymbol{\Phi}_N\cdot\boldsymbol{w}_N\big((k+1)M_N+l_N-2\big)\\
&\quad+\boldsymbol{w}_N\big((k+1)M_N+l_N-1\big)\\
&=\boldsymbol{\Phi}_N^2\cdot\big\{\boldsymbol{\Phi}_N\cdot\boldsymbol{x}_N\big((k+1)M_N+l_N-3\big)+\boldsymbol{w}_N\big((k+1)M_N+l_N-3\big)\big\}\\
&\quad+\sum_{l=0}^{1}\boldsymbol{\Phi}_N^l\cdot\boldsymbol{w}_N\big((k+1)M_N+l_N-l-1\big)\\
&=\boldsymbol{\Phi}_N^3\cdot\boldsymbol{x}_N\big((k+1)M_N+l_N-3\big)\\
&\qquad+\sum_{l=0}^{2}\boldsymbol{\Phi}_N^l\cdot\boldsymbol{w}_N\big((k+1)M_N+l_N-l-1\big)\\
&=\boldsymbol{\Phi}_N^3\cdot\big\{\boldsymbol{\Phi}_N\cdot\boldsymbol{x}_N\big((k+1)M_N+l_N-4\big)+\boldsymbol{w}_N\big((k+1)M_N+l_N-4\big)\big\}\\
&\qquad+\sum_{l=0}^{2}\boldsymbol{\Phi}_N^l\cdot\boldsymbol{w}_N\big((k+1)M_N+l_N-l-1\big)\\
&=\boldsymbol{\Phi}_N^4\cdot\boldsymbol{x}_N\big((k+1)M_N+l_N-4\big)+\boldsymbol{\Phi}_N^3\cdot\boldsymbol{w}_N\big((k+1)M_N+l_N-4\big)\\
&\qquad+\sum_{l=0}^{2}\boldsymbol{\Phi}_N^l\cdot\boldsymbol{w}_N\big((k+1)M_N+l_N-l-1\big)\\
&=\boldsymbol{\Phi}_N^4\cdot\boldsymbol{x}_N\big((k+1)M_N+l_N-4\big)\\
&\qquad+\sum_{l=0}^{3}\boldsymbol{\Phi}_N^l\cdot\boldsymbol{w}_N\big((k+1)M_N+l_N-l-1\big)\\
&=\ \cdots\ \cdots\\
&=\boldsymbol{\Phi}_N^M\cdot\boldsymbol{x}_N(kM+l_N)+\sum_{l=0}^{M-1}\boldsymbol{\Phi}_N^l\cdot\boldsymbol{w}_N\big((k+1)M_N+l_N-l-1\big)
\end{aligned} \tag{A.1}$$

So, one has

$$\boldsymbol{x}_N\left((k+1)M_N+l_N\right)=\boldsymbol{\Phi}_N^M\cdot\boldsymbol{x}_N(kM_N+l_N)+\boldsymbol{w}_N^*(kM_N+l_N) \tag{A.2}$$

$$\boldsymbol{z}_N(kM+l_N)=\boldsymbol{H}_N x_N(kM_N+l_N)+\boldsymbol{v}_N(kM_N+l_N) \tag{A.3}$$

where

$$\boldsymbol{w}_N^*(kM_N+l_N)=\sum_{l=0}^{M-1}\boldsymbol{\Phi}_N^l\cdot\boldsymbol{w}_N\left((k+1)M_N+l_N-l-1\right) \tag{A.4}$$

and

$$\begin{aligned}&E\left\{\boldsymbol{w}_N^*(kM_N+l_N)\cdot\left[\boldsymbol{w}_N^*(kM+l_N)\right]^T\right\}\\&=E\left\{\left[\sum_{l=0}^{M-1}\boldsymbol{\Phi}_N^l\cdot\boldsymbol{w}_N\left((k+1)M_N+l_N-l-1\right)\right]\right.\\&\quad\left.\times\left[\sum_{l=0}^{\boldsymbol{\Phi}}\boldsymbol{\Phi}_N^l\cdot\boldsymbol{w}_N\left((k+1)M_N+l_N-l-1\right)\right]^T\right\}\\&=E\left\{\sum_{l=0}^{M-1}\boldsymbol{\Phi}_N^l\times\begin{bmatrix}\boldsymbol{w}_N[(k+1)M_N+l_N-l-1]\\ \times\boldsymbol{w}_N^T[(k+1)M_N+l_N-l-1]\end{bmatrix}\right.\\&\quad\left.\times\left(\boldsymbol{\Phi}_N^l\right)^T\right\}\\&=\sum_{l=0}^{M-1}\boldsymbol{\Phi}_N^l\boldsymbol{Q}_N\left(\boldsymbol{\Phi}_N^l\right)^T\delta_{k,j}\\&=\boldsymbol{Q}_N^*\delta_{k,j}\end{aligned} \tag{A.5}$$

Thereby

$$\begin{aligned}&E\left\{\begin{pmatrix}\boldsymbol{w}_N^*(kM_N+l_N)\\ \boldsymbol{v}_N(kM_N+l_N)\end{pmatrix}\times\left(\boldsymbol{w}_N^{*\,T}(jM_N+l_N)\quad \boldsymbol{v}_N^T(jM_N+l_N)\right)\right\}\\&=\begin{pmatrix}\boldsymbol{Q}_N^* & \boldsymbol{S}_N\\ \boldsymbol{S}_N^T & \boldsymbol{R}_N\end{pmatrix}\delta_{k,j}\end{aligned} \tag{A.6}$$

The proof is finished.

■

Then, the parallel filtering fusion algorithm based on the measurements of sensor N is as follows [3].

1) One step state predict during the fusion period

$$\begin{aligned}\hat{\boldsymbol{x}}_N(kM_N+l_N\mid kM_N+l_N-1)&=\overline{\boldsymbol{\Phi}}_N\hat{\boldsymbol{x}}_N(kM_N+l_N-1\mid kM_N+l_N-1)\\&\quad+\boldsymbol{S}_N\boldsymbol{R}_N^{-1}\boldsymbol{z}_N(kM_N+l_N-1)\end{aligned} \tag{23}$$

$$\begin{aligned}&\boldsymbol{P}_N(kM_N+l_N\mid kM_N+l_N-1)\\&=\overline{\boldsymbol{\Phi}}_N\boldsymbol{P}_N(kM_N+l_N-1\mid kM_N+l_N-1)\overline{\boldsymbol{\Phi}}_N^T+\overline{\boldsymbol{Q}}_N\end{aligned} \tag{24}$$

where

$$\begin{cases}\overline{\boldsymbol{\Phi}}_N=\boldsymbol{\Phi}_N-\boldsymbol{S}_N\boldsymbol{R}_N^{-1}\boldsymbol{H}_N,\ \ \overline{\boldsymbol{Q}}_N=\boldsymbol{Q}_N-\boldsymbol{S}_N\boldsymbol{R}_N^{-1}\boldsymbol{S}_N^T\\ \boldsymbol{z}(kM_N+l_N-1)=\boldsymbol{z}_N(kM_N+l_N-1)\end{cases} \tag{25}$$

2) One step state predict between the fusion periods

$$\begin{aligned}&\hat{\boldsymbol{x}}_{l_N-1}\left((k+1)M_N+l_N-1\mid kM_N+l_N-1\right)\\&=\boldsymbol{\Phi}_N^M\hat{\boldsymbol{x}}_{l_N-1}\left(kM_N+l_N-1\mid kM_N+l_N-1\right)\\&+\boldsymbol{S}_N\boldsymbol{R}_N^{-1}\begin{pmatrix}\boldsymbol{z}\left(kM_N+l_N-1\right)\\ -\boldsymbol{H}_N\hat{\boldsymbol{x}}_{l_N-1}\left(kM_N+l_N-1\mid kM_N+l_N-1\right)\end{pmatrix}\end{aligned} \tag{26}$$

$$\begin{aligned}&\boldsymbol{P}_{l_N-1}\left((k+1)M_N+l_N-1\mid kM_N+l_N-1\right)\\&=\boldsymbol{\Phi}_N^M\boldsymbol{P}_{l_N-1}\left(kM_N+l_N-1\mid kM_N+l_N-1\right)\left(\boldsymbol{\Phi}_N^M\right)^T\\&\quad+\boldsymbol{Q}_N^*-\boldsymbol{S}_N\boldsymbol{R}_N^{-1}\boldsymbol{S}_N^T\end{aligned} \tag{27}$$

By use of Eq.(23), (26), Eq. (23) can be rewritten to

$$\begin{aligned}&\hat{\boldsymbol{x}}_N(kM_N+l_N\mid kM_N+l_N-1)\\&=\overline{\boldsymbol{\Phi}}_N\hat{x}_N(kM_N+l_N-1\mid kM_N+l_N-1)\\&\quad+\hat{\boldsymbol{x}}_{l_N-1}\left((k+1)M_N+l_N-1\mid kM_N+l_N-1\right)\\&\quad-\overline{\boldsymbol{\Phi}}_N^M\hat{\boldsymbol{x}}_{l_N-1}(kM_N+l_N-1\mid kM_N+l_N-1)\end{aligned} \tag{28}$$

where

$$\overline{\boldsymbol{\Phi}}_N^M=\boldsymbol{\Phi}_N^M-\boldsymbol{S}_N\boldsymbol{R}_N^{-1}\boldsymbol{H}_N \tag{29}$$

3) State update at every time in the fusion period

$$\begin{aligned}&\hat{\boldsymbol{x}}_N(kM_N+l_N\mid kM_N+l_N)\\&=\boldsymbol{A}_N(kM_N+l_N)\hat{\boldsymbol{x}}_N(kM_N+l_N\mid kM_N+l_N-1)\\&\quad+\boldsymbol{K}_N(kM_N+l_N)\boldsymbol{z}(kM_N+l_N)\end{aligned} \tag{30}$$

$$\begin{aligned}&\boldsymbol{P}_N^{-1}(kM_N+l_N\mid kM_N+l_N)\\&=\boldsymbol{P}_N^{-1}(kM_N+l_N\mid kM_N+l_N-1)+\boldsymbol{H}_N^T\boldsymbol{R}_N^{-1}\boldsymbol{H}_N\end{aligned} \tag{31}$$

where

$$\boldsymbol{A}_N(kM_N+l_N)=\boldsymbol{I}-\boldsymbol{K}_N(kM_N+l_N)\boldsymbol{H}_N \tag{32}$$

$$\boldsymbol{K}_N(kM_N+l_N)=\boldsymbol{P}_N(kM_N+l_N\mid kM_N+l_N)\boldsymbol{H}_N^T\boldsymbol{R}_N^{-1} \tag{33}$$

4) Update for corresponding sate between fusion periods

$$\begin{aligned}&\hat{\boldsymbol{x}}_{l_N}(kM_N+l_N\mid kM_N+l_N)\\&=\boldsymbol{A}_{l_N}(kM_N+l_N)\hat{\boldsymbol{x}}_{l_N}\left(kM_N+l_N\mid(k-1)M_N+l_N\right)\\&+\boldsymbol{K}_{l_N}(kM_N+l_N)\boldsymbol{z}(kM_N+l_N)\end{aligned} \tag{34}$$

$$\boldsymbol{P}_{l_N}^{-1}(kM_N + l_N \mid kM_N + l_N) = \boldsymbol{P}_{l_N}^{-1}\left(kM_N + l_N \mid (k-1)M_N + l_N\right) + \boldsymbol{H}_N^T \boldsymbol{R}_N^{-1} \boldsymbol{H}_N \quad (35)$$

where

$$\boldsymbol{A}_{l_N}(kM_N + l_N) = \boldsymbol{I} - \boldsymbol{K}_{l_N}(kM_N + l_N)\boldsymbol{H}_N \quad (36)$$

$$\boldsymbol{K}_{l_N}(kM_N + l_N) = \boldsymbol{P}_{l_N}(kM_N + l_N \mid kM_N + l_N)\boldsymbol{H}_N^T \boldsymbol{R}_N^{-1} \quad (37)$$

$$\boldsymbol{z}(kM_N + l_N) = \boldsymbol{z}_N(kM_N + l_N) \quad (38)$$

and

$$\boldsymbol{A}_N(kM_N + l_N) = \boldsymbol{P}_N(kM_N + l_N)\boldsymbol{P}^{-1}(kM_N + l_N \mid kM_N + l_N - 1) \quad (39)$$

$$\boldsymbol{A}_{l_N}(kM_N + l_N) = \boldsymbol{P}_{l_N}(kM_N + l_N)\boldsymbol{P}_{l_N}^{-1}\left(kM_N + l_N \mid (k-1)M_N + l_N - 1\right) \quad (40)$$

So, Eq.(30) and Eq.(31) can be rewritten to

$$\begin{aligned} \hat{\boldsymbol{x}}_N(kM_N + l_N \mid kM_N + l_N) &= \boldsymbol{P}_N(kM_N + l_N \mid kM_N + l_N) \\ &\cdot \Big\{\boldsymbol{P}_N^{-1}(kM_N + l_N \mid kM_N + l_N - 1)\hat{\boldsymbol{x}}_N(kM_N + l_N \mid kM_N + l_N - 1) \\ &+ \boldsymbol{P}_{l_N}^{-1}(kM_N + l_N \mid kM_N + l_N)\hat{\boldsymbol{x}}_{l_N}(kM_N + l_N \mid kM_N + l_N) \\ &- \boldsymbol{P}_{l_N}^{-1}\left(kM_N + l_N \mid (k-1)M_N + l_N\right)\hat{\boldsymbol{x}}_{l_N}\left(kM_N + l_N \mid (k-1)M_N + l_N\right)\Big\} \end{aligned} \quad (41)$$

$$\begin{aligned} \boldsymbol{P}_N^{-1}(kM_N + l_N \mid kM_N + l_N) &= \boldsymbol{P}_N^{-1}(kM_N + l_N \mid kM_N + l_N - 1) \\ &+ \boldsymbol{P}_{l_N}^{-1}(kM_N + l_N \mid kM_N + l_N) \\ &- \boldsymbol{P}_{l_N}^{-1}\left(kM_N + l_N \mid (k-1)M_N + l_N\right) \end{aligned} \quad (42)$$

Because it involves many variables in the above-given algorithm, in order to provide clear understanding Figure.3 shows all variables to compute $\hat{\boldsymbol{x}}_N(kM_N + l_N \mid kM_N + l_N)$ and $\boldsymbol{P}_N(kM_N + l_N \mid kM_N + l_N)$.

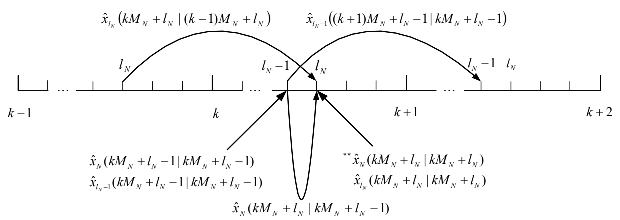

Figure.3 All variables to compute the global estimate at $kM_N + l_N$

This subsection gives the parallel filtering algorithm for which every sampling point only has one sensor measurement. However, Figure.2 shows that it is possible that some sampling point could have several measurements, namely $\boldsymbol{z}(kM_N + l_N)$ is no longer single measurement. In this case, the sequential filtering fusion can be introduced to deal with it. As a result, it is the key to distinguish how many measurements every sampling time in the fusion period has. Then, the judgment scheme is given by the next subsection.

B. Measurment judgment scheme

For the multisensory dynamic system with the sampling of integer times $L(L = 1,2,\cdots)$, the law about the change of measurement number at every sampling point. Then, the judgment scheme to measurement number at every sampling point in the fusion period sees Figure.4.

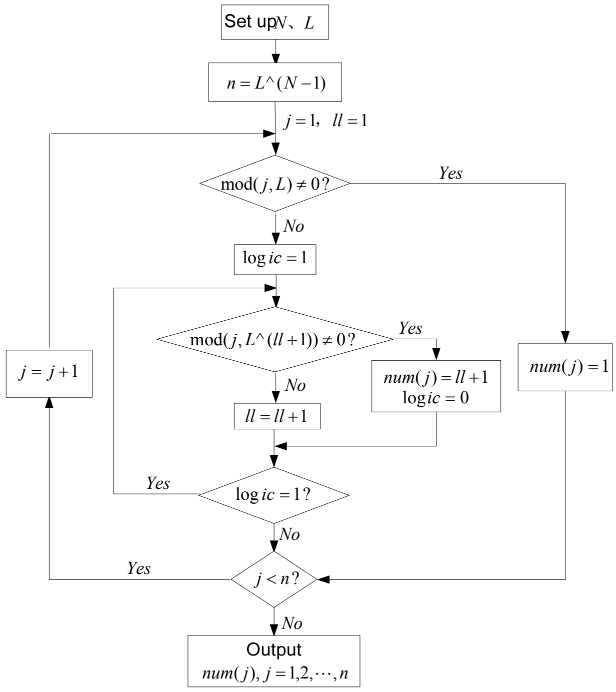

Figure.4 The judgment scheme to measurement number at every sampling point in the fusion period

In this figure, mod (*,*) is modulo operation and the output parameter $num(j)(j = 1,2,\text{L}, n)$ represents the mapped measurement number at every sampling point in the fusion period. Clearly, above-mentioned scheme can only judge the measurement number at every sampling point and cannot explain which sensor they belong to. For the multisensor system researched in this paper, the measurement at time l_N $(1 \le l_N \le L^{N-1})$ can be given as follows

$$\begin{cases} \boldsymbol{z}_N(kM_N + l_N) & if \quad \text{mod}(l_N, L) \ne 0 \\ \boldsymbol{z}_{N-l}(kM_{N-l} + \dfrac{l_N}{L^l}) & if \quad \text{mod}(l_N, L) = 0 \end{cases} \quad (43)$$

where $l = 0,\cdots,\ num(l_N) - 1$.

C. Algorithm Summary

According to the analysis in subsection *A* and *B*, we sum up the parallel filtering fusion algorithm as follows:

1) Map sampling points of all of sensors to the time axis of sensor N, and take the time of sensor N as basis to perform fusion filtering.

2) Set up $\boldsymbol{x}_0$, $\boldsymbol{P}_0$, and sampling times L.

3) $k=0$, $l_N=1$.

4) Perform (26), (27), (28) and (24) sequentially.

5) Use (34) and (35) to compute the estimate of sensor N $\hat{\boldsymbol{x}}_{l_N}(kM_N+l_N \mid kM_N+l_N)$ and corresponding covariance $\boldsymbol{P}_{l_N}(kM_N+l_N \mid kM_N+l_N)$.

6) According to (41) and (42) to compute the estimate $\hat{\boldsymbol{x}}_N(kM_N+l_N \mid kM_N+l_N)$ and the estimate covariance $\boldsymbol{P}_N(kM_N+l_N \mid kM_N+l_N)$.

7) Use the judgment scheme given by Figure.4 to distinguish the measurement number at this time.

8) If $num(l_N)=1$, else $l_N=l_N+1$, go to 4). Else continue.

9)Adopt the sequential filtering fusion method in [9] to fuse other measurements $\boldsymbol{z}_{N-l}(kM_{N-l}+l_N/L^l)$ $(l=1,\cdots,num(l_N)-1)$, and assign the taken estimate and error covariance to $\hat{\boldsymbol{x}}_N(kM_N+l_N \mid kM_N+l_N)$ and $\boldsymbol{P}_N(kM_N+l_N \mid kM_N+l_N)$ respectively.

10) If $l_N=M_N$, then $k=k+1$ and $l_N=1$, go to 4). Else $l_N=l_N+1$, go to 4).

11) Finally, compute $\hat{\boldsymbol{x}}_N(kM_N+l_N \mid kM_N+l_N)$, $\boldsymbol{P}_N(kM_N+l_N \mid kM_N+l_N)$.

12) End.

IV. Computer Simulation

This section uses computer simulation to only validate the effectiveness of the proposed parallel filtering fusion algorithm for the asynchronous sampling system. All of results are the mean of 100 Monte Carlo simulations.

A. Example1

For the system given by Eq.(7) and Eq.(8), we take $N=5$, $L=2$, $\boldsymbol{\Phi}_N=0.98$, $\boldsymbol{Q}_N=0.1$, $H_i=1$, $\boldsymbol{R}_i=1$, $\boldsymbol{S}_i=0.2$, where $i=1,2,\cdots,5$. Original value $\boldsymbol{x}_0=10$, $\boldsymbol{P}_0=100$.

Then, the simulation results are shown by Figure.5, Figure.6, and Figure.7. The absolute error mean is given by Table.I.

TABLE I. ABSOLUTE ERROR MEAN OF ESTIMATE

Algorithm	The parallel filtering fusion algorithm
Absolute error mean of Estimate	0.2925

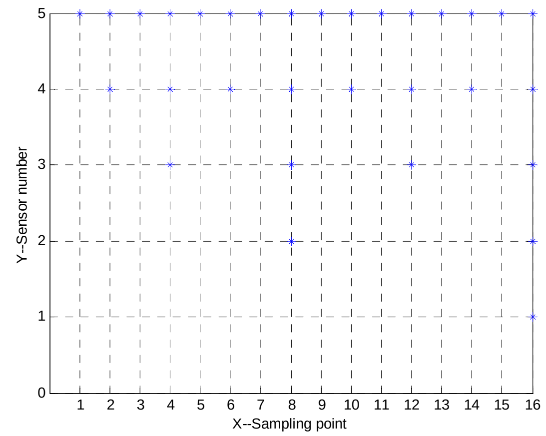

Figure.5 Multisensor measurements with $L=2$

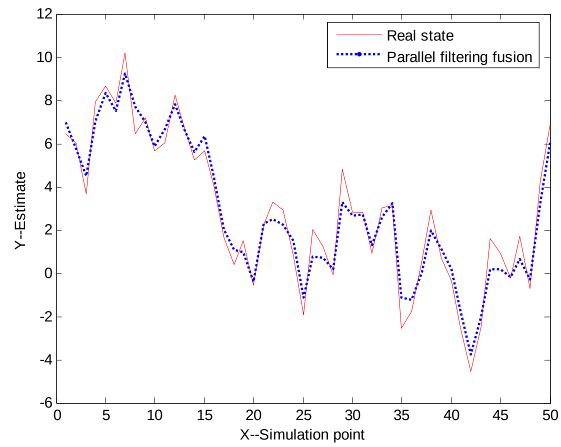

Figure 6 Estimate result of the proposed parallel filtering fusion

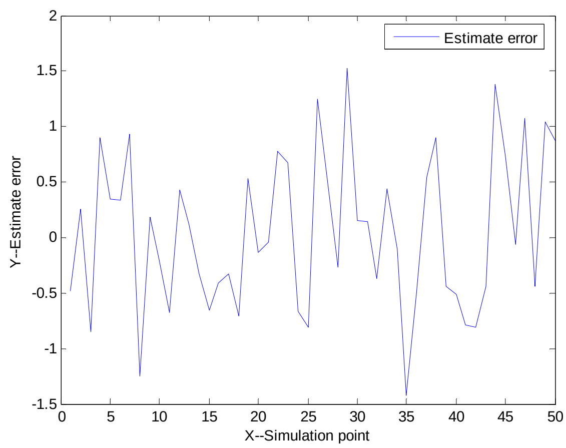

Figure.7 Estimate error of the new algorithm

From Figure.5 to Figure.7, and Table.1, we can get the following conclusions:

1) Figure.5, which demonstrates the measurement distribution of multisensor dynamic system with L=2, shows that measurement number of every sensor satisfies

Eq.(6). It also means that the judgment scheme is also effective.

2) It shows that the proposed algorithm in this paper can effectively deal with data fusion of integer times sampling and achieve outstanding tracking estimate effect. In a word, the proposed parallel filtering fusion method can effectively adapt the multisensor system with integer times sampling and can realize good estimate result.

V. CONCLUSION

This paper studies the design of data fusion algorithm for asynchronous multisensor system with integer times sampling, accordingly by introducing parallel filtering technology a novel data fusion algorithm to different sampling rate is proposed. The derivation process and simulation result are presented to validate its effectiveness. There are many open issues, for example, to consider the communication delay and transmission error in the parallel filtering fusion.

REFERENCES

[1] Chenglin Wen, Donghua Zhou, Quan Pan, and Hongcai Zhang, "Distributed Information Fusion Algorithm for Single Sensor Synamic System On The Basis Of Multiscale Dynamic Models,"*Acta Automatic Sinica of China*, vol.27, no.2, pp.158~165, 2001.

[2] Jie Wang, Chongzhao Han, and Xiaorong Li, "Asynchronous Multisesnro Data Fusion," *Journal* C*ontrol and Decision of China*, vol.16, no.6, pp.877-881, 2001.

[3] Alouani A T, Rice T R, "On asynchronous data fusion," *Proc of the Annual Southeastern Symposium on System Theory*. Athens, pp.143-146, 1994.

[4] Alouani A T, Rice T R, "Performance analysis of an asynchronous track fusion and architecture," *Proc of SPIE*. Orlando, 1997, 194-205.

[5] Hamid R. Hashemipour, Sumit Roy, Alan J. Laub, " Decentralized structures for parallel kalman filtering," *IEEE Transactions on Automatic Control*, vol.33, no.1, pp. 88-94, 1988.

[6] Chenglin Wen, "Multiscale Data Fusion for Multi Sensor Single Model Dynamic Systems," *Acta Electronica Sinica*, vol.29, no.3, pp.341-345,2001.

[7] Liping Yan, Bing Wang, and Feng Lv, "A New Algorithm of Multiscale Fusion Estimation Based on Kalman Filtering," *Journal of Henan University of China* (*Natural Science*), vol.32, no.2, pp.36-39, 2002.

[8] Baoshu Wang, FangsheLi, "The Research On Multiple Targets Tracking Based On The Data Fusion Technique," *Jounal of Xidian University of China*, vol.25, no.3, pp.269-272, 1998.

[9] Chenglin Wen, Bing Lv, Quanbo Ge, "A Data Fusion Algorithm Based on Filtering Step by Step," *Acta Electronica Sinica of China*, vol.32, no.8, pp. 1264-1267, 2004.

[10] Quanbo Ge, Guo'an Wang, Tianhao Tang, and Chenglin Wen, "The Research on Asynchronous Data Fusion Algorithm Based on Sampling of Rational Number Times,", *Acta Electronica Sinica of China*, vol.34, no.3, pp. 543-548, 2006

[11] L.Y.Yan, B.S.Liu, and D.H.Zhou, "The modeling and estimation of asynchronous multirate multisensor dynamic systems," *Aerospace Science and Technology*, no.10, pp.63-71, 2006.

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