

# A Scheduling Strategy in Fusion Estimation with Bandwidth Constrained

Kuan Li, Yueqin Wu, Xiaoquan Xu, Youmei Hu and Kun Han

*Institute of detection technology and smart sensing, Chongqing University of Posts and Telecommunications, Chongqing adamleek@163.com*

**Keywords:** Scheduling Strategy, Multi-Sensor Fusion, Bandwidth Constrained.

**Abstract:** This paper presents a sensor scheduling strategy for multi-sensor fusion estimation system to meet the bandwidth constrained. First the sensors are divided into several groups. Then the local optimal estimation of each subsystem is transmitted periodically. By reducing the transmission of information at a time, it not only meets the limitation of communication bandwidth, but also saves the energy of sensor nodes and prolongs the lifetime of network. The kalman fusion estimator, which is suitable for this scheduling strategy is redesigned to get the option fusion estimation. Finally, a simulation of target tracking is used to illustrate the effectiveness of the proposed sensor scheduling strategy.

## 1 INTRODUCTION

The purpose of the multi-sensor fusion estimation system is to cooperatively perceive, collect the information of the perceived objects and then send them to the fusion estimation center, which can accurately extract the information of the detection objects through the fusion estimation center (You K and Xie L, 2011). The introduction of wireless communication network brings mobility and flexibility to the original communication network, and reduces the cost of networking, but also brings many new challenges. Among them, the wireless communication network constraints. For this problem, researchers have done a great deal of research work and achieved a lot of achievements. However, there are still many problems to be further study. The current methods to solve the problem of bandwidth limitation can generally be divided into three types, quantizing (Sani and Vosoughi, 2016; Liu and Xu, 2014; Li and Alegib, 2009), dimensionality reduction (Schizas and Giannakis, 2007; Zhu and Schizas, 2009) and sensing scheduling (Han and Mo, 2014; Han and Mo, 2016).

An adaptive quantitative strategy is presented to design a distributed estimator to meet the constraints of bandwidth limitation (Liu and Xu, 2014; Li and Alegib, 2009). Schizas and Zhu discussed how to design the dimension compression algorithm, and gave the proof of the existence of the optimal compression matrix under the linear minimum

variance optimization criterion (Schizas and Giannakis, 2007; Zhu and Schizas, 2009). The channel is divided into high-precision channel and low-precision channel. Reducing energy consumption and evaluating performance are both taken into consideration, then the opportunistic sensing scheduling with high accuracy and low accuracy was proposed. All of the above two methods were in the perspective of data transmission to consider the issue (Han and Mo, 2014; Han and Mo, 2016).

Because of limited communication resources, multiple sensors share wireless channels. If all sensors send data at the same time, it is easy to get blocked and lose packets. In this paper, we present a sensor scheduling strategy to meet the bandwidth constraints. Firstly, the sensor in the whole system is divided into several discrete subsystems. Subsystems transfer the optimal local estimate in the sense of linear minimum variance to the fusion estimation center. The fusion center estimates performance based on the optimal matrix-weighted fusion criterion. Finally, a simulation of fusion estimation algorithm is used to verify the effectiveness of sensor scheduling strategy that we proposed in the fusion estimation.

## 2 PROBLEM DESCRIPTION AND SCHEDULING STRATEGY

### 2.1 Dynamic physical processes

In this paper, we consider the multi-sensor information fusion problem with bandwidth constrained, as shown in figure 1.

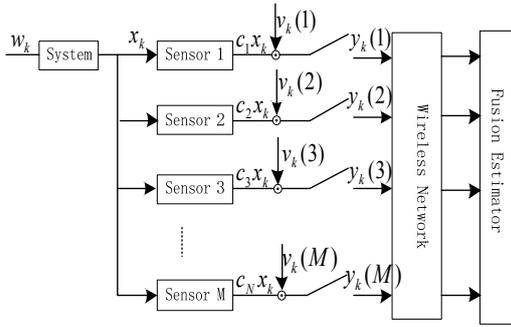


Figure 1. Multi-Sensor Fusion System Structure

The discrete time invariant system model is as follows:

$$x(k+1) = Ax(k) + Bw(k) \quad (1)$$

$$y_i(k) = C_i x(k) + v_i(k), i = 1, 2, \dots, m \quad (2)$$

where  $x(k) \in R^n$  and  $y_i(k) \in R^m$  represent system state and measurement output of  $i$ th sensor respectively.  $A, B, C_i$  are the coefficient matrix of the appropriate dimensions.  $w(k) \in R^n$  and  $v_i(k) \in R^m$  are uncorrelated Gaussian white noises with mean zero and covariance  $Q, R_{v_i}$ . Assuming the initial value of system state is  $x(0) = x_0$ , where  $x_0$  is a gaussian random variable with mean  $\mu_0$ .

### 2.2 Scheduling Strategy

For the system shown in the figure 1, there are  $m$  sensors that need to send the measurement information over the wireless network to the fusion estimation center node. Due to the bandwidth limitation, only  $a$  sensors are allowed to send their own measurement data. we named the  $m$  sensors as  $s_1, s_2, \dots, s_m$ . Then the  $m$  sensors according to the principle of proximity is divided into  $N$  groups and the number of sensors in each group is less than or equal to  $a$ . The sensors set is defined as  $s = \{s_1, \dots, s_i, \dots, s_m\}$  and the group set

is  $\hat{s}_h = \{s_{h_1}, \dots, s_{h_2}, \dots, s_{h_{\Delta(h)}}\}$  where  $h = \{1, 2, \dots, N\}$ .

According to the above transmission strategy, we can know that  $s$  and  $\hat{s}_h$  are satisfied:

$$s = \hat{s}_1 \cup \hat{s}_2 \dots \cup \hat{s}_N, \hat{s}_i \cap \hat{s}_j = \emptyset (i \neq j)$$

$$\sum_{h=1}^N \Delta(\hat{s}_h) = m, \text{number}(\hat{s}_h) = a \quad (3)$$

where  $\text{number}(A)$  is the number of elements in set  $A$ . In this way, only one group of sensors in the  $\hat{s}_h$  set is allowed to send measurement data in each sampling period. The fusion center has all the measurement information from  $(k-N+1)$ th sampling period to the  $k$ th sampling period of all this group sensors. For example, there are four sensors in this system, and the number of sensors which allowed to send data is two. It means  $s = 4, a = 2$ . The sensors node set is  $s = \{s_1, s_2, s_3, s_4\}$ . We divided the sensors in two groups.  $N = 2, \hat{s}_1 = \{s_1, s_2\}, \hat{s}_2 = \{s_3, s_4\}$ . The measurement data of the sensors in  $\hat{s}_1$  is transmitted to the fusion center when  $k = 1, 3, 5, \dots$ . The measurement data of the sensors in  $\hat{s}_2$  is transmitted to the fusion center when  $k = 2, 4, 6, \dots$ .

### 2.3 problem description

The problem we hope to solve is to design a distributed kalman fusion estimator that satisfies the constraint equation (4) based on the above transmission strategy.

$$\arg \min_{\hat{x}_*(t)} E\{(x(t) - \hat{x}_*(t))^T (x(t) - \hat{x}_*(t))\} \quad (4)$$

## 3 DESIGN OF DISTRIBUTED KALMAN FUSION ESTIMATOR

The optimal estimator  $\hat{x}_h$  in the sense of the linear minimum variance of the  $i$ th subsystem can be calculated based on the kalman filter(Deng and Gao,2005):

$$\begin{cases} \hat{x}_h(k) = [I_n - C_h^r] A \hat{x}_h(k-1) + K_h(k) y_h^r(k) \\ P_h(k|k-1) (C_h^r)^T [C_h^r P_h(k|k-1) (C_h^r)^T + R_h]^{-1} \end{cases} \quad (5)$$

$$\begin{cases} P_h(k|k) = [I_n - K_h(k) C_h^r] P_h(k|k-1) \\ P_h(k+1|k) = A P_h(k|k) A^T + B Q B^T \end{cases} \quad (6)$$

The forecast of the  $t$  steps ahead is:

$$\hat{x}_h(k+t|k) = A^{t-1} \hat{x}_h(k+1|k) \quad (7)$$

The covariance matrix is:

$$\begin{aligned}
 P_h(k+t|k) &= E\{(x_h(k+t) - \hat{x}_h(k+t|k)) \\
 &\quad (x_h(k+t) - \hat{x}_h(k+t|k))^T\} \\
 &= A^{t-1}P_h(k+t|k)(A^{t-1})^T \\
 &\quad + \sum_{j=2}^t A^{t-j}BQB^T(A^{t-j})^T
 \end{aligned} \tag{8}$$

According to [9], we can define that:

$$\begin{cases} \hat{x}_a(t|t) = [x_1^T(t|t) \cdots x_L^T(t|t)]^T, I_0 = [I_n \cdots I_n]^T \\ \hat{P}(t|t) = E\{(I_0 x(t) - \hat{x}_a(t))(I_0 x(t) - \hat{x}_a(t))^T\} \end{cases} \tag{9}$$

The optimal distributed kalman fusion estimator in the sense of linear minimum variance is as follows(Sun and Deng, 2004):

$$\hat{x}_o(t|t) = \sum_{i=1}^L F_i(t)\hat{x}_i(t|t) \tag{10}$$

For the fusion estimator, the minimum covariance matrix of the fusion error is:  $P_o(t|t) = E\{(x(t) - \hat{x}_o(t|t))[x(t) - \hat{x}_o(t|t)]^T\}$

$$P_o(t|t) = (I_0^T \hat{P}^{-1}(t|t) I_0)^{-1} \tag{11}$$

The optimal weight matrix can be calculated by (12).

$$[F_1(t), F_2(t), \dots, F_L(t)] = (I_0^T \hat{P}^{-1}(t|t) I_0)^{-1} I_0^T \hat{P}^{-1}(t|t) \tag{12}$$

Lemma1: Define  $\tilde{x}_i(k+t|k) = x_i(k+t|k) - \hat{x}_i(k+t|k)$ .

The error covariance matrix of *i*th group sensors and *j*th group sensors  $P_{ij}(k|k, k-t)$  is computed by the following recursive equation.

$$\begin{aligned}
 P_{ij}(k|k, k-t) &= E\{\tilde{x}_i(k|k)\tilde{x}_j^T(k|k-t)\} \\
 &= \left( \prod_{r=0}^{t-1} [(I - K_i(k-r)C_i^r)A] \right) \\
 &\quad \times [I - K_i(k-j+1)C_i^j]BQ(A^{j-1}B)^T
 \end{aligned} \tag{13}$$

Lemma 2: The error covariance matrix of *t*<sub>1</sub>th step forecast of *i*th group sensors and *t*<sub>2</sub>th step forecast of *i*th group sensors  $P_{ij}(k|k-t_1, k-t_2)$  is computed by the following recursive equation.

$$\begin{aligned}
 P_{ij}(k|k-t_1, k-t_2) &= E\{\tilde{x}_i(k|k-t_1)\tilde{x}_j^T(k|k-t_2)\} \\
 &= A^{t_1}P_{ij}(k-t_1|k-t_1, k-t_2)(A^{t_1})^T \\
 &\quad + \sum_{j=1}^{t_1} A^{j-1}BQ(A^{j-1}B)^T
 \end{aligned} \tag{14}$$

Proof: The proof of Lemma1 and Lemma 2 are omitted due to page limitation.

Based on the above statement, the computation procedures for the fusion estimator with bandwidth constraints can be summarized as follows:

---

**Algorithm I:**

---

- 1、Divided the sensors into *N* groups. The groups are then numbered, which provides for the
- 

periodic sending of sensor information .

- 2、Given the initial value  $P_i(0|0)$ ,  $P_{ij}(0|0)$ ,  $P(0)$ ,  $\hat{x}(0)$  .
  - 3、Calculate the local optimal estimation  $\hat{x}_h(k)$  of each sensor separately , Based on standard kalman filtering and(5-7) calculate remaining groups' optimal estimate  $\hat{x}_h(k|k-N+1)$  .
  - 4、Calculate  $P_{ii}$  by(6-8),and  $P_{ij}$  by(13-14).
  - 5、The result of the fourth step is brought into (12) to get the optimal fusion estimate.
  - 6、Return to the third step and continue to calculate the optimal fusion estimate for the next moment.
- 

## 4 SIMULATION

This simulation considers a goal of variable speed motion and use four sensors for target tracking.  $x(t) = [s(t) \quad \dot{s}(t) \quad \ddot{s}(t)]^T$ . According to the proposed sensor packet transmission strategy, the sensor nodes are divided into two groups,  $\hat{s}_1 = \{s_1, s_2\}$ ,  $\hat{s}_2 = \{s_3, s_4\}$ . The information transmitted to the fusion estimation center is estimated according to a fusion estimation algorithm. The discrete time invariant system model is (1) and (2).

Where:

$$A = \begin{bmatrix} 1 & T & T^2 \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix}, B = \begin{bmatrix} 0.5T^2 \\ T \\ 1 \end{bmatrix}, C_1 = C_2 = C_3 = C_4 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$v_i(t)$  and  $v_j(t)(i \neq j)$  are uncorrelated noise.  $Q = 1$ . The covariance of the sensors are:

$$\begin{aligned}
 R_{v1} &= \begin{bmatrix} 0.9 & 0 \\ 0 & 0.5 \end{bmatrix}, R_{v2} = \begin{bmatrix} 0.3 & 0 \\ 0 & 0.8 \end{bmatrix}, R_{v3} = \begin{bmatrix} 0.6 & 0 \\ 0 & 0.4 \end{bmatrix}, \\
 R_{v4} &= \begin{bmatrix} 0.7 & 0 \\ 0 & 0.2 \end{bmatrix}.
 \end{aligned}$$

The sampling period is  $T = 1$  .

According to the initialization parameters given above, combined with the second part of the distributed kalman fusion estimation algorithm can get the target state trajectory curve. As shown below.

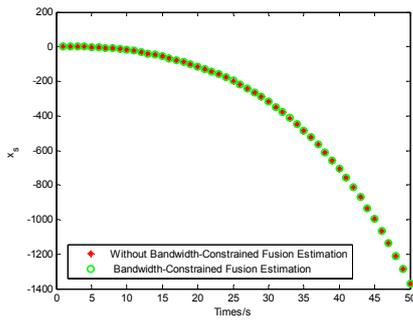


Figure 2 : The first component

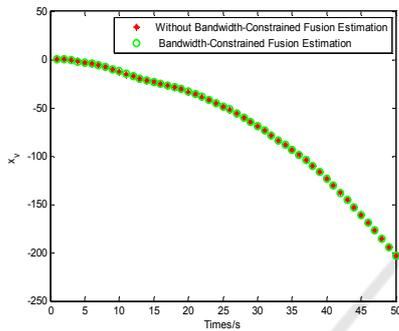


Figure 3: The second component

Figure 2、Figure 3、Figure 4 respectively show the estimation of the status component with bandwidth limitation and no bandwidth limitation. It can be seen that the fusion estimation algorithm based on scheduling transmission strategy described in this paper can achieve similar effect under the condition of limited bandwidth as the estimate without bandwidth limitation. The validity of scheduling strategy and estimation algorithm is verified.

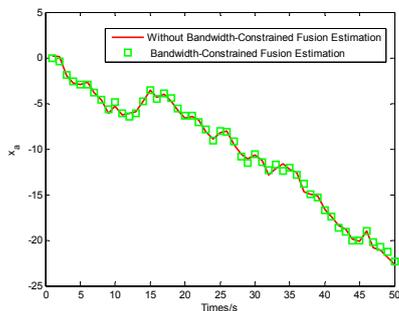


Figure 4: The third component

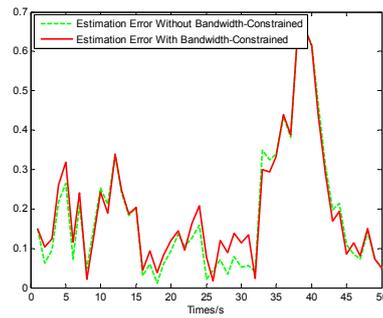


Figure 5: Comparison of estimation errors

Figure 5 is the estimation error of the fusion estimation and the true value without bandwidth limitation and the estimation error of the fusion estimation and the true value with bandwidth limitation. It also shows the effectiveness of the estimation algorithm under the scheduling strategy proposed in this paper.

## 5 CONCLUSION

In this paper, a scheduling strategy of packet transmission for multi-sensor fusion system is proposed to solve the problem of limited bandwidth. Firstly, the sensors in the system are divided to multiple subsystems. Only one local optimal estimation of subsystem can send its measurement information. And the other subsystems are sent measurement periodically. The Distributed Kalman Fusion Estimator for the system and the optimal estimation is obtained by the way of matrix weighting. The simulation show that the scheduling strategy of periodic transmission of sensor information for each group can effectively obtain the fusion estimation value, and verify the applicability and effectiveness of this scheduling method for large-scale multi-sensor systems.

## REFERENCES

- You K, Xie L, Sun S, et al. 2011. *Quantized filtering of linear stochastic systems*[J]. Transactions of the Institute of Measurement & Control, 32(3):683-698.
- Sani A, Vosoughi A. 2016. *Distributed Vector Estimation for Power-and Bandwidth- Constrained Wireless Sensor Networks*[J]. IEEE Transactions on Signal Processing, 64(15):3879-3894.
- Liu G, Xu B, Chen H, et al, 2014. *Adaptive quantization for distributed estimation in cluster-based wireless*

- sensor networks*[J]. AEUE-International Journal of Electronics and Communications,68(6):484-488.
- Li J, Alregib G. 2009. *Distributed Estimation in Energy-Constrained Wireless Sensor Networks*[J]. IEEE Transactions on Signal Processing, 57(10):3746-3758.
- Schizas I D, Giannakis G B, Luo Z Q,2007. *Distributed Estimation Using Reduced Dimensionality Sensor Observations*[M]. IEEE .
- Zhu H, Schizas I D, Giannakis G B. 2009. *Power-Efficient Dimensionality Reduction for Distributed Channel-Aware Kalman Tracking Using WSNs*[J]. IEEE Transactions on Signal Processing, 57(8):3193-3207.
- Han D, Mo Y, Wu J, et al.2014. *Stochastic Event-Triggered Sensor Schedule for Remote State Estimation*[J]. Automatic Control IEEE Transactions on, 60(10):2661-2675.
- Han D, Mo Y, Wu J, et al. 2016. *An Opportunistic Sensor Scheduling Solution to Remote State Estimation Over Multiple Channels*[J].IEEE Transactions on Signal Processing, 64(18):4905-4917.
- Sun S L, Deng Z L. 2004,*Muti-sensor optimal information fusion Kalman flter*. Automatica, 40(6): 1017-1023.
- Deng Z L, Gao Y, Mao L, Li Y, Hao G,2005. *New approach to information fusion steady-state Kalman fltering*. Automatica,2005,41(10): 1695-1707.

