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A Distributed Kalman Filter for Actuator Fault Estimation of Deep Space Formation Flying Satellites

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Abstract—**In this paper, a new distributed Kalman filter scheme is proposed to estimate actuator faults for deep space formation flying satellites. The method can also be applied to large-scale systems such as sensor networks and power systems. For a hierarchical large-scale system, the overlapping block-diagonal state space (OBDSS) representation of the system is transformed into our proposed constrained-state block-diagonal state space (CSBDSS) model. The proposed model becomes purely diagonal which simplifies and allows the distributed implementation of the Kalman filters. The constrained-state condition needs to be satisfied at each Kalman filtering iteration which is shown to be equivalent to solving local constrained optimization cost functions. Simulation results presented confirm the effectiveness of our proposed analytical work.**

Keywords: Distributed, Kalman Filter, Formation Flying, Deep Space.

I. INTRODUCTION

Formation flying is a new concept that is introduced for a team of satellites [1],[2]. Because of the high precision specifications and requirements in formation positioning and maneuvering, estimation techniques have been recently investigated in the literature for state and fault estimation. Due to the distributed nature of formation flying satellites, decentralized filtering techniques are of most interest in this area. In [3], decentralized estimation algorithms are surveyed and applied to the state estimation of formation flying satellites. The simulation results show that the decentralized reduced-order filter results in simultaneous near optimal estimates as well as balance of the communication and computational resources among the satellites. Moreover, a hierarchical architecture is presented to embed the decentralized estimators while scaling the problem to large number of vehicles fleet. In [4] and [5], estimation is performed by using parallel operation of full-order observers with local measurements. A necessary condition on the communication topology is developed to guarantee the stability of simultaneous parallel estimators and controllers.

The work in [6] and [7] are pioneers in distributing the Kalman filters design among the vehicles in a fleet. Most efforts on distribution of Kalman filters are based on full-order observers [8],[9], which are not communication-wise efficient. The work in [10],[11], and recently in [12],[13], deal with reduced-order distributed Kalman filters to reduce the local computational burden. However, these methods have certain limitations and deficiencies. In [10] and [11], the state space dynamics is decoupled and the system matrix is forced into a completely block-diagonal form, which is not fully consistent with the original overlapping block-diagonal matrix of the system. In [12] and [13], the overall system model is divided into several subsystems according to the physical considerations of the system. A local Kalman filter is then designed for state estimation in each subsystem. Among the local Kalman filters, the common observations are fused using bipartite fusion graphs and consensus averaging algorithm. However, it is assumed that the correlations among distant states in the state vector are relatively weak.

In this work, the problem of actuator fault estimation in satellite formations is studied. The states of the formation are augmented with the actuator fault parameters to form an overall overlapping block-diagonal state space (OBDSS) model of the formation. The OBDSS model is transformed into our proposed constrained-state block-diagonal state space (CSBDSS) model. In order to estimate the states of the CSBDSS model, we propose a constrained-state distributed Kalman filter (CSDKF), which takes advantage of the block-diagonal structure of the CSBDSS model, while satisfying the constrained-state restriction by solving local optimization problems among the distributed Kalman filters.

II. PROBLEM FORMULATION

We consider satellite formation flying in deep space [1] where the orbital model of a satellite in the *x*-, *y*-, and *z*-axes are approximated by three double integrators, and the corresponding actuators as well as actuator faults are modeled by three gains. It should be noted that the dynamics of a satellite corresponding to each axis is independent from the other axes in deep space, which makes the estimation and control problem a lot easier when compared to the planetary orbital environment missions [1]. We also consider in the models the effects of solar pressure [14] which is the dominant disturbance in deep space. For simplicity, we only consider the

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x-axis dynamics, and all the results can be similarly extended to the other two axes. Therefore, the x-axis orbital dynamics of a satellite is governed by

$$\theta_{x_i}(k+1) = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix} \theta_{x_i}(k) + \begin{bmatrix} 0 \\ T\dfrac{b_{x_i}+f_{x_i}}{m_i} \end{bmatrix} u_{x_i}(k)$$

$$z_{x_i}(k) = \begin{bmatrix} 1 & 0 \end{bmatrix} \theta_{x_i}(k)$$

where $\theta_{x_i} = (x_i, v_{x_i})^T \in R^2$, $u_{x_i} \in R$, and $z_{x_i} \in R$ are the x-axis state vector (consisting of position x_i and velocity v_{x_i}), input (actuator force), and output (measurement) of the satellite #i ($i \in \{1,2,...,n\}$), respectively, in the local inertial frame. Moreover, the x-axis actuator gain and its corresponding fault parameter for the satellite #i are modeled by b_{x_i} and f_{x_i}, respectively. The total mass of the satellite #i is denoted by m_i, and T is the sampling period used to obtain a discrete-time model.

In deep space, GPS measurements of absolute states are highly inaccurate, and instead estimation and coordination algorithms based on inter-satellite relative measurements that are provided by local high precision autonomous formation flying (AFF) sensors [15] are used. These relative measurements couple the dynamics of the satellites through the output channels and make the decentralized control and cooperative estimation problems more challenging. For the purpose of simultaneous joint estimation of states and actuator faults in this work, the state vector is augmented by the actuator fault gains to form a *fault-augmented relative-measurement relative-state model*. For illustrative purposes the model for formation of three satellites, as shown in Fig. 1, is given as follows

$$\theta^a_{x_{123}}(k+1) = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & T & 0 & 0 & 0 & 0 \\ -T\dfrac{u_{x_1}}{m_1} & 0 & 1 & T\dfrac{u_{x_2}}{m_2} & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & T & 0 \\ 0 & 0 & 0 & -T\dfrac{u_{x_2}}{m_2} & 0 & 1 & T\dfrac{u_{x_3}}{m_3} \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}}_{A_{x_{123}}(k)} \theta^a_{x_{123}}(k)$$

$$+ \underbrace{\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ -T\dfrac{b_{x_1}}{m_1} & T\dfrac{b_{x_2}}{m_2} & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & -T\dfrac{b_{x_2}}{m_2} & T\dfrac{b_{x_3}}{m_3} \\ 0 & 0 & 0 \end{bmatrix}}_{B_{x_{123}}} \begin{bmatrix} u_{x_1}(k) \\ u_{x_2}(k) \\ u_{x_3}(k) \end{bmatrix} \qquad (1)$$

$$z^a_{x_{123}}(k) = \underbrace{\begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}}_{C_{x_{123}}} \theta^a_{x_{123}}(k)$$

where $\theta^a_{x_{123}} = (f_{x_1}, x_{12}, v_{x_{12}}, f_{x_2}, x_{23}, v_{x_{23}}, f_{x_3})^T$ is the fault-augmented state in which $x_{ij} = x_j - x_i$ and $v_{x_{ij}} = v_{x_j} - v_{x_i}$ are the relative x-axis position and velocity, respectively.

The above model is in the form of a *bilinear* system. Using results from observability of bilinear systems [16], one can verify that the system (1) is generically observable. The model (1) is in the form of an *overlapping block-diagonal state space (OBDSS) model*, which has a hierarchical structure similar to many other large-scale system applications including sensor networks and distributed interconnected power systems. Centralized Kalman estimation is clearly not an option for large-scale systems of this type. Therefore, an efficient algorithm for distribution of Kalman filters is required in order to provide the joint estimation of states and actuator faults.

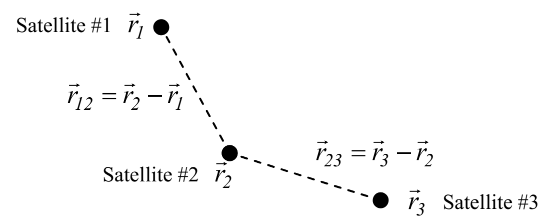

Fig. 1. Formation of three satellites with relative measurements (dashed lines).

III. Constrained-State Block-Diagonal State Space

As discussed in the previous section, full-order distributed estimation algorithms are by nature computationally inefficient due to matrix calculations and manipulations. On the other hand, complex reduced-order algorithms that are introduced in the literature are either inconsistent with the overall OBDSS model of the system, or rely on case-based specific assumptions. In this work, we propose a distributed Kalman estimation method that transforms the OBDSS model into an equivalent *constrained-state block-diagonal state space (CSBDSS) model*. Our proposed CSBDSS model has all the advantages of a standard *block diagonal state space (BDSS) model*, which simplifies the distributed implementation of the Kalman estimation, given that a *constrained-state* condition is satisfied and verified at each iteration of the estimation filtering. It will be shown subsequently that this constrained-state verification procedure reduces to a local constrained optimization problem (4) that aims at minimization of the trace of the error covariance matrix, while satisfying the limitations that are imposed by the constrained-state condition.

Consider the system that is represented by the triple (A, B, C) as in equation (1). We decompose matrices A and B as shown below

$$A_k^{(1)}\begin{bmatrix} \times & \times & \times & \times & 0 & 0 & 0 \\ \times & \times & \times & \times & 0 & 0 & 0 \\ \times & \times & \times & \times & 0 & 0 & 0 \\ 0 & 0 & 0 & \times & 0 & 0 & 0 \\ 0 & 0 & 0 & \times & \times & \times & \times \\ 0 & 0 & 0 & \times & \times & \times & \times \\ 0 & 0 & 0 & \times & \times & \times & \times \end{bmatrix} A_k^{(2)} \quad , \quad B_k^{(1)}\begin{bmatrix} \times & \times & 0 \\ \times & \times & 0 \\ \times & \times & 0 \\ 0 & \times & 0 \\ 0 & \times & \times \\ 0 & \times & \times \\ 0 & \times & \times \end{bmatrix} B_k^{(1)}$$

Using the above notation, the OBDSS model (1) can be decomposed into two subsystems $s^{(1)}$ and $s^{(2)}$ as follows

$$s^{(1)}:\begin{cases} X_k^{(1)}=\begin{bmatrix} x_1^{(1)}(k) \\ x_2^{(1)}(k) \\ x_3^{(1)}(k) \\ x_4^{(1)}(k) \end{bmatrix} = A_{k-1}^{(1)}X_{k-1}^{(1)} + B_{k-1}^{(1)}\underbrace{\begin{bmatrix} u_{x_1}(k-1) \\ u_{x_2}(k-1) \end{bmatrix}}_{U_{k-1}^{(1)}} \\ Y_k^{(1)} = \underbrace{\begin{bmatrix} 0 & 1 & 0 & 0 \end{bmatrix}}_{C_k^{(1)}} X_k^{(1)} \end{cases}$$

$$s^{(2)}:\begin{cases} X_k^{(2)}=\begin{bmatrix} x_4^{(2)}(k) \\ x_5^{(2)}(k) \\ x_6^{(2)}(k) \\ x_7^{(2)}(k) \end{bmatrix} = A_{k-1}^{(2)}X_{k-1}^{(2)} + B_{k-1}^{(2)}\underbrace{\begin{bmatrix} u_{x_2}(k-1) \\ u_{x_3}(k-1) \end{bmatrix}}_{U_{k-1}^{(2)}} \\ Y_k^{(2)} = \underbrace{\begin{bmatrix} 0 & 1 & 0 & 0 \end{bmatrix}}_{C_k^{(2)}} X_k^{(2)} \end{cases}$$

where $X_k^{(i)} = \lfloor x_m^{(i)}(k) = x_m(k) \mid x_m(k) \in X_k, m \in I(i) \rfloor$, X_k is the set of all states in the system, and $I(i)$ is the set of the indices of all states in subsystem *#i*. For example, for the scenario in Fig. 1, $I(1)=\{1,2,3,4\}$ which indicates that subsystem *#1* contains the states $x_1^{(1)}, x_2^{(1)}, x_3^{(1)}, x_4^{(1)}$ and $I(2)=\{4,5,6,7\}$ which indicates that subsystem *#2* contains the states $x_4^{(2)}, x_5^{(2)}, x_6^{(2)}, x_7^{(2)}$. The subscript pertains to the state index and the superscript pertains to the subsystem number. In other words, $x_p^{(i)}$ indicates that the subsystem *#i* includes the state x_p. Augmenting the two subsystems results in the following constrained-state block-diagonal state space (CSBDSS) model with the constrained-state X_k^{CS} as shown below

$$X_k^{CS} = \begin{bmatrix} x_1^{(1)}(k) \\ x_2^{(1)}(k) \\ x_3^{(1)}(k) \\ x_4^{(1)}(k) \\ x_4^{(2)}(k) \\ x_5^{(2)}(k) \\ x_6^{(2)}(k) \\ x_7^{(2)}(k) \end{bmatrix} = \underbrace{\begin{bmatrix} A_{k-1}^{(1)} & 0 \\ 0 & A_{k-1}^{(2)} \end{bmatrix}}_{A_{k-1}^{CS}} X_{k-1}^{CS} + \begin{bmatrix} B_{k-1}^{(1)} \\ B_{k-1}^{(2)} \end{bmatrix} U_{k-1}$$

$$Y_k = \begin{bmatrix} C_k^{(1)} & 0 \\ 0 & C_k^{(2)} \end{bmatrix} X_{k-1}^{CS} \qquad (2)$$

As can be seen from equation (2), the matrix A^{CS} is block diagonal, which makes the development of distributed Kalman filtering a lot easier when compared to the overlapping block diagonal matrix A in its original form in equation (1). However, the constrained-state X_k^{CS} requires a special consideration in the distributed Kalman filtering development to ensure that the following constraint is satisfied at each filtering iteration, namely

$$mean(\hat{x}_4^{(1)}(k)) = mean(\hat{x}_4^{(2)}(k))$$

It should be noted that the equality constraint above is merely imposed on the mean of the corresponding common state estimates. In general, for the case of *n* overlapping blocks, the *n* subsystems of the CSBDSS model are formulated as follows ($i=1,2,...,n$)

$$\begin{aligned} X_k^{(i)} &= A_{k-1}^{(i)}X_{k-1}^{(i)} + B_{k-1}^{(i)}U_{k-1}^{(i)} \\ Y_k^{(i)} &= C_k^{(i)}X_k^{(i)} \end{aligned} \qquad (3\text{-a})$$

(Subsystems $s^{(i)} \in \Gamma$)

$$\forall s^{(i)}, s^{(j)} \in S;\quad \forall q \in I(i) \cap I(j);\quad x_q^{(i)} = x_q^{(j)} \qquad (3\text{-b})$$

(State Constraints)

where Γ is the set of all subsystems $s^{(i)}$. The necessity of the state constraints is that our proposed equivalent CSBDSS model (as in equation (2)) should realize and be consistent with the original OBDSS model (as in equation (1)). Fig. 2 shows the schematic of the CSBDSS model (2).

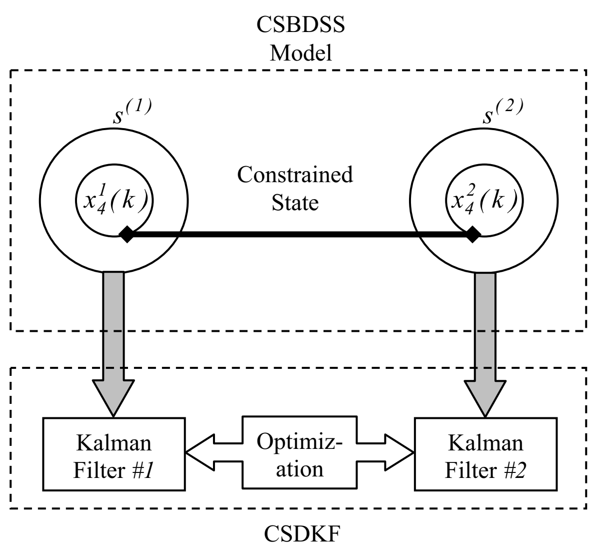

Fig. 2. Schematic of the CSBDSS model estimated by a CSDKF.

In the next section, distributed Kalman filters will be designed to cooperatively estimate the states of the CSBDSS model, while satisfying the constrained-state restriction by solving local optimization problems among the distributed Kalman filters.

IV. Constrained-State Distributed Kalman Filter

Consider the subsystem #*i* in equation (3-a). The CSDKF is realized according to the standard two steps "prediction" and "observation" as follow

<u>Prediction:</u>

$$\overline{X}_k^{(i)} = A_{k-1}^{(i)}\hat{X}_{k-1}^{(i)} + B_{k-1}^{(i)}U_{k-1}^{(i)}$$

$$\overline{P}_k^{(i)} = A_{k-1}^{(i)}\hat{P}_k^{(i)}(A_{k-1}^{(i)})^T + Q_{k-1}^{(i)}$$

<u>Observation:</u>

$$\hat{X}_k^{(i)} = \overline{X}_k^{(i)} + K_k^{(i)}\underbrace{(Y_k^{(i)} - C_k^{(i)}\overline{X}_k^{(i)})}_{\Delta Y_k^{(i)}}$$

$$\hat{P}_k^{(i)} = (I - K_k^{(i)}C_k^{(i)})\overline{P}_k^{(i)}(I - K_k^{(i)}C_k^{(i)})^T + K_k^{(i)}R_k^{(i)}(K_k^{(i)})^T$$

where

$$K_k^{(i)} = \begin{bmatrix} K_k^{(i),\alpha} \\ K_k^{(i),\beta} \\ \vdots \\ K_k^{(i),\delta} \end{bmatrix} \quad (\alpha,\beta,\ldots,\delta \in I(i))$$

$$\forall x_j \quad local \quad (n(S(j)) = 1 \quad or \quad S(j) = \{i\}):$$

$$\begin{aligned} K_k^{(i),j} &= arg \quad min \quad \hat{\sigma}_j^{(i)}(k) \\ &= \underset{x_j}{Row}\left((C_k^{(i)}\overline{P}_k^{(i)})^T\left(C_k^{(i)}\overline{P}_k^{(i)}(C_k^{(i)})^T + R_k^{(i)}\right)^{-1}\right) \\ &= \underset{x_j}{Row}(\overline{P}_k^{(i)})(C_k^{(i)})^T\left(C_k^{(i)}\overline{P}_k^{(i)}(C_k^{(i)})^T + R_k^{(i)}\right)^{-1} \\ &= \overline{P}_k^{(i),j}(C_k^{(i)})^T\left(C_k^{(i)}\overline{P}_k^{(i)}(C_k^{(i)})^T + R_k^{(i)}\right)^{-1} \end{aligned}$$

$$\forall x_j \quad common \quad (n(S(j)) \geq 2 \quad or \quad S(j) = \{p,q,\ldots,r\}):$$

$$\begin{aligned} &\left(K_k^{(p),j}, K_k^{(q),j}, \ldots, K_k^{(r),j}\right) \\ &= arg \quad min \quad \hat{\sigma}_j^{(p)}(k) + \hat{\sigma}_j^{(q)}(k) + \cdots + \hat{\sigma}_j^{(r)}(k) \\ &\quad s.t. \\ &\forall m \in S(j),\ \exists \hat{x}_j,\ \overline{x}_j^{(m)}(k) + K_k^{(m),j}\Delta Y_k^{(m)} = \hat{x}_j(k) \end{aligned} \tag{4}$$

(Local Constrained Optimization Problem)

where $Q^{(i)}$ and $R^{(i)}$ are zero-mean white Guassian random processes representing the dynamics and sensor noise of subsystem #*i*, respectively, and $\hat{\sigma}_j^{(i)}$ is the variance of the state $x_j^{(i)}$ calculated by the subsystem #*i*. $\underset{x_j}{Row}(M)$ is the only row of matrix M that corresponds to the state x_j, and $S(j)$ is the set of all subsystems #*i* that include the state x_j with the exclusive label $x_j^{(i)}$. The state x_j is considered as "local" if it shows up in one subsystem ($S(j) = \{i\}$, $n(S(j)) = 1$, where $n(.)$ represents the *cardinality* value) that is denoted by $x_j^{(i)}$, and the state x_j is considered as "common" if it shows up in multiple subsystems ($S(j) = \{p,q,\ldots,r\}$ or $n(S(j)) \geq 2$) that are denoted by $x_j^{(p)}, x_j^{(q)}, \ldots, x_j^{(r)}$, respectively. Finally, $\hat{x}_j$ is the estimate of the common constrained state x_j to which all of the Kalman filters corresponding to subsystems in $S(j)$ will converge so that the constrained-state condition is satisfied.

In case of a local state $x_j^{(i)}$, the row vector $K_k^{(i),j}$ can be calculated locally and independently for the only subsystem #*i*. But in case of a common state $x_j^{(m)}$ ($m \in S(j)$), the row vectors $K_k^{(m),j}$ should be calculated simultaneously in a centralized manner. Therefore, the calculation of the row vectors $K_k^{(m),j}$ requires stringent communication with the neighboring subsystems that make the performance highly brittle to computational and communicational failures, delays and intermittences. In the following section, the effectiveness of our proposed CSDKF is validated by simulation results.

V. Simulation Results

For conducting simulations, we consider the formation of three satellites in deep space (DS), as depicted in Fig. 1. The covariance matrices of the dynamic equation uncertainty and the sensor noise are $Q = 10^{-4} I_{7\times7}$ and $R = 10^{-4} I_{2\times2}$, respectively. We consider the fault scenario of *10%*, *20%*, and *30%* losses of effectiveness in the *x*-axis actuators of the satellites *#1*, *#2*, and *#3*, respectively. Our objective is to estimate the *x*-axis actuator fault parameters in all the three satellites. The inter-satellite relative measurements are made between the satellites *#1* and *#2*, and the satellites *#2* and *#3*.

The overall state space model of the system consists of two blocks overlapping (common) in the actuator fault parameter of satellite *#2*. Therefore, we transform this OBDSS model into our proposed CSBDSS model, in which the constrained-state condition is imposed on the fault parameter of satellite *#2*. The estimates and estimation errors of the three fault parameters are shown in Figs. 3 to 5 using our proposed distributed Kalman filtering technique. It can be seen that the maximum estimation error in all the three estimates is 0.05. Therefore, our proposed CSDKF successfully converges to the desired values, while the constrained-state condition is satisfied at all iterations.

For comparison, the three fault parameters are also estimated by using a centralized Kalman filter in Figs. 6 to 8. Comparing Figs. 3 to 5 with Figs. 6 to 8, respectively, it follows clearly that our distributed estimation approach does not result in any significant performance degradation, which confirms the effectiveness of our proposed approach.

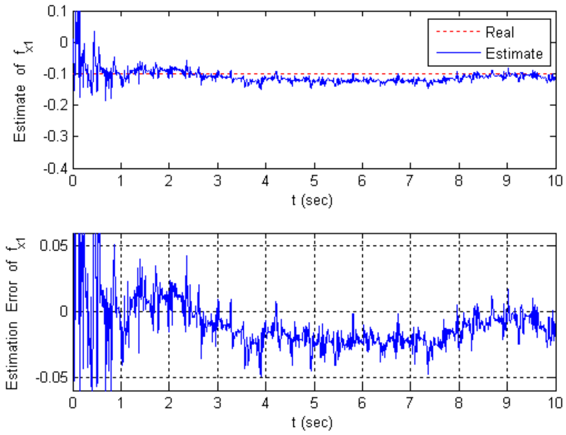

Fig. 3. Distributed estimation for the fault parameter in satellite #1.

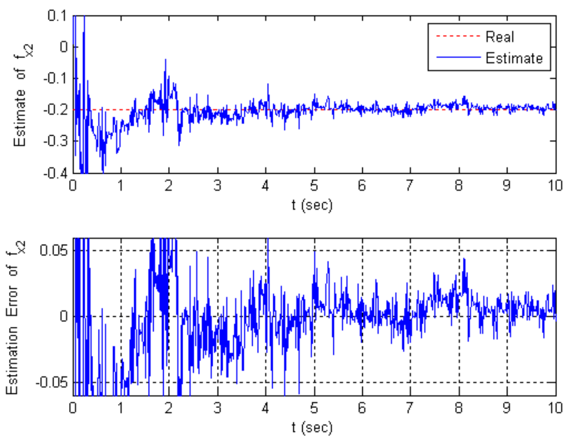

Fig. 4. Distributed estimation for the fault parameter in satellite #2.

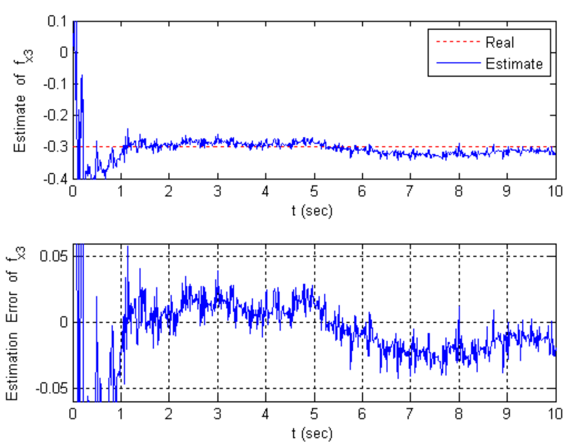

Fig. 5. Distributed estimation for the fault parameter in satellite #3.

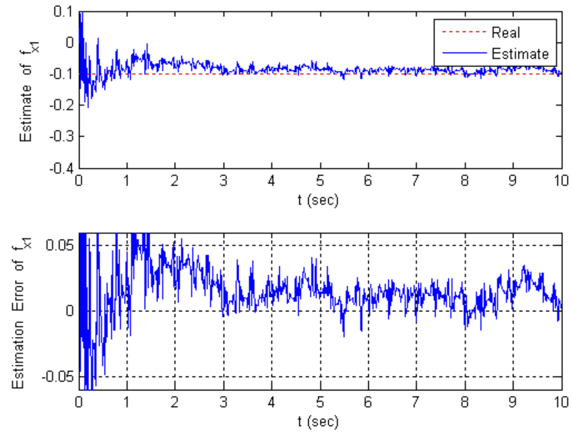

Fig. 6. Centralized estimation for the fault parameter in satellite #1.

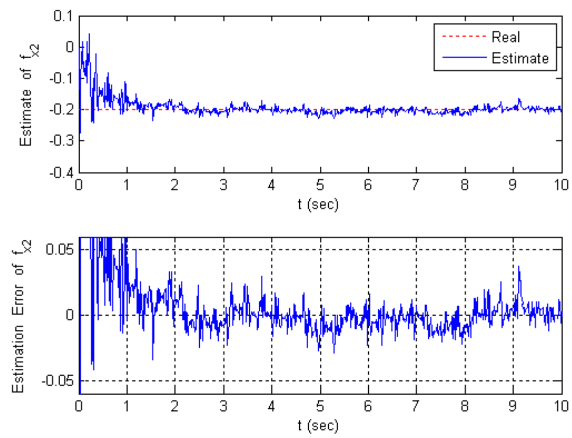

Fig. 7. Centralized estimation for the fault parameter in satellite #2.

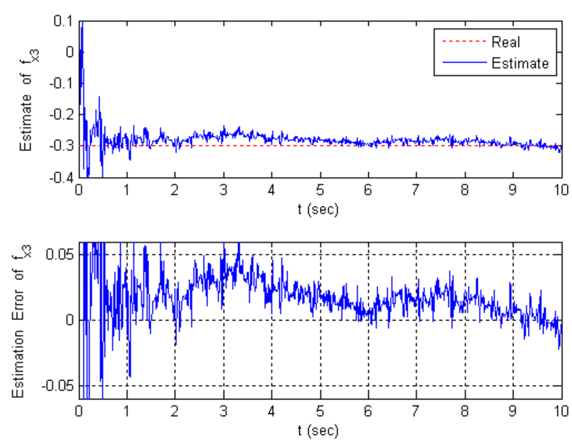

Fig. 8. Centralized estimation for the fault parameter in satellite #3.

In comparison with the available techniques in the literature, the advantages of our proposed distributed Kalman estimation scheme can be listed as follows:

- Our proposed CSBDSS model is purely block diagonal, which makes it convenient to distribute centralized Kalman filters according to decoupled and independent blocks.
- Although the initial OBDSS model is transformed into a pure block diagonal model, the interactions among the initial overlapping blocks are captured and preserved by the constrained-state condition. In other words, unlike the conventional reduced-order distributed Kalman filtering techniques, the constrained-state condition in our proposed method ensures that the pure block diagonal model fairly represents the behavior of the original overlapping blocks.
- The validation of the constrained-state condition is achieved through local constrained optimization procedures (equation (4)), which requires computational resources that unlike full-order distributed Kalman filtering techniques do not increase with the order of the large-scale system. This property substantiates the desirable scalability of our proposed distributed Kalman estimation technique.

VI. CONCLUSIONS

In this paper, we have investigated the problem of actuator fault estimation in formation flying satellites in deep space. The fault-augmented relative-state relative-measurement model of the formation flying is shown to be in the form of an overlapping block-diagonal state space (OBDSS) representation. We proposed to transform the OBDSS model into a constrained-state block-diagonal state space (CSBDSS) model. A constrained-state distributed Kalman filter (CSDKF) strategy is proposed to estimate the states of the CSBDSS model, while satisfying the constrained-state condition through local optimization formulations among the distributed filters. Simulation results presented confirm the validity of our proposed approach.

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