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Local condition-based finite-horizon distributed H_∞-consensus filtering for random parameter system with event-triggering protocols[☆]

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ABSTRACT

This paper investigates the distributed $H_\infty-$consensus filtering problem for a class of discrete time-varying systems with random parameters and event-triggering protocols. An event-triggering protocol for each node is employed to reduce the burden of the network communication. A novel matrix named by information matrix is proposed to describe the complicated correlations among the elements of random matrix. By virtue of the presented information matrix, a weighted covariance matrix can be easily obtained to analyze the system with random parameters. With the aid of the newly constructed dissipation matrix and vector supplied rate functions, a set of local coupled conditions for each node is obtained such that the stochastic vector dissipativity-like over the finite-horizon of the filtering error dynamics can be guaranteed. As well, these sufficient conditions together could effectively solve the distributed $H_\infty-$consensus filtering problem. Notably, the designed filtering algorithm can be implemented on each node to obtain the desirable distributed filter gains. Finally, the effectiveness and applicability of the proposed algorithm is illustrated by a numerically simulative example.
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1. Intrcoduction

With the rapid development of the sensor technology and the network technology, distributed filtering in the context of the sensor network has gained considerable concern. This probably ascribes to the broad applications of distributed filtering in many areas, such as information acquisition and processing, signal detection, intelligent robotics, environment monitoring, see [21,34] for a survey. Recently, H_∞ filtering technique together with the consensus strategy has been extended to the distributed case, that is, distributed $H_\infty-$consensus filtering. Some interesting results have been made on many complicated system dynamics with various network-induced phenomena, such as missing measurements [1,36,31], transmission delays [1,8], communication link failures [36], randomly varying nonlinearities [5,23], randomly switching topology [33], stochastic parameters [5], Markovian jump nonlinear systems [2], the piecewise linear systems [11].

Generally speaking, sensor network has a large number of nodes, wherein every node sends and receives information through the network, as such, a lot of communication resources will be consumed. Too much communication, however, is a big burden for the limited bandwidth. For this point, it is essentially interesting to save network communication recourses with losing few system performance. Obviously, compared with the centralized manner, the distributed manner implies that the messages from one node won't be sent to the information fusion center but to its neighbor nodes, then the communication resources can be saved. So far, there has been a tremendous interest in the distributed filtering [1–3,5,7,8,23,26,31–33,35,36]. Besides, another effective way in saving the communication is the so-called event-triggering protocol [6–9,18,20,22,24,27–29,30,37,38].

Event-triggering protocol is employed to determine whether the newly estimation (or sampled state, innovation) is sent to the filter (or controller) by using the predefined triggering condition. In such a case, not all data could be successfully transmitted. Instead, only those necessary data in guaranteeing the system performance are down. In view of large number of nodes in the sensor network, reducing the frequency of the sending data can effectively prolong the life of nodes and save the communication

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resources. Meanwhile, we wish to retain the desirable system performance. Therefore, it is quite vital to investigate the distributed filtering with respect to the event-triggering protocols [8] has generalized the idea from [37] to the distributed event-triggered H_∞ filtering with communication delays, where a novel co-design method was developed to determine the desired filter gains and the threshold parameters [22] has extended the recursive filtering method [12] to the distributed case with the event-triggering protocols, where the event-triggering conditions were constructed according to the local innovation of node. Also, the event-triggering term was regarded as disturbances and employed the traditional robust inequality to design the recursive distributed filters [6] investigated the event-triggered distributed filtering problem, where the transmitted data might be lost after the event-triggering conditions were violated. In light of the above observations, the obtained design algorithms are dependent of the information of all nodes in the sensor network. As we know, the computation complexity is tightly relative to the number of all the nodes. The more information are taken into consideration, the heavier computation burden will come. For this reason, we are motivated to seek a local performance analysis method to figure out the computation burden problem.

Specifically, the local performance analysis is carried out on the dynamics of a single node in the sensor network. Accordingly, it yields the local algorithm, which can be separately presented for each node. Moreover, such local algorithm is exclusively implemented on each node, thus an indeed distributed manner comes out. One idea of the local performance analysis stemmed from the well-known vector dissipativity theory [10]. The critical procedure is to construct the vector dissipation inequality including the vector storage function, the vector supply rate function and the dissipation matrix. Nevertheless, due to the employment of the event-triggering protocol, one technique problem is how to investigate the vector dissipativity inequality subject to the event-triggering protocols.

Actually, the sensor nodes and the plant are often in stochastic manners due to many factors, such as temperature, humidity, electromagnetic signal, and etc. Thus, the system matrix and the measurement matrix can be formulated by random matrices composed of the random variables. Such a class of systems is referred to as random parameter systems [4,5,13,19], and there might be complicated correlations among these random variables. Thus, it is vital to formulate these correlations for the investigation of random parameter systems. Also, during the analysis, we need to calculate the weighted covariance matrix defined by the weighted quadratic form of random matrix. Nevertheless, the covariance information cannot be directly used, since the random matrix and its transpose are coupled by the weighted matrix. Notice that the references as [5,13,19] have individually presented the covariances of any pair of elements in the random matrix. In this way, the weighted covariance matrix was obtained by calculating its elements individually [5,13,19], which inevitably increased the computation burden. Obviously, such a time-consuming technique is unapplicable to the distributed filtering problem. It is noted that, the matrix manipulations are usually utilized into the analysis and synthesis of the system. Therefore, we novelly present the information matrix instead of individually presenting the covariance element. What's more, by virtue of this matrix, a formula for calculating the weighted covariance matrix is provided.

In this paper, we concern the finite-horizon $H_\infty-$consensus filtering with random parameters and event-triggering protocols. The objective is to design a locally distributed filtering algorithm based on the local performance analysis. Our main contributions are summarized as follows: (1) A novel matrix called as information matrix is proposed to describe the covariance of any pair of elements in the random matrix; (2) By means of the information matrix, the calculation formula for the weighted-covariance matrix is presented; (3) The distributed filtering algorithm could be implemented separately on each node in parallel, thus the computation burden could be effectively reduced. In addition, the locally sufficient conditions are not only dependent of its own information, but also dependent of the information of its neighbors; (4) The proposed distributed filtering method is scalable. Namely, its complexity is isolated from the number of all the nodes, i.e. the network size, and is only relative to the number of its neighbors.

Motivated by the above discussions, we aim to investigate the finite horizon distributed $H_\infty-$consensus filtering with random parameters and event-triggering protocols. The rest of this paper is organized as follows. In Section 2, the distributed $H_\infty-$consensus filtering problem for the linear time-varying systems is formulated, where the event-triggering protocol is described for each node and the information matrix is proposed for the random matrix. In Section 3, by utilizing the information matrix, the weighted covariance matrix formula is presented via the Kronecker product and the Hadamard product, and then a set of local coupled sufficient conditions for each node is derived through the vector dissipativity such that the filtering error dynamics with event-triggering protocol satisfies the $H_\infty-$consensus performance constraint. Finally, the filter gains of each node are designed with the aid of a set of RLMIs. One illustrative example is utilized in Section 4 to verify the effectiveness and the applicability of the proposed filtering algorithm, and a conclusion is drawn in Section 5.

Notation. In this paper, $\mathbb{R}^l$ and $\mathbb{R}^{l\times m}$ denote, respectively, the l-dimensional Euclidean space and the set of all $l\times m$ real matrices. For a matrix M, M^T represents its transpose, $M \geq\geq 0$ indicates that every element of matrix M is nonnegative. Given a column vector $\vartheta_k \in \mathbb{R}^n$, $\|\vartheta_k\|^2_{Q_k} = \vartheta_k^T Q_k \vartheta_k$. I denotes the identity matrix of compatible dimension. The notation $X \geq Y$ (respectively, $X > Y$), where X and Y are symmetric matrices, means that $X - Y$ is nonnegative-definite (respectively, positive definite). In symmetric block matrices, the symbol $*$ is used as an ellipsis for terms induced by symmetry. $\mathbf{1}$ denote special vector or matrix that every component is 1. A nonnegative matrix $W \in \mathbb{R}^{n\times n}$ is column sub-stochastic if $\mathbf{1}^T W \leq\leq \mathbf{1}^T$. $\mathbb{E}\{R^T W R\}$ denotes the weighted covariance matrix for given random matrix R and weighted matrix W. For any two matrices A and B, $A\otimes B$ denotes the Kronecker product, where $[A\otimes B]_{ij} = A_{ij}B$. Further, if these two matrices A and B have same dimensions, $A\circ B$ denotes the Hadamard product, where $[A\circ B]_{ij} = A_{ij}\cdot B_{ij}$. Matrices, if they are not explicitly stated, are assumed to have compatible dimensions.

2. Problem formulation

First, formulate the sensor network with N nodes distributed in space. Its topology is represented by a digraph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A})$ with the set of nodes $\mathcal{V} = \{i | i = 1, 2, \ldots, N\}$, the set of edges $\mathcal{E} = \{(i, j) | (i, j) \in \mathcal{V}\times\mathcal{V}\}$, and the adjacency matrix $\mathcal{A} = [a_{ij}]$. If $(i, j) \in \mathcal{E}$ and $i \neq j$, then $a_{ij} = 1$; otherwise $a_{ij} = 0$. $a_{ij} = 1$ means that node j can provide information to node i. The in-degree of node i is denoted as p_i satisfying $p_i = \sum_{j=1}^N a_{ij}$. The out-degree of node i is denoted as q_i satisfying $q_i = \sum_{j=1}^N a_{ji}$. The set of neighbors of node i with in-degree p_i is denoted by $\mathcal{N}_i = \{j_1, j_2, \ldots, j_{p_i}\}$.

Consider a discrete time-varying plant defined on $k \in \mathcal{K} := \{0, 1, \ldots, n-1\}$:

$$\begin{cases} x_{k+1} = A_k x_k + B_k w_k, \\ z_k = E_k x_k, \\ x_0 = \phi \end{cases} \tag{1}$$

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