Review Article

A Survey on Distributed Filtering and Fault Detection for Sensor Networks

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In recent years, theoretical and practical research on large-scale networked systems has gained an increasing attention from multiple disciplines including engineering, computer science, and mathematics. Lying in the core part of the area are the distributed estimation and fault detection problems that have recently been attracting growing research interests. In particular, an urgent need has arisen to understand the effects of distributed information structures on filtering and fault detection in sensor networks. In this paper, a bibliographical review is provided on distributed filtering and fault detection problems over sensor networks. The algorithms employed to study the distributed filtering and detection problems are categorised and then discussed. In addition, some recent advances on distributed detection problems for faulty sensors and fault events are also summarized in great detail. Finally, we conclude the paper by outlining future research challenges for distributed filtering and fault detection for sensor networks.

1. Introduction

1.1. Sensor Networks. Sensor networks have recently been undergoing a quiet revolution in all aspects of the hardware implementation, software development, and theoretical research. In addition to the universal attributes of complex networks, sensor networks do possess their own characteristics due mainly to the large number of inexpensive wireless devices (nodes) densely distributed and loosely coupled over the region of interest. The past decade has seen successful applications of sensor networks in many practical areas ranging from military sensing, physical security, and air traffic control to distributed robotics and industrial and manufacturing automation. Accordingly, theoretical research on sensor networks has gained an increasing attention from multiple disciplines including engineering, computer science, and mathematics. Lying in the core part of the area are the distributed estimation and filtering problems that have recently been attracting growing research interests.

For distributed estimation/filtering problems, the inherently asynchronous sensor network is comprised of a large number of sensor nodes with computing and wireless communication capabilities, where the nodes are spatially distributed to form a wireless ad hoc network and every node has its own notion of time. Each individual sensor in a sensor network locally estimates/filters the system state from not only its own measurement but also its neighbouring sensors' measurements according to the given topology. The possible complexity of such a topology poses many challenges for scientists and engineers, and it is difficult to analyse these networks thoroughly with currently available estimation/filtering algorithms. Therefore, there is an urgent need to research on modelling, analysis of behaviours, systems theory, estimation, and filtering in sensor networks. Numerous fundamental questions have been addressed about the connections between sensor network topology and dynamic properties including stability, controllability, robustness, and other observable aspects. However, some major problems have not been fully investigated, such as the behaviour of stability, estimation, and filtering for sensor networks with incomplete/imperfect/stochastic topology, as well as their applications in, for example, distributed signal processing.

Sensor networks have already become an ideal research area for control engineers, mathematicians, and computer scientists to manage, analyze, interpret, and synthesize functional information from real-world sensor networks. Sophisticated system theories and computing algorithms have been exploited or emerged in the general area of distributed sensor networks, such as analysis of algorithms, artificial intelligence, automata, computational complexity, computer security, concurrency and parallelism, data structures, knowledge discovery, DNA and quantum computing, randomisation, semantics, symbol manipulation, numerical analysis, and mathematical software. This survey aims to bring together the latest approaches to understanding, estimating, and filtering complex sensor networks in a distributed way. The references discussed in this paper include, but are not limited to the following aspects of sensor networks: (1) systems analysis of distributed sensor networks; (2) distributed parameter identification of sensor networks; (3) robustness and fragility analysis of distributed sensor networks; (4) methods and algorithms for sensor network dynamics; and (5) distributed estimation and filtering with limited communication constraints.

1.2. Distributed Filtering. Over the past ten years or so, the sensor networks (SNs) have proven to be a persistent focus of research attracting an ever-increasing attention in the areas of systems and communication. A typical sensor network is composed of a large number of spatially distributed autonomous sensor nodes and also a few control nodes, where each sensor has wireless communication capability as well as some level of intelligence for signal processing and for disseminating data [1–7]. The development of sensor networks was originally motivated by military applications such as distributed localization, power spectrum estimation, and target tracking problems. With recent intensive research in this area, sensor networks have a wide-scope domain of applications in areas such as environment and habitat monitoring, health care applications, traffic control, distributed robotics, and industrial and manufacturing automation [1–3, 8, 9].

As one of the most fundamental collaborative information processing problems, the distributed filtering or estimation problem for sensor networks has gained particular concerns from many researchers and a wealth of the literature has appeared on this topic; see, for example, [10–19] and the references therein. For distributed filtering problems, the information available on an individual node of the sensor network is not only from its own measurement but also from its neighboring sensors' measurements according to the given topology. As such, the main difficulty in designing distributed filters lies in how to cope with the complicated coupling issues between one sensor and its neighboring sensors and how to reflect such couplings in the filter structure specification.

1.3. Distributed Fault Detection. On another research front, the fault detection problem has been an active field of research for the past decades because of the ever increasing demand for higher performance, higher safety, and reliability standards [20–33]. In sensor networks, sensor nodes have strong hardware and software restrictions in the light of

processing power, memory capability, battery supply, and communication throughput, and faults are likely to occur frequently due to the low cost and the uncontrolled or even harsh environment where the sensor nodes are deployed. It is thus indispensable for the sensor networks to be able to detect, locate the faulty sensor nodes, and take actions to exclude them from the network during normal operation in order to ensure the network quality of service. Recently, some localized and distributed generic algorithms have been addressed in wireless sensor networks and a number of results about the distributed fault detection and fault tolerance have been published in the literature.

1.4. Structure of the Survey. The focus of this paper is to provide a timely review on the recent advances of the distributed filtering and fault detection issues for sensor networks. The rest of this paper is outlined as follows. In Section 2, the related results in the area of distributed filtering for wireless sensor networks are reviewed. The study contains a classification of different methods concerning distributed filtering. A comparison of different approaches is briefly summarized. Section 3 discusses the distributed fault detection problems over sensor networks. Both the distributed faulty sensors detection and distributed fault-event detection are carried out and explained separately. In Section 4, we give some concluding remarks and also point out some future directions.

2. Distributed Filtering for Sensor Networks

2.1. Traditional Kalman Filtering Approach. In recent years, the distributed filtering problem for sensor networks has received a fast growing research interest and some efficient distributed filtering/state estimation algorithms have been available in the literature; see, for example, [10, 11, 34–39] and the references therein.

The available algorithms, which can estimate stationary signals with low-cost and track nonstationary processes with reduced complexity, have a variety of engineering applications such as battlefield surveillance and target tracking. For example, a distributed Kalman filtering (DKF) algorithm has been introduced in [38] through which a crucial part of the solution is utilized to estimate the average of n signals in a distributed way. Accordingly, this elegant algorithm has been developed in [34–36, 40, 41] with different sensing models and dynamic consensus protocols. The notion of distributed bounded consensus filters has been introduced in [19] and the convergence analysis has been conducted for the corresponding distributed filters. In [14, 17, 42], the optimal distributed estimation algorithm has been proposed to adaptively update the weights for minimizing the estimated mean-square error. The diffusion-based Kalman filtering and smoothing algorithm has been established in [10, 11], where the information is diffused across the network through a sequence of Kalman iterations and data aggregation. In multisensor linear systems, several efficient algorithms including the centralised sensor fusion, distributed sensor fusion, and multialgorithm fusion to minimize the Euclidean estimation

error of the state vector have been presented in [43, 44]. In [45–47], the distributed particle filtering algorithm has been investigated as a response to offload the computation from the central unit as well as to reduce converge cast communication. References [48, 49] have introduced the maximum-likelihood approach in order to achieve the best possible variance for a given bandwidth constraint.

Looking into the issues discussed above, it can be observed that most available literature concerning the distributed filtering problems have been mainly limited to the traditional Kalman filtering theory that requires exact information about the plant model.

2.2. Robust and/or H_∞ Filtering Approach.

2.2. Robust and/or H_∞ Filtering Approach. In the presence of modeling errors, parameter uncertainties, and external disturbance, it is difficult to ensure the robustness of the traditional Kalman filters especially when the unavoidable parameter drifts or external disturbances occur. Note that the robust performance of the available distributed filters has not been paid adequate research attention despite its clear engineering significance. In this sense, it is of great significance to include the robust and/or H_∞ performance requirements for the distributed filtering problems.

Very recently, a new distributed H_∞-consensus performance has been defined in [50] to quantify bounded consensus regarding the filtering errors over a finite horizon, the distributed filtering problem has been addressed for a class of linear time-varying systems in the sensor network, and the filter parameters have been designed recursively by resorting to the different linear matrix inequalities. The H_∞-consensus performance presented in [50] has been utilized in [39] to deal with the distributed H_∞ filtering problem for a class of polynomial nonlinear stochastic systems in sensor networks. Subsequently, the desired distributed H_∞ filters have been designed in terms of the solution to certain parameter-dependent linear matrix inequalities. A stochastic sampled-data approach has been addressed in [16] to investigate the distributed H_∞ filtering in sensor networks. In [51], an H_∞-type performance measure of disagreement between adjacent nodes of the network has been included and a robust filtering approach has been proposed to design the distributed filters for uncertain plants.

2.3. Filtering with Incomplete Information.

2.3. Filtering with Incomplete Information. It is worth noting that most reported results concerning the distributed filtering/estimation algorithms are for linear and/or deterministic systems. Since nonlinearities are ubiquitous in practice, it is necessary to consider the distributed filtering problem for target plants described by nonlinear systems. On the other hand, distributed filtering in a sensor network inevitably suffers from the constrained communication and computation capabilities that would degrade the network performances.

It is well known that, accompanied by the rapid development of network technologies, the network-induced phenomena have been thoroughly investigated for filtering and control problems of networked systems [13, 21, 52–73]. Considering the case that the occurrence of incomplete information in sensor networks is more complex and

severer due primarily to the network size, communication constraints, limited battery storage, strong coupling, and spatial deployment, the distributed filtering problem has been investigated in [74–76] for several classes of nonlinear stochastic systems over lossy sensor networks. The issue of average H_∞ performance constraints has been brought up in [74], and then the distributed H_∞ filtering problem has been investigated for system with repeated scalar nonlinearities and multiple probabilistic packet losses. Moreover, in [75], the distributed filtering problem has been further extended to the nonlinear time-varying systems with limited communication. The lossy sensor network suffers from quantization errors and successive packet dropouts that are described in a unified framework. A new distributed finite-horizon filtering technique by means of a set of recursive linear matrix inequalities has been proposed to satisfy the prescribed average filtering performance constraint.

In addition, the distributed H_∞ filtering problem has been investigated in [76] for a class of discrete-time Markovian jump nonlinear time-delay systems with deficient statistics of modes transitions. In [77], a new approach has been proposed in virtue of the solvability of certain coupled recursive Riccati difference equations (RDEs) to deal with the distributed H_∞ state estimation problem for a class of discrete time varying nonlinear systems with both stochastic parameters and stochastic nonlinearities.

3. Distributed Fault Detection for Sensor Networks

Wireless sensor networks (WSNs) are a multihop self-organized network system through wireless communication in which the failed nodes may decrease the service quality of the entire WSNs and create huge burden to the limited energy. In recent years, a growing number of efforts have been focused on the development of the fault detection methods for sensor nodes.

In [78], the online model-based detection of sensor faults has been first investigated by the cross-validation-based technique in which statistical methods are utilized to identify the sensors that are most likely to be faulty. This technique is centralized and can be applied to a broad set of fault models. A distributed fault detection scheme for sensor networks has been proposed in [79] to identify the faulty sensors, where each sensor node makes a decision based on the comparisons between its own sensing data and neighbors' data. The scheme, however, has the shortcoming of reducing the fault detection accuracy in the case that the number of neighbor's nodes to be diagnosed is small. In [80], an improved distributed fault detection algorithm based on weighted average value has been addressed by defining a new detection criterion to remedy the shortcoming that mentioned above. The scheme detects the sensor fault using spatial and time information simultaneously, where each sensor node identifies its own status based on local neighbor's average sensed data with some thresholds, hence maintaining low false alarm rate.

By using the spatial correlation of sensor measurements, a weighted median fault detection scheme has been introduced in [81] to detect the faults in WSNs. Reference [82]

has studied the problem of designing a distributed fault-tolerant decision fusion in the presence of sensor faults, where sensor fault detection scheme has been put forward to eliminate unreliable local decisions when performing distributed decision fusion. In [83], an agreement-based fault detection mechanism has been presented to detect cluster-head failures in clustered underwater sensor networks. Furthermore, a schedule generation scheme for a cluster head has been introduced to generate the transmission schedule of the forward and backward frames. The distributed fault detection problem has been investigated in [84] for WSNs, where each sensor node discerns its own status in view of local comparisons of sensed data with some thresholds and transfers the test results. It is well known that the basic idea of the distributed fault detection methods for sensor nodes is to check out the failed nodes by exchanging data and mutually testing among neighbor's nodes in this sensor networks.

It is worth pointing out that, apart from the development of distributed fault detection methods for sensor nodes, the distributed fault-event detection, which serves as a much more useful application in a sensor network, has also received much research attention. In [85], a distributed Bayesian fault recognition algorithm has been presented to solve the fault-event detection problem in sensor networks, where the randomized decision scheme and the threshold decision scheme have been used to derive analytical expressions for their detected performance. The proposed algorithm has the superiority of being completely distributed and localized each node by obtaining the information from neighboring sensors in order to make its decisions. A localized fault identification algorithm has been proposed in [86] to identify the faulty sensors and detect the reach of events in sensor networks, where each sensor node compares its own sensed data with the median of neighbors' data in order to determine its own status. In [87], a fault detection scheme for an event-driven wireless sensor network has been addressed by using an external manager, which can perform more complex functions compared to the sensor nodes. In [88], a fault-tolerant energy-efficient detection scheme has been presented to introduce the sensor fault probability into the optimal event detection process. For a given detection error bound, the minimum neighbors are selected to minimize the communication volume during the fault correction. It is also noted that the proposed distributed fault detection methods for sensor networks have a widely application fields such as the management of a reservoir [89] and integration of supply networks [90].

4. Conclusions and Future Work

In this paper, we have discussed and reviewed results, mostly from relatively recent work, on the problems of distributed filtering and fault detection for sensor networks. The various distributed filtering and fault detection technologies over sensor networks have been surveyed in great detail. Based on the literature review, some related topics for the future research work are listed as follows.

(i) A trend for future research is to generalize the methods obtained in the existing results to the distributed filtering and fault detection problems for nonlinear stochastic complex networks systems with randomly occurring incomplete information.

(ii) The nonlinearities considered in the existing results have some constraints that may bring somewhat conservative results. An additional trend for future research is to investigate the distributed filtering and fault detection problems for the general nonlinear systems for sensor networks.

(iii) Another future research direction is to further investigate the problems of nonparametric and robust sequential distributed detection for sensor networks.

(iv) The techniques such as conditional statistical tests and multivariate procedures in the presence of nonparametric hypotheses can be applied fruitfully in distributed fault detection applications.

Conflict of Interests

The authors declare that they have no conflict of interests related to this study.

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