Estimation, Filtering and Fusion for Networked Systems with Network-Induced Phenomena: New Progress and Prospects

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Abstract

In this paper, some recent advances on the estimation, filtering and fusion for networked systems are reviewed. Firstly, the network-induced phenomena under consideration are briefly recalled including missing/fading measurements, signal quantization, sensor saturations, communication delays, and randomly occurring incomplete information. Secondly, the developments of the estimation, filtering and fusion for networked systems from four aspects (linear networked systems, nonlinear networked systems, complex networks and sensor networks) are reviewed comprehensively. Subsequently, some recent results on the estimation, filtering and fusion for systems with the network-induced phenomena are reviewed in great detail. In particular, some latest results on the multi-objective filtering problems for time-varying nonlinear networked systems are summarized. Finally, conclusions are given and several possible research directions concerning the estimation, filtering, and fusion for networked systems are highlighted.

Index Terms

Estimation; filtering; multi-sensor data fusion; networked systems; network-induced phenomena.

I. Introduction

The networked systems have attracted increasing research attention due to their successful applications in a wide range of areas, such as aircraft, space and terrestrial exploration, access in hazardous environments, factory automation, remote diagnostics and troubleshooting, automated highway systems, unmanned aerial vehicles, manufacturing plant monitoring and condition-based maintenance of complex machinery [1]. The

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advantages of the usage of networked systems include flexible architecture, the reduction of installation and maintenance costs, decreasing the implementation difficulties and so on. However, the network-induced phenomena arise inevitably due to the insertion of the communication network with limited communication capacity [2]–[5]. Such network-induced phenomena include, but are not limited to, communication delays, missing/fading measurements, signal quantization, sensor saturations, variable sampling/transmission intervals, and out-of-sequence-measurement updates. Recently, a class of newly emerged network-induced phenomena (randomly occurring incomplete information) has gained some initial research interest in signal processing and control areas. Note that the network-induced phenomena could greatly degrade the performance of the networked systems and may even lead to the instability of the controlled systems [6], [7]. Consequently, it is not surprising that both analysis and synthesis problems for networked systems have received considerable research attention in the past decade.

The filtering problem has long been one of the foundational research problems in signal processing and control engineering [8]–[12]. The past two decades have witnessed the rapid developments and extensive applications of the filtering algorithms in practice, such as guidance, navigation, target tracking, remote sensing, image processing, econometrics, and monitoring of manufacturing processes. Therefore, the design of the filtering algorithms has received increasing research attention. According to different performance indices (minimized variance constraint, set-valued constraints, guaranteed H_∞ performance requirements and so on), a great number of filtering algorithms have been developed for networked systems, such as Kalman filtering [13], [14], extended Kalman filtering [15]–[18], set-valued filtering [19], [20], set-membership filtering [21], H_2 filtering [22]–[24], H_∞ filtering [25], [26], and consensus filtering [27], [28]. On the other hand, the design of linear optimal estimators (including filter, predictor and smoother) for networked systems has gained a great deal of research attention as conducted in [29]–[32].

On another research frontier, it is well known that the data fusion techniques can provide the fusion schemes by combining the information from different sources so as to achieve a satisfactory performance. Over the past decades, the data fusion techniques have been successfully applied in a variety of areas such as the target tracking, navigation, detection, robotics, video and image processing, business intelligence, and sensor networks. Therefore, considerable research effort has been devoted to the multi-sensor data fusion problems for complex dynamical systems. In fact, as mentioned in [33], there are a great number of challenging issues in the multi-sensor data fusion fields including data imperfection, outliers and spurious data, conflicting data, data modality, data correlation, data association, data alignment/registration, processing framework, operational timing, static versus dynamic phenomena, data dimensionality and so on. For more information about the challenging problems of the multi-sensor data fusion, we refer the readers to the survey paper [33] where more comprehensive interpretations have been provided. In what follows, we confine the addressed topic to the multi-sensor data fusion for networked systems and endeavor to introduce some recent advances on the network-based multi-sensor data fusion approaches from the perspective of algorithm developments. The multi-sensor data fusion algorithms can be generally classified into two types: centralized fusion and distributed fusion algorithms, where the schematic diagrams of centralized and distributed fusions in network environment are given as in Figs. 1–2 respectively. We will further discuss the recent developments of the multi-sensor fusion of networked systems later.

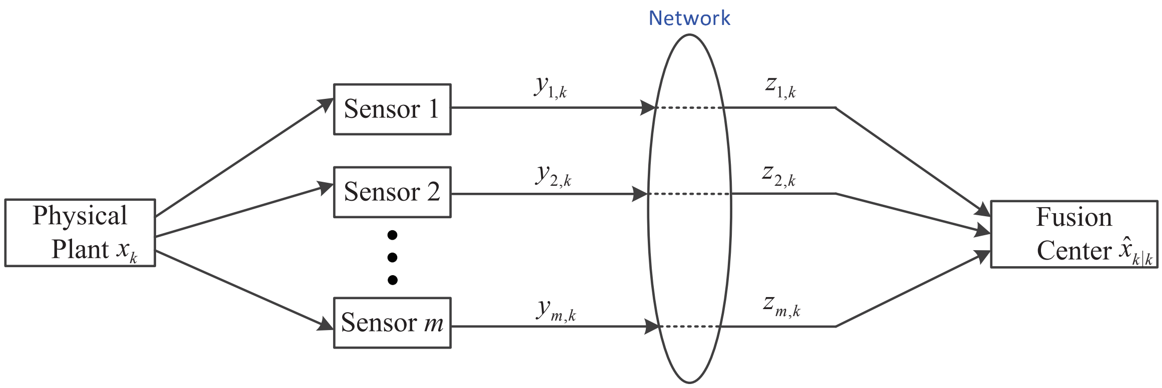

Fig. 1. Schematic structure of centralized fusion over network

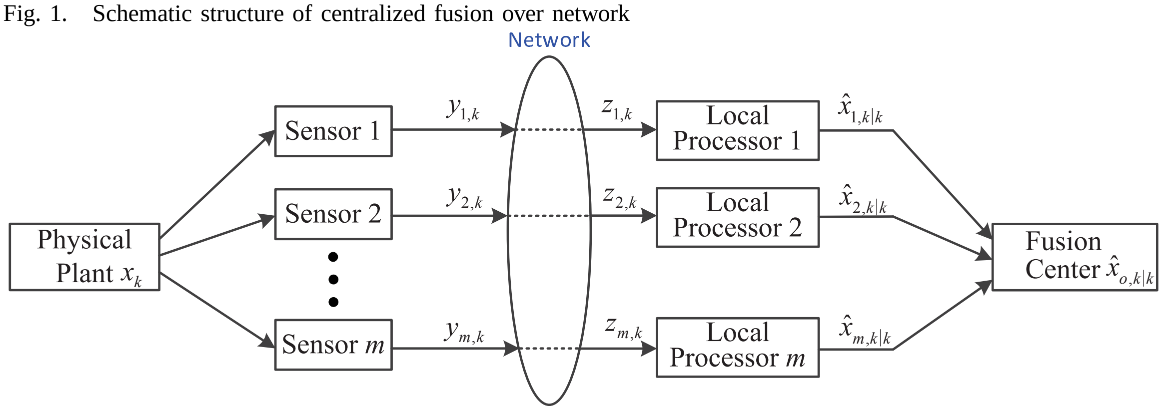

Fig. 2. Schematic structure of distributed fusion over network

In this paper, we aim to provide a timely review on the recent advances of the estimation, filtering and fusion algorithms for networked systems with network-induced phenomena. The addressed network-induced phenomena include missing/fading measurements, communication delays, signal quantization, sensor saturations, randomly occurring uncertainties, randomly occurring nonlinearities, randomly occurring signal quantization, randomly occurring sensor saturations and so on. The recent developments of the network-induced phenomena are firstly discussed. Secondly, we review the analysis and synthesis problems of the networked systems from four aspects, including linear networked systems, nonlinear networked systems, complex networks and sensor networks. In the same section, several estimation, filtering and fusion schemes for networked systems are surveyed in great detail. Thirdly, latest results on estimation, filtering and fusion approaches for networked systems with network-induced phenomena are reviewed. Finally, conclusions are drawn and some possible research directions are pointed out.

The remainder of this paper is organized as follows. In Section II, the network-induced phenomena are discussed. In section III, the developments of the estimation, filtering, fusion problems for networked systems are summarized. In section IV, some latest results on the estimation, filtering and fusion problems for complex dynamical systems with network-induced phenomena are reviewed. Both conclusions and some future research topics are provided in section V.

II. Network-Induced Phenomena

Over the past decade, a great deal of research attention has been received regarding the modeling and analysis of the network-induced phenomena including missing/fading measurements, signal quantization, sensor saturations, communication delays, variable sampling/transmission intervals, out-of-sequence-measurement updates, randomly occurring incomplete information etc. Accordingly, many important approaches have been given to examine the effects from the network-induced phenomena onto the system performance. In this section, some representative network-induced phenomena will be briefly reviewed.

A. Missing/Fading Measurements

The traditional estimation and filtering algorithms rely on an ideal assumption that the measurement outputs are available always. Nevertheless, the imperfect communication would occur in practical engineering especially in the networked systems, namely, the measurement outputs may contain noise only at certain instants and the desired signals are missing due probably to temporal sensor failures or network transmission delay/loss [34]–[39]. During the past two decades, among the probabilistic ways for modeling the missing measurements, the Bernoulli probability distribution has been extensively employed due to its simplicity and practicality, where the Bernoulli random variable takes value on 1 representing the perfect signal delivery and it takes value on 0 standing for the measurement missing. Accordingly, many important papers have been published concerning on the estimation, filtering and fusion for networked systems based on several methods such as the linear matrix inequality method [25], difference linear matrix inequality method [27], innovation analysis approach [30], Hamilton-Jacobi-Isaacs inequality approach [35], and backward/forward Riccati difference equation method [7], [37]. When comparing between different approaches, it is worth mentioning that the linear matrix inequality (difference linear matrix inequality) method is applicable for the analysis problem of time-invariant (time-varying) linear/nonlinear networked *complex dynamical systems* and gives the feasible solutions, the innovation analysis approach is suitable for handling the analysis problem of linear time-invariant/time-varying networked systems and can provide the *optimal solutions* in the minimum mean-square error sense, the Hamilton-Jacobi-Isaacs inequality approach is helpful for addressing the analysis and synthesis problems of time-invariant networked systems with *general nonlinearities* but it is commonly difficult to obtain the feasible solution, and backward/forward Riccati difference equation method has the advantage to deal with the analysis and synthesis problem for *time-varying* linear/nonlinear networked systems and provide the sub-optimal solutions. A more detailed comparison is given in Table I with hope to better understand the differences among the existing methods.

On the other hand, the measurement signals during the network transmissions may fade/degrade in a probabilistic way rather than be lost completely [49], [51], [52], [55]–[57]. It is easy to see that the missing measurements are extreme cases of the fading measurements. By using sequences of random variables obeying a certain probability distribution over known intervals with available conditional probabilities, the phenomena of the multiple fading measurements have been modeled in [52] and a Kalman-like recursive filtering algorithm has been developed via the forward Riccati difference equation approach. Besides, in

TABLE I
COMPARISONS AMONG DIFFERENT METHODS

Methods	Applications	Solutions	References
Linear matrix inequality method	*time-invariant* complex dynamical systems	feasible	[25], [40]–[44]
Difference linear matrix inequality method	*time-varying* complex dynamical systems	feasible	[21], [27], [45], [46]
Innovation analysis approach	*linear time-invariant/time-varying* systems	optimal	[30]–[32], [39], [47], [48]
Hamilton-Jacobi-Isaacs inequality approach	*general nonlinear time-invariant* systems	feasible	[35]
Backward Riccati difference equation method	*nonlinear time-varying* systems	sub-optimal	[37], [49], [50]
Forward Riccati difference equation method	*nonlinear time-varying* systems	sub-optimal	[7], [16], [51]–[54]

[49], [56], [57], the N-order Rice fading channel has been modeled by sequences of independent and identically distributed Gaussian random variables with known means and variances, where the multi-path induced fading stemming mainly from multi-path propagation has been considered when dealing with the control and estimation problems for networked systems and the impact from the fading measurements onto the control/estimation performance has been examined.

B. Signal Quantization

In the networked environment, signals are often quantized before the transmissions because of the finite-word length of the packets [58]–[61]. During the implementation, a device or algorithmic function performing the quantization is called a quantizer and an analog-to-digital converter can be seen as an example of a quantizer. Note that the signal quantization would affect the achievable performance of the networked systems and, hence, there is a need to conduct the analysis on various quantizers and examine the effects from the quantization onto the system performance. Recently, the signal quantization problem has become a research focus and attracted an ever-increasing interest. Accordingly, some methods have been proposed in [62]–[64] to handle the uniform quantization (the quantizers have same sensitivity) and in [65]–[67] to deal with the logarithmic quantization (the quantization levels are linear in logarithmic scale). As discussed in [68], a logarithmic quantizer can provide better efficiency in terms of the data rate for system performance than a uniform quantizer. So far, a great deal of effort has been devoted to address the filtering problems for networked systems with signal quantization and some effective filtering algorithms have been developed in [53] with variance constraints and in [69], [70] with H_∞ performance requirements. For example, the fault detection filtering algorithms have been given in [69], [70] for linear networked systems with logarithmic quantization by using the linear matrix inequality technique. However, it is worthwhile to mention that most reported results have been concerned with time-invariant networked systems with signal quantization only and the corresponding filter design problem for *time-varying* networked systems has not been paid adequate research attention.

C. Sensor Saturations

As is well known, sensors may not always be capable of providing signals with unlimited amplitudes due to physical/technological restrictions. The occurrence of the sensor saturations could affect the implementation precision of the developed filtering algorithms and may even cause severe degradation of the filtering performance if not handled properly. In the past ten years, the filtering problems for networked systems with sensor saturations have gained some initial research attention and some preliminary results have appeared handling the sensor saturations in recent literature [71], [72]. The main challenge with this topic is how to design a filtering algorithm by making full use of the available information about the sensor saturations subject to specified performance requirements (minimized variance, guaranteed H_∞ constraints etc). Recently, by using the sector-bounded approach in [73], [74], a decomposition technique has been given to facilitate the filter design for networked systems and a great number of papers have been published. For example, in [75], a probability-guaranteed H_∞ performance index has been defined over a finite-horizon, and a probability-guaranteed H_∞ filtering algorithm has been developed for a class of time-varying nonlinear networked systems subject to random parameter matrices and sensor saturations. However, when it comes to the variance-constrained filtering and estimation problems for *time-varying* nonlinear networked systems with sensor saturations, the related results are very few and the situation is even worse when the randomly occurring incomplete information is also considered.

D. Communication Delays

The communication delays are frequently encountered in modern industrial systems (chemical process, long transmission lines in pneumatic, and communication networks) due to the finite switching speed of amplifiers or finite speed of information processing [76]–[84]. In the past two decades, many efficient approaches have been given to reduce the conservatism caused by the time delays, such as the bounding technique [85], the descriptor system method [86], the slack matrix variables technique [87] and the delay-fractioning approach [88], [89]. Generally speaking, the objective of conducting the delay-dependent analysis includes two aspects (conservatism and complexity): 1) development of the delay-dependent conditions to provide a maximal allowable delay; and 2) development of the delay-dependent conditions by using as few decision variables as possible while achieving the same maximal allowable delay. When comparing between different methods, both the conservatism and the complexity serve as the criteria, and there exists a tradeoff between the conservatism and the complexity. Hence, it is difficult to look for a globally optimal approach which is least conservative yet with least computational burden. Compared with the bounding technique, the slack matrix variables technique and the descriptor system method, the delay-fractioning approach is efficient in reducing the conservatism caused by the time-delays at the cost of introducing more computational complexity especially when the number of fractions goes up. Fortunately, it is not difficult to handle the computational complexity problem nowadays due to the rapid developments of the computing techniques. Based on the reported delay analysis methods, a great number of results have been published concerning the synthesis problem of the time-delay systems. Note that most of the relevant results have been concerned with the *deterministic delays* only, while the communication delays induced by network transmissions would be random and time-varying. As such, the random communication delays have received some initial research interests and the problems of estimation, filtering and fusion have been studied for networked systems with random communication delays [39], [90]–[93]. For example, the filtering problems have been studied in [39], [90], [92], [93] for networked systems with random communication delays modeled by Bernoulli random variables. In [91], the optimal filtering problem has been investigated for networked systems with random communication delays modeled by Markov chain.

E. Randomly Occurring Incomplete Information

Recently, accompanying with the increasing of the network scale, the randomly occurring incomplete information has become a hot research topic that has gained some initial research attention. The randomly occurring incomplete information may occur intermittently in a probabilistic way with certain types and intensity. For example, in a networked system such as the internet-based three-tank system for leakage fault diagnosis, the nonlinearities may occur in a probabilistic way due to random abrupt variations and the occurrence probability can be estimated via the statistical tests [94]. It is well recognized that the existence of the randomly occurring incomplete information would highly degrade the system performance if not handled properly. So far, a series of estimation and filtering schemes has been developed for networked systems with randomly occurring incomplete information in the literature, and great efforts have been made to deal with the randomly occurring nonlinearities in [49], [95]–[99], the randomly occurring uncertainties in [94], [97], the randomly occurring sensor saturations in [40], [72], the randomly occurring sensor delays in [31], [32], [38], [100], [101], the randomly occurring signal quantization in [41], [102], and the randomly occurring faults in [103]. Accordingly, several techniques for analysis and synthesis of the networked systems have been given, including innovation analysis approach [31], [32], linear matrix inequality approach [97], Hamilton-Jacobi-Isaacs inequality method [100], difference linear matrix inequality method [41], Riccati difference equation approach [101], [102], and game theory method [54].

III. Analysis and Synthesis of Networked Systems

Over the past two decades, the networked systems have been received an ever-increasing research attention due to its engineering insights in a variety of areas such as the guidance and navigation, air traffic control, factory automation, remote diagnostics and troubleshooting and automated highway systems [104]–[107]. In this section, the methodologies of modeling, estimation, filtering and fusion for networked systems in the literature are briefly surveyed.

A. Linear Networked Systems

During the past decade, the estimation problems of the linear networked systems have gained considerable research attention and a great number of methods have been given including innovation analysis approach, linear matrix inequality method, game theory approach, etc. For example, the linear optimal estimation problems have been studied in [30]–[32], [39] for linear discrete time-varying networked systems with packet dropouts, and the linear optimal estimators (including filter, predictor and smoother) have been designed based on the innovation analysis approach. Due to the limited capacity of the communication networks, the multiple network-induced phenomena (random transmission delays, packet dropouts) may occur simultaneously during the signal transmissions. For instance, in [31], [32], both the random transmission delays and the packet dropouts have been discussed in a unified framework. Compared with the results in [30], it is worth mentioning that the consecutive packet dropouts in [31] are finite and the consecutive packet dropouts in [32] can be infinite. In contrast to the modeling method of the random transmission delays based on the Bernoulli probability distribution in [31], [32], the phenomenon of random transmission delays has been modeled in [91] by a multi-state Markov chain and the optimal filtering problem has been studied for networked systems subject to random transmission delays. To further reflect the engineering reality and improve the estimation performance, the phenomena of random transmission delays and packet dropouts occurring in two sides (from sensor to estimator and from controller to actuator) have been modeled in [92] within a unified framework, and the optimal estimators (including filter, predictor and smoother) in the linear minimum variance sense have been designed by using the orthogonal projection approach.

When the state-space model of the signal is unknown, some estimation algorithms for linear networked systems can be found in the literature [47], [48]. To be specific, based on the innovation analysis approach, the linear recursive filtering and smoothing algorithms have been presented in [47] to handle the phenomenon of multiple random delayed measurements with different delay rates, and the recursive least-squares linear estimation algorithms have been given in [48] to deal with uncertain observations, one-step delay and packet dropouts in a unified framework. On the other hand, by employing the linear matrix inequality technique, the design problems of optimal H_∞ and H_2 filters have been investigated in [24], [42] for linear networked systems with multiple packet dropouts. Based on the quasi Markov-chain approach, the filtering algorithms have been given in [108] for linear networked systems in the simultaneous presence of random delay, packet dropouts and missing measurements. Besides, in [54], a robust filtering scheme has been provided for a class of linear time-varying systems with stochastic uncertainties, finite-step correlated process noises and missing measurements via the min-max game theory approach.

B. Nonlinear Networked Systems

As is well known, the nonlinearity is a ubiquitous feature existing in almost all practical systems that contributes significantly to the complexity of system modeling [89], [103], [109]–[112]. The occurrence of the nonlinearity would cause undesirable dynamic behaviors. Therefore, the filtering problems for general nonlinear networked systems have received considerable research attention and some useful methods have been given in [17], [35], [100], [113]–[116]. In terms of the Hamilton-Jacobi-Isaacs inequality method, the H_∞ filtering problems have been investigated in [35], [100] for a general class of discrete-time nonlinear stochastic systems with missing measurements and random sensor delays, where sufficient criteria have been proposed to guarantee that the filtering error dynamics is stochastically stable irrespective of the presence of the missing measurements and random sensor delays. In [17], [113], [114], the extended Kalman filtering approaches have been given for general nonlinear networked systems with intermittent observations, state delay, and sensor failures, respectively. By using the Riccati equation method, the unscented Kalman filtering problems have been studied in [115], [116] for nonlinear networked systems with intermittent observations and packet dropout respectively, and sufficient conditions have been given to ensure the stochastic stability of the filtering error covariance, where the intermittent observations phenomenon in [115] is modeled by a Bernoulli random variable and the packet dropout phenomenon in [116] is characterized by a time-homogeneous Markov process.

In contrast to general nonlinearities, another class of nonlinearities (stochastic nonlinearities) deserves particular research attention since they occur randomly due probably to sudden environment changes, intermittent network congestion, changes in the interconnections of subsystems, random failures and repairs of the components, modification of the operating point of a linearized model of nonlinear systems [117]. Such stochastic nonlinearities include the state-dependent multiplicative noise disturbance as a special case. The filtering problems for networked systems with stochastic nonlinearities have already stirred some research interests and some latest results can be found in [16], [43], [45], [52], [101] based on several analysis techniques. For example, by using the Riccati-like difference equation approach, the extended Kalman filter has been designed in [16] for a class of time-varying networked systems with stochastic nonlinearities and multiple missing measurements. Moreover, the locally optimal Kalman-like filtering algorithms have been developed in [52], [101] for time-varying networked systems with stochastic nonlinearities, where the compensation schemes have been proposed to attenuate the effects from random sensor delays, random parameter matrices and gain-constraints onto the filtering performance. By using the recursive linear matrix inequality method, the robust H_∞ filter has been constructed in [45] for a class of time-varying networked systems with stochastic nonlinearities and variance constraints. In [43], the filtering algorithm has been given for a class of discrete time-delay systems with stochastic nonlinearities by employing the semi-definite programme method.

Over the past two decades, as discussed in [118]–[120], the fuzzy-logic scheme has proven to be one of effective approaches for modeling the nonlinear networked systems. Therefore, the multi-objective filtering problems for nonlinear networked systems via the fuzzy method have gained considerable research attention. For example, based on the fuzzy interpolation method, a fuzzy stochastic partial differential system has been introduced in [121] to approximate the nonlinear stochastic partial differential system with random external disturbance and measurement noise, and a robust H_∞ filtering algorithm has been developed by solving the linear matrix inequalities. In [57], a sequence of random variables obeying the Bernoulli distribution has been employed to model the phenomena of the randomly occurring uncertainties and the randomly occurring interval time-varying delays, and the fuzzy filtering problem has been studied for a class of nonlinear networked systems with channel fadings characterized by the Rice fading model. In addition, the intermittent measurements have been modeled in [44], [122] by using Bernoulli random variables with known occurrence probabilities and H_∞ filtering algorithms have been developed for nonlinear networked systems based on the T-S fuzzy-model approach. In contrast to the modeling of the network-induced phenomena by using the Bernoulli probability distribution, a different modeling method has been introduced in [23], where the Markov chain has been used to model the random transmission delays and the H_2/H_∞ filtering problem within fuzzy setting has been investigated for a class of nonlinear networked systems. Moreover, the event-triggered fuzzy filtering methods have been given in [123], [124] for nonlinear networked systems, where the developed filtering algorithms are capable of decreasing the communication load and energy consumption during the signal transmissions.

C. Complex Networks and Sensor Networks

Complex networks are composed of a group of interconnected nodes under certain topological structures [125], [126]. As is well known, the scale-free networks and small-world networks are two popular classes of complex networks characterized by the power-law degree distributions [127] and the short path lengths as well as high clustering [128]. During the past decade, the dynamical behavior analysis of the complex networks has become a very active research topic due to its application potentials in a wide range of real-world networks such as biological networks, computer networks, electrical power grids, cyber-physical systems, technological networks and social networks. Because of the importance and popularity of the complex networks, a rich body of research results has been published concerning various aspects of the network structure [129], [130]. Note that the system states are not always available in reality due to physical constraints, technological restrictions or expensive cost for measuring. Hence, it is also of great significance to estimate the states of the network nodes based on the available measurements. Accordingly, increasing research attention has been devoted to deal with the state estimation problems for *time-invariant/time-varying* complex networks with network-induced phenomena, see [131], [132] for some recent results.

On the other hand, the sensor networks equipped with distributed autonomous sensors have proven to be persistent research focuses which have gained an increasing attention in a variety of areas, and a great number of estimation schemes have been given in the literature [133]. It should be pointed out that the network-induced phenomena are inevitable in the sensor measurement outputs due to the noisy environment and limited communication capacity. The occurrence of the network-induced phenomena would greatly degrade the networked system performance or even lead to the divergence of the developed estimation schemes if not tackled properly. Hence, much work has been done on the topics of estimation, fusion, and distributed H_∞ filtering for networked systems over sensor networks in [134]–[137] and the references therein. For example, the estimation and fusion problems have been studied for networked systems over sensor networks in [36], [136], [138], [139] with missing measurements, in [136], [139]–[141] with time-delays, in [142] with sensor saturations, in [143] with signal quantization, and in [144] with channel errors. We will return to the topics of estimation and fusion for complex networks/sensor networks later, and more details concerning the recent advances will be presented in the following section.

IV. Latest Progress

Recently, the study on estimation, filtering and fusion for networked systems has attracted an increasing research interest and some important results have been reported in the literature. Here, we highlight some of the newest work, where the estimation, filtering and fusion algorithms have been presented to attenuate the effects from the network-induced phenomena onto the estimation performance under variance or H_∞ constraints.

A. Filtering and Estimation for Networked Systems

1) Filtering for Networked Systems: Recently, the modeling and filtering problems for *time-varying* systems have received increasing research attention owing to the fact that almost all real-world systems have certain parameters/structures that are time-varying. Therefore, some efficient filtering algorithms have been proposed for time-varying networked systems based on the Riccati-like difference equation approach or difference linear matrix inequality method. To mention a few, a Kalman-type filter has been designed in [52] for a class of time-varying nonlinear systems with random parameter matrices, correlated noises and fading measurements. Based on the result in [52], the recursive filtering problem has been investigated in [101] for time-varying nonlinear systems subject to finite-step correlated measurement noises, probabilistic sensor delays and gain-constraint. The developed filtering algorithm in [101] has the ability to attenuate the effects from the random sensor delays and gain-constraint onto the filtering performance and, moreover, it could be useful for addressing the gain-constrained issues arose in practical engineering with specified objectives, for example, to guarantee the unbiasedness property of the state estimates, simplify filter structure and handle the case of state estimates with linear equality constraint. In [145], the robust non-fragile filtering problem has been investigated for a class of linear time-varying systems subject to multiple packet dropouts and finite-step auto-correlated measurement noises, and a locally optimal filtering algorithm has been given. Subsequently, a globally optimal filtering scheme in the minimum mean-square error sense has been proposed in [146] by properly taking the statistical properties of correlated noises into account for the same addressed systems as in [145]. In [147], an optimal filtering algorithm has been given for linear time-varying system in the presence of the stochastic sensor gain degradations. Very recently, by using the backward Riccati equation method, an effective H_∞ filtering scheme has been presented in [37] to handle the missing measurements and quantization effects in a same framework, and the developed result has been applied to address the mobile robot localization problem.

Parallel to the filtering problems for linear time-varying networked systems, the filtering problems for nonlinear time-varying networked systems have started to stir the initial research interest. For example, the recursive filtering problems have been studied in [16], [53] for two general classes of nonlinear networked time-varying systems with the multiple missing measurements and quantization measurements respectively, where some new recursive filtering algorithms have been developed by properly estimating the linearization error and based on the stochastic analysis technique. It has been shown that an optimal upper bound of the filtering error covariance can be obtained at each sampling instant by employing the filtering schemes in [16], [53]. In addition, more freedom degree and better filtering performance can be achieved by tuning the weight parameters, and the explicit forms of the filter parameters have been given in terms of the solutions to Riccati-like difference equations. Furthermore, a new non-fragile filter has been designed in [102] for a class of nonlinear time-varying networked systems with incomplete measurements consisting of the randomly occurring missing measurements and signal quantization, and a new filtering compensation algorithm has been given based on the Riccati-like difference equation approach. In addition, a *probability-guaranteed H_∞ finite-horizon filtering method* has been proposed in [75] for a class of *time-varying* nonlinear systems with sensor saturations by utilizing difference linear matrix inequality technique, where the uniform distribution has been used to characterize the stochastic uncertainties in the system matrices and a new H_∞ performance index with probability performance constraint has been introduced for time-varying systems in order to meet the specified engineering requirements. Very recently, in [148], the envelope-constrained H_∞ filter has been constructed for a class of discrete time-varying networked systems with fading measurements and randomly occurring nonlinearities, where a novel envelope-constrained performance criterion over a finite horizon has been defined to further quantify the transient behavior of the filtering error.

2) State Estimation for Complex Networks: With respect to the state estimation problem for complex networks with network-induced phenomena, we mention some representative results as follows. In [149], the state estimator has been designed for an array of coupled discrete-time complex networks with discrete and distributed time delays. In [132], [150], the state estimation problems have been studied for complex networks with missing measurements, and sufficient criteria have been given to ensure the asymptotical stability of the estimation error in the mean-square sense by verifying the feasibility of certain linear matrix inequalities. The state estimation problem has been studied in [72] for a class of discrete nonlinear complex networks with randomly occurring phenomena, where the randomly occurring sensor saturations and randomly varying sensor delays have been addressed in a unified framework. In [151], the state estimation problem has been investigated for two-dimensional complex networks with randomly occurring nonlinearities and randomly varying sensor delays, where sufficient criteria have been given to guarantee the globally asymptotical stability of the two-dimensional estimation error dynamics in the mean square sense and the explicit expression of the estimator gains has also been provided. Based on the recursive linear matrix inequality approach, the state estimation algorithms have been given in [41], [152] for discrete *time-varying* complex networks. It is worth mentioning that, in [41], the authors have made the first attempt to discuss the uncertainties entering into the inner coupling matrix and introduce a new measurement model which can characterize the sensor saturations, signal quantization, and missing measurements in a unified framework. Very recently, in [153], the recursive state estimation problem has been investigated for an array of discrete time-varying coupled stochastic complex networks with missing measurements. By using the Riccati-like difference equations approach, new state estimation algorithm with *covariance constraint* has been developed for the first time and the estimator parameter has been characterized by the solutions to two Riccati-like difference equations.

B. Distributed Filtering and Fusion for Networked Systems over Sensor Networks

1) Distributed Estimation and Filtering for Networked Systems over Sensor Networks: In parallel to the recent developments of the networked control systems, in recent years, some initiatives have been made on the problems of distributed estimation and filtering for time-invariant/time-varying networked systems over sensor networks. Accordingly, several techniques have been proposed including linear matrix inequality method, recursive/parameter-dependent linear matrix inequality approach, and backward/forward Riccati difference equation method and so on. For example, by using the linear matrix inequality approach, a stochastic sampled-data scheme has been proposed in [154] to address the distributed filtering problem for time-invariant nonlinear systems over sensor networks, a distributed state estimator has been designed in [155] for discrete-time systems over sensor networks with randomly varying nonlinearities and missing measurements, and the distributed filters have been constructed in [25], [142] for nonlinear systems over sensor networks with randomly occurring saturations, quantization errors and successive packet dropouts. Besides, in [97], [99], the event-triggered distributed state estimation problems have been investigated for nonlinear systems over sensor networks with randomly occurring uncertainties, randomly occurring nonlinearities and packet dropouts.

Parallel to the distributed state estimation and filtering problems for time-invariant networked systems over sensor networks, the corresponding research for *time-varying* systems has gained the preliminary attention due to its engineering insights. By using the difference linear matrix inequality method, the H_∞ filtering problems have been studied for time-varying systems over sensor networks in [156] with multiple missing measurements and in [46] with quantization errors as well as successive packet dropouts, where sufficient conditions have been given to ensure the pre-specified H_∞ performance requirements by testing the feasibility of a set of linear matrix inequalities. By using the backward Riccati difference equation method, the distributed H_∞ state estimation problem has been studied in [50] for a class of discrete time-varying nonlinear systems over sensor networks with stochastic parameters and stochastic nonlinearities, and a necessary and sufficient condition has been given to ensure the pre-defined H_∞ performance constraint. In [157], a distributed filter has been designed for a class of linear discrete time-varying stochastic systems via event-based communication mechanism, and a locally optimal distributed filtering algorithm has been given based on the forward Riccati difference equation approach which is suitable for *online applications*.

2) Multi-Sensor Fusion for Networked Systems: As mentioned above, the multi-sensor data fusion algorithms can be generally classified into two types: centralized fusion and distributed fusion algorithms. In this section, some new multi-sensor fusion schemes based on different weighted fusion mechanisms for networked systems are reviewed. In [158], by using the innovation analysis technique and augmentation approach, the optimal centralized fusion estimators (including filter, predictor and smoother) in the minimum variance sense have been designed for a class of linear discrete time-varying stochastic systems with random delays, packet dropouts and uncertain observations, where the stability of the developed estimation algorithms has been discussed and sufficient criterion has been given to verify the existence of the centralized fusion steady-state estimators. Recently, by employing similar technique as in [158], the optimal centralized and distributed fusion estimation problems have been addressed in [159] for linear discrete time-varying multi-sensor system with different packet dropout rates, and the centralized fusion estimators (including filter, predictor and smoother) in the linear minimum variance sense have been firstly designed and, subsequently, the distributed fusion estimation algorithm based on the scalar-weighted fusion mechanism has also been provided in order to decrease the computational cost and improve the reliability.

On the other hand, according to the matrix-weighted fusion mechanism, several distributed fusion algorithms have been developed in order to improve the fault-tolerance ability [160]–[163]. To be more specific, the Kalman-like distributed fusion filters (one-step predictors) have been constructed in [160] for linear multi-sensor time-varying stochastic system in the simultaneous presence of parameter uncertainties, missing measurements and unknown measurement disturbances, and the optimal filter gains have been obtained based on the linear unbiased minimum variance criterion. In [161], the distributed fusion estimation algorithm has been given for linear discrete time-varying stochastic systems with multi-sensor missing observations, where the case of the finite-step observations missing has been discussed. Moreover, a multi-sensor distributed fusion estimation algorithm has been developed in [162] for networked systems, where the measurements of all sensors are transmitted individually over different communication channels with individual random delay and packet dropout rates. Besides, when there exist the auto-correlated and cross-correlated noises, a robust distributed weighted Kalman filter fusion method has been presented in [163] for a class of uncertain time-varying systems with stochastic uncertainties without resorting the state augmentation method. By using the projection theory, an optimal fusion algorithm has been given in [164] for a class of multi-sensor stochastic singular systems with multiple state delays and measurement delays.

In [165], based on the federated filtering algorithm, a novel networked multi-sensor data-fusion scheme has been proposed to deal with the effects from both the packet losses and the transmission delays. A globally optimal distributed Kalman filtering fusion method has been proposed in [166] for a class of time-varying systems, where the developed fusion algorithm has the advantage to decrease the computational burden and address the case when the filtering error covariance is singular. For the case that the state-space model of the signal is unavailable, both distributed and centralized fusion schemes have been developed in [167] to deal with the phenomena of the multi-sensor random measurement delays which are modeled by the homogeneous Markov chains and, subsequently, the extended result has been given in [168] to handle the missing measurements and random measurement delays with individual delay rate in a unified framework. Moreover, the distributed Kalman filtering fusion problems have been studied in [38], [169] for networked systems with missing measurements, random transmission delays and packet dropouts, new distributed fusion Kalman filters have been designed based on the innovation analysis method and matrix-weighted fusion mechanism. With respect to the multi-sensor fusion for nonlinear networked systems, a few results can be found in the literature. In [170], the centralized and distributed H_∞ fusion filters have been designed for a class of discrete nonlinear stochastic systems with time-invariant delay and missing measurements. It has been shown that, for both missing measurements and time-delay, the fusion error in [170] is globally asymptotically stable in the mean-square sense and the prescribed H_∞ performance can be achieved.

V. CONCLUSIONS AND FUTURE WORKS

In this paper, we have reviewed some recent advances on estimation, filtering and fusion for time-invariant/time-varying stochastic networked systems. Firstly, the developments of the network-induced phenomena have been surveyed. Secondly, the analysis and synthesis of the networked systems have been discussed, where the linear/nonlinear networked systems, complex networks and sensor networks with network-induced phenomena have been mainly summarized. Subsequently, some recent advances on estimation, filtering and fusion for networked systems have been reviewed. In particular, the multi-objective filtering algorithms (involving variance constraint, H_∞ performance requirement, and probability performance constraint) have been surveyed for time-varying nonlinear networked systems. Based on the literature review, some related topics for further research work can be listed as follows.

- The estimation and filtering problems for networked systems with more general nonlinearities would be one of future research topics, especially when both variance constraint and multiple network-induced phenomena are considered simultaneously.
- The distributed filtering problem for networked systems is of engineering significance, especially when it comes to the distributed filtering problem for time-varying nonlinear networked systems. Hence, the design of distributed filter for time-varying nonlinear networked systems would be an interesting research direction.
- The multi-sensor fusion problem for nonlinear networked systems would be a challenging research topic.
- A potential trend for future research is to generalize the current methods to tackle the estimation and filtering problems for nonlinear networked systems under the event-triggered mechanism.
- Another interesting research direction is to address the estimation and filtering problems for nonlinear networked systems under different communication protocols (round-robin protocol and try-once-discard protocol).
- The performance analysis of the estimation/filtering algorithm constitutes one of future research topics, such as the convergence of the developed algorithm and the monotonicity/sensibility with respect to the statistical information of the network-induced phenomena.

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