Nonlinear Filtering With Sample-Based Approximation Under Constrained Communication: Progress, Insights and Trends

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***Abstract*—The nonlinear filtering problem has enduringly been an active research topic in both academia and industry due to its ever-growing theoretical importance and practical significance. The main objective of nonlinear filtering is to infer the states of a nonlinear dynamical system of interest based on the available noisy measurements. In recent years, the advance of network communication technology has not only popularized the networked systems with apparent advantages in terms of installation, cost and maintenance, but also brought about a series of challenges to the design of nonlinear filtering algorithms, among which the communication constraint has been recognized as a dominating concern. In this context, a great number of investigations have been launched towards the networked nonlinear filtering problem with communication constraints, and many sample-based nonlinear filters have been developed to deal with the highly nonlinear and/or non-Gaussian scenarios. The aim of this paper is to provide a timely survey about the recent advances on the sample-based networked nonlinear filtering problem from the perspective of communication constraints. More specifically, we first review three important families of sample-based filtering methods known as the unscented Kalman filter, particle filter, and maximum correntropy filter. Then, the latest developments are surveyed with stress on the topics regarding incomplete/imperfect information, limited resources and cyber security. Finally, several challenges and open problems are highlighted to shed some lights on the possible trends of future research in this realm.**

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***Index Terms*—Communication constraints, maximum correntropy filter, networked nonlinear filtering, particle filter, sample-based approximation, unscented Kalman filter.**

I. Introduction

WITH the proliferation of large-scale systems and intricate mission scenarios, it is quite common in practice that the states of interest are not directly accessible and, instead, only a few measurements corrupted by stochastic noises are available to allow statistical inferences about the concerned states [1]. In this context, the filtering or state estimation problem has become a fundamental yet active research topic over the past several decades and triggered an extensive range of applications such as target tracking [2], image processing [3], weather forecasting [4], microseismic monitoring [5], frequency estimation in smart grid [6], and satellite navigation [7]. Ever since the pioneering work of Kalman [8], the celebrated Kalman filtering paradigm for linear systems with Gaussian noises has been brought into public view and a great deal of attention has been kindled to push the envelope towards more pervasive nonlinear systems in engineering reality. When expatiating on the nonlinear filtering approaches, a kind of filter that should be first mentioned is the extended Kalman filter, which makes a local linearization around the state estimates [9]. Apparently, the inherent deficiency of the extended Kalman filter lies in that it necessitates the gradients of system models and might not be applicable to highly nonlinear or discontinuous systems.

To get rid of dependence on the error-prone linearization, some derivative-free and sample-based alternatives have been developed by leveraging different selection rules on the samples and associated weights. Examples falling into this category include the unscented Kalman filter [10], cubature Kalman filter [11] and sparse-grid quadrature filter [12], just to name a few. A common feature of these filters is to select a set of weighted samples (in a deterministic way) to propagate the first two moments (i.e., the mean and covariance) of the posterior distribution, which renders it notably suitable to handle Gaussian noises. Nevertheless, due basically to the complicated operating environments and imperfect transmission conditions, it has been broadly recognized that the non-Gaussian noises are ineluctable in a plethora of real-world applications such as the radar and sonar systems, outdoor mobile communication channels, and image processing [13]–[16]. Taking the global navigation satellite system as an example, the saturation phenomenon of the analog-to-digital converters induced by jamming/interference would lead to the non-Gaussian property of measurements, and the multi-path propagation constitutes another source of non-Gaussian noises in adverse signal conditions [17].

The past several decades have seen considerable research attention paid to the filtering problem subject to non-Gaussian noises. Inspired by the fact that any non-Gaussian density can be approximated by a weighted sum of Gaussian densities with desired accuracy, various Gaussian sum filtering algorithms have been proposed in existing literature, where the non-Gaussian noises have been characterized by the Gaussian mixture models [18], [19]. A practical concern hindering the potential applications of Gaussian sum approaches is the selection of Gaussian terms whose number increases exponentially over time [20]. In fact, for nonlinear non-Gaussian systems, a simple yet powerful methodology called particle filtering has captured a great deal of interest from both academia and industry [21]. By resorting to the sequential importance sampling and Bayesian state estimation theory, the underlying idea behind particle filtering is to approximate the posterior probability density by stochastically drawing a group of weighted samples (or particles). The rapid advances of computers in recent years along with increasing filtering demands (induced by various difficult/complicated tasks) have injected new vitality and impetus to the design and analysis of particle filters, and substantial results have been available in the literature, see e.g., [22]–[24] and the references therein.

It has been known that the particle representation will be equivalent to the true posterior density as the number of particles tends to infinity [21], [25]. Clearly, when the computing resource is a major concern, the particle filtering scheme might not be the most appealing choice despite its outstanding ability in handling non-Gaussian noises. Very recently, a computationally efficient approach called maximum correntropy filtering has begun to stir some preliminary research interest [26], [27]. As a localized similarity measure, the correntropy is able to capture high-order statistics and thus exhibits great potentials in non-Gaussian signal processing [28]. By exploiting a recursive structure similar to the traditional Kalman filter, a maximum correntropy Kalman filter has been proposed in [26] for linear systems, where the common minimum mean-square error criterion has been replaced by the maximum correntropy criterion. After that, many maximum correntropy filtering algorithms have been reported with emphasis on different aspects, such as system models [29], kernel functions [30], and computational complexity [31]. It should be pointed out that the maximum correntropy filtering is categorized into the sample-based schemes in this paper for two reasons: 1) It is often the case in practical implementations that only a few samples are available when evaluating the correntropy; and 2) The maximum correntropy criterion has been widely combined with other sample-based nonlinear filtering frameworks (e.g., unscented Kalman filter) to facilitate the filter design for nonlinear and non-Gaussian systems [32]–[35].

Accompanying with the revolution of network communication technology, the networked systems have come into vogue and found extensive applications in numerous realms due primarily to their attractive advantages including ease of installation, reduced wiring cost, and increased system flexibility and maintainability [36]–[38]. For a typical networked system, the signal transmission among different components (e.g., sensors, estimators, controllers, and actuators) is realized through a shared communication network. With the increasing scale of data transmission, a critical issue called network congestion might arise, and this is particularly true for the networks with constrained communication resources. Meanwhile, the network congestion would further give rise to certain imperfect transmission such as the packet dropout and disorder, time delay, and fading measurement, which are generally referred to as the network-induced phenomena [39], [40]. In the existing literature, there have been mainly two kinds of strategies (i.e., active and passive ones) to tackle such communication constraints. For the active one, some engineering-motivated communication mechanisms have been adopted to schedule the massive data transmissions, thereby preventing the occurrence of imperfections [41]–[43]. For the passive one, by appropriately modeling the network-induced phenomena, some compensation schemes have been delicately developed to guarantee the desired performance, see e.g., [44] and the references therein.

It should also be mentioned that the shared communication network, as a cornerstone of networked systems, is very likely to offer an open door for the malicious attackers or eavesdroppers to destroy the availability, integrity and confidentiality of transmitted messages [45]–[47]. In practical engineering, the information tampering/leakage would cause severe performance degradation, economic losses and even human casualties, see the Stuxnet worm attack towards Iranian industrial control systems [48]. As such, the cyber-security-related communication constraint has gradually become an increasingly promising topic and attracted considerable research interest from a diversity of disciplines. In the context of filtering or state estimation, the existing literature has mainly been concentrated on the following two facets: 1) Design various schemes to compensate for the effects of malicious cyber-attacks (e.g., deception attack [49], denial-of-service attack [50], and man-in-the-middle attack [51]); and 2) Design various strategies (e.g., encoding-decoding or encryption-decryption mechanisms) to guarantee the information security/privacy, see [52], [53] and the references therein. Nevertheless, most research attention has been devoted to the linear systems, and the corresponding results regarding secure nonlinear filtering problem have been scattered. In this sense, it is necessary to summarize the recent works on such a topic.

Motivated by the clear engineering significance and urgent practical need, the researchers have never ceased to survey the progress made on the nonlinear filtering problem, which gives rise to many timely review papers initiated from different standpoints, see Table I for state-of-the-art surveys published in the past decade with their main focuses clearly listed. Besides, a very early survey (published in 2006) on the sampling nonlinear filter can be found in [60]. Nevertheless, to the best of our knowledge, there is a lack of detailed surveys for the networked nonlinear filtering problems with sample-based approximation from the perspective of communication con-

TABLE I
REPRESENTATIVE SURVEYS ON THE NONLINEAR FILTERING PROBLEMS

Date of Publication	Reference	Plant	Topic/Focus
Jan., 2013	[54]	General nonlinear systems	Review and discussion on the parametric Bayesian filters, including extended Kalman filter, iterated extended Kalman filter, unscented Kalman filter, central difference filter, Gauss-Hermite filter, and Gaussian sum filter.
Jan., 2017	[55]	Linear/nonlinear systems	A review on the main Gaussian filtering approaches including linear optimal filters, nonlinear filters, adaptive filters, and robust filters.
Nov., 2017	[56]	General nonlinear systems	Some advanced results obtained for the single-target particle filter and the challenges identified in the context of multi-target tracking.
Feb., 2018	[57]	General nonlinear systems	A tutorial review of the Bayesian state estimation methods, ranging from the Kalman filter to the extended Kalman filter, unscented Kalman filter, ensemble Kalman filter and other filters with a broader horizon (e.g., Gaussian filter, Gaussian-sum filter, particle filter, and moving horizon estimator).
Mar., 2020	[58]	Multi-sensor systems/sensor networks	Summary of several distributed fusion filtering methods, and recent results on distributed H_∞ filtering/estimation and multi-sensor distributed fusion filtering for networked nonlinear systems.
Jul., 2020	[19]	General nonlinear systems	Major results for Gaussian filtering since unscented Kalman filter by using the advanced numerical approximation techniques (e.g., cubature rules and quadrature rules), designing the square-root and Gaussian-sum filter variants, and considering the continuous-discrete dynamics.
Dec., 2020	[59]	Cyber-physical systems	Some recent results for secure state estimation schemes under different performance criteria and defense strategies, and some latest works on secure control strategies.
Jan., 2021	[40]	Networked nonlinear systems	Summary of the latest developments on the nonlinear recursive filtering schemes including extended Kalman filter, unscented/cubature Kalman filter, set-membership filter and H_∞ filter.

straints, which greatly inspires this current survey. In comparison with the existing literature, this survey possesses the following three significant features: 1) This paper makes one of the first attempts to offer a systematic, concise and accessible review on the latest developments of the sample-based networked nonlinear filtering schemes under communication constraints; 2) The up-to-date results are surveyed from three engineering-oriented aspects, namely, incomplete/imperfect information compensation, resource saving, and security preservation, which can assist the practitioners in selecting proper schemes according to the actual requirements; and 3) Some challenging and promising research directions are explicitly pointed out to flourish the related fields. To be sure, it is scarcely possible to summarize the existing literature in an exhaustive manner and instead, we try to give a flavor of recent advances and new trends of the subject under consideration.

The rest of this survey is organized as follows. Section II revisits three types of sample-based nonlinear filtering approaches including unscented Kalman filter and its family, particle filter as well as maximum correntropy filter. Section III reviews the latest progress made on the sample-based networked nonlinear filtering problem under communication constraints with emphasis on incomplete/imperfect-information-compensated filtering schemes, resource-saving filtering schemes, and security-guaranteed filtering schemes. Section IV draws some conclusion remarks and summarizes a few challenging issues with aim to facilitate the future research. The overall structure of this survey is depicted in Fig. 1.

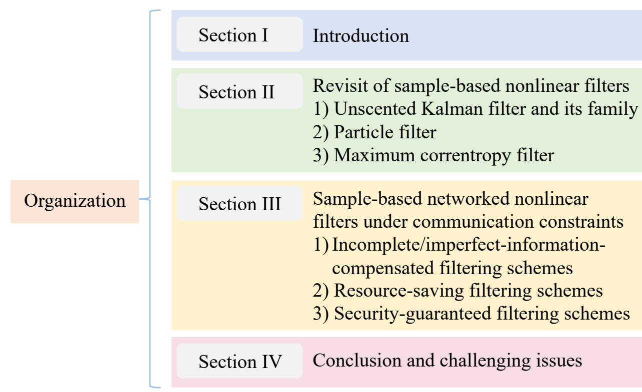

Fig. 1. Overall structure of this survey.

II. REVISIT OF SAMPLE-BASED NONLINEAR FILTERS

In this section, we will briefly revisit three types of representative sample-based nonlinear filters, namely, the unscented Kalman filter (the filter with a deterministic sampling technique), particle filter (the filter with a stochastic sampling technique), and maximum correntropy filter (the filter designed in an information-theoretic sense).

Before proceeding to the specific filtering schemes, let us introduce a general class of discrete-time nonlinear systems in the following form:

$$\begin{cases} x_{l+1} = g_l(x_l) + \eta_l \\ z_l = h_l(x_l) + \nu_l \end{cases} \tag{1}$$

where $x_l \in \mathbb{R}^{n_x}$ and $z_l \in \mathbb{R}^{n_y}$ denote, respectively, the system state to be estimated and the noisy measurement output. The subscript l represents the time index. $g_l(\cdot): \mathbb{R}^{n_x} \mapsto \mathbb{R}^{n_x}$ and $h_l(\cdot): \mathbb{R}^{n_x} \mapsto \mathbb{R}^{n_y}$ denote, respectively, the known nonlinear system transition and measurement functions. $\eta_l \in \mathbb{R}^{n_x}$ and $\nu_l \in \mathbb{R}^{n_y}$ stand for, respectively, the process noise with probability density function $p_{\eta_l}(\cdot)$ and measurement noise with probability density function $p_{\nu_l}(\cdot)$. In the scenario of Gaussian noises, the probability density functions $p_{\eta_l}(\cdot)$ and $p_{\nu_l}(\cdot)$ are usually specified by $\mathbb{N}(0, Q_l)$ and $\mathbb{N}(0, R_l)$, where $\mathbb{N}(\mu, \Sigma)$ denotes the Gaussian density with mean μ and covariance Σ.

Remark 1: It should be pointed out that for several special classes of networked systems, such as complex networks, multi-sensor systems and sensor networks, there generally exist a group of interacted nodes or spatially distributed sensors (with a prescribed network communication topology), see e.g., [58], [61], [62] and the references therein. In this case, the system dynamics would be more complicated than (1). Nevertheless, in this section, we are dedicated to introducing the underlying ideas behind three sample-based nonlinear filtering strategies of interest, which can be generalized to these special networked systems via certain adaptations. As such, the system dynamics of form (1) is considered in this paper without loss of generality.

The purpose of the considered nonlinear filtering problem can be stated in a nutshell as follows: given the available noisy measurement outputs z_l and the nonlinear system dynamics (1), calculate the estimate of state x_l in a recursive fashion. Now, we are in a position to introduce three representative nonlinear filtering schemes.

A. Unscented Kalman Filter and Its Family

The unscented Kalman filter, proposed back in the 1990s by Julier *et al.* [63], has received enduring research attention from a wide range of communities due to its superiority over the extended Kalman filter in filtering performance and application scopes. As the name suggests, the unscented Kalman filter inherits the prediction-correction structure of the traditional Kalman filter and utilizes a technique called unscented transformation to bypass the direct approximation of a nonlinear function. The unscented transformation is essentially a deterministic sampling technique, which generates a set of sigma points $\{\xi_l^k\}$ around means with specific weights $\{\omega^k\}$ and then propagates these sigma points through nonlinear functions to capture the mean and covariance of the posterior density. In order to give an intuitive exposition, the detailed process of the traditional unscented Kalman filter in one cycle is shown as follows [10], [19]:

1) Given the state estimate $\hat{x}_l$ and covariance Σ_l, generate a set of $2n_x+1$ sigma points

$$\begin{aligned}
&\xi_l^0 = \hat{x}_l\\
&\xi_l^k = \hat{x}_l + \left[\sqrt{(n_x+\rho)\Sigma_l}\,\right]_k\\
&\xi_l^{k+n_x} = \hat{x}_k^i - \left[\sqrt{(n_x+\rho)\Sigma_l}\,\right]_k,\ k=1,2,\ldots,n_x
\end{aligned}$$

where the term $[\sqrt{(n_x+\rho)\Sigma_l}]_k$ denotes the kth column of the matrix square root of $(n_x+\rho)\Sigma_l$, and ρ is a constant.

2) Propagate the sigma points via the nonlinear state transition function, and calculate the prior mean and covariance

$$\begin{aligned}
&\xi_{l+1|l}^k = g_l(\xi_l^k), \quad k=0,1,2,\ldots,2n_x\\
&\hat{x}_{l+1|l} = \sum_{k=0}^{2n_x}\omega^{m,k}\xi_{l+1|l}^k\\
&\Sigma_{l+1|l} = \sum_{k=0}^{2n_x}\omega^{c,k}(\xi_{l+1|l}^k-\hat{x}_{l+1|l})(\xi_{k+1|k}^k-\hat{x}_{l+1|l})^T + Q_l
\end{aligned}$$

where $\omega^{m,k}$ and $\omega^{c,k}$ are, respectively, the weights for the calculations of mean and covariance. A typical setting of weights is $\omega^{m,0}=\omega^{c,0}=\frac{\rho}{n_x+\rho}$ and $\omega^{m,k}=\omega^{c,k}=\frac{1}{2(n_x+\rho)}$ for $k=1,2,\ldots,2n_x$.

3) Propagate the sigma points via the nonlinear measurement function, and calculate the measurement prediction and related covariances

$$\begin{aligned}
&\zeta_{l+1|l}^k = h_{l+1}(\xi_{l+1|l}^k), \quad k=0,1,2,\ldots,2n_x\\
&\hat{z}_{l+1|l} = \sum_{k=0}^{2n_x}\omega^{m,k}\zeta_{l+1|l}^k\\
&\Sigma_{z,l+1} = \sum_{k=0}^{2n_x}\omega^{c,k}(\zeta_{l+1|l}^k-\hat{z}_{l+1|l})(\zeta_{l+1|l}^k-\hat{z}_{l+1|l})^T + R_{l+1}\\
&\Sigma_{xz,l+1} = \sum_{k=0}^{2n_x}\omega^{c,k}(\xi_{l+1|l}^k-\hat{x}_{l+1|l})(\zeta_{l+1|l}^k-\hat{z}_{l+1|l})^T.
\end{aligned}$$

4) Determine the filter gain G_{l+1}, and update the state estimate

$$\begin{aligned}
G_{l+1} &= \Sigma_{xz,l+1}\Sigma_{z,l+1}^{-1}\\
\hat{x}_{l+1} &= \hat{x}_{l+1|l} + G_{l+1}(z_{l+1}-\hat{z}_{l+1|l})\\
\Sigma_{l+1} &= \Sigma_{l+1|l} - G_{l+1}\Sigma_{z,l+1}(G_{l+1})^T.
\end{aligned}$$

Up to now, many variants of the unscented Kalman filter have been put forward from a diversity of incentives, such as reducing the computational complexity, improving the estimation accuracy and enhancing the numerical stability. Nevertheless, these improvements are not the emphasis of this survey. Interested readers can refer to [64], [65] for some details. On the other hand, it should be pointed out that the unscented Kalman filter actually represents a class of nonlinear filters based on the deterministic sampling method, and its family (usually regarded as a subset of the Bayesian filtering family) includes the cubature Kalman filter with cubature rules [11], Gauss-Hermite quadrature filter with Gauss-Hermite quadrature rules [20], and sparse-grid quadrature filter with sparse-grid quadrature rules [12]. Remarkably, there exist certain relationships among these aforementioned nonlinear filters, despite the fact that they are developed based on different sampling rules. For example, the cubature Kalman filter can be interpreted as an equivalent form of the traditional unscented Kalman filter with zero scaling parameters [19], and the unscented Kalman filter is actually identical to the sparse-grid quadrature filter with the accuracy level-2 [12].

B. Particle Filter

The particle filter, also known as the sequential Monte Carlo filter, is able to provide a Monte-Carlo-simulation-based approximate solution to the optimal sequential Bayesian estimation problem [66]. Different from the above-mentioned filtering schemes with deterministic samples, the particle filter exploits a group of stochastically selected samples $\{x_l^k\}_{k=1}^K$ with associated weights $\{\omega_l^k\}_{k=1}^K$ (called weighted particles) to approximate the true posterior density of target state, i.e., $p(x_l|z_{1:l})=\sum_{k=1}^K\omega_l^k\delta(x_l-x_l^k)$. Here, K denotes the number of particles and $\delta(\cdot)$ stands for the Dirac delta function. The significant feature of the particle filter is the relaxation of constraints on system models and noise distributions, which endows such a method with great application prospects, especially in case of sufficient computation resources. The main procedure of the particle filter in one cycle is elaborated as follows [21]:

1) Given the set of weighted particles $\{x_l^k, \omega_l^k\}_{k=1}^K$ at time instant l, draw new particles from a proposal density function $q(x_{l+1}|x_l, z_{l+1})$, namely,

$$x_{l+1}^k \sim q(x_{l+1}|x_l^k, z_{l+1}), \quad k = 1, 2, \ldots, K.$$

2) Calculate the normalized importance weights based on the incoming new measurement

$$\bar{\omega}_{l+1}^k = \omega_l^k \frac{p(z_{l+1}|x_{l+1}^k)p(x_{l+1}^k|x_l^k)}{q(x_{l+1}^k|x_l^k, z_{l+1})}$$

$$\omega_{l+1}^k = \frac{\bar{\omega}_{l+1}^k}{\sum_{i=1}^K \bar{\omega}_{l+1}^i}.$$

3) Update the state estimate based on the discrete representation of posterior density

$$\hat{x}_{l+1} = \int x_{l+1} p(x_{l+1}|z_{1:l+1}) dx_{l+1} = \sum_{k=1}^K \omega_{l+1}^k x_{l+1}^k.$$

4) Perform the resampling operation (i.e., replicating the particles with large weights and removing the particles with negligible weights) to reduce the phenomenon of particle degeneracy.

It should be mentioned that in the existing literature, many improvements have been made on the standard particle filter from different perspectives, such as the filter structure [67], proposal density [68], measure of effective sample size [69], resampling method [70], computational efficiency [71], and adaptiveness to complicated missions [61], [72]. Interested readers can consult these works and the references therein.

C. Maximum Correntropy Filter

As another powerful tool to handle the non-Gaussian noises, the maximum correntropy filter, developed in an information-theoretic sense, has begun to attract increasing attention in recent years. The fundamental motivation behind the maximum correntropy filter is that the correntropy criterion (with capability of extracting higher-order statistics) can provide better performance (e.g., robustness and accuracy) than the common minimum mean-square error criterion in non-Gaussian environments [28]. In what follows, let us briefly introduce the definition of correntropy. For any two scalar random variables X and Y, the correntropy $C(X, Y)$ is characterized by the expectation of a kernel function $\tau(X, Y)$ [26], [28]

$$C(X, Y) = \mathbb{E}\{\tau(X, Y)\} = \iint_{x,y} \tau(x, y) p_{X,Y}(x, y) dx dy$$

where $p_{X,Y}(x, y)$ denotes the joint probability density function of X and Y. Since it is often the case in practice that only a few samples $\{x_k, y_k\}_{k=1}^K$, rather than the analytical expression of the density $p_{X,Y}(x, y)$, are available, the correntropy is usually approximated by

$$C(X, Y) \approx \frac{1}{K} \sum_{k=1}^K G_\upsilon(x_k - y_k) = \frac{1}{K} \sum_{k=1}^K \exp\left(-\frac{(x_k - y_k)^2}{2\upsilon^2}\right)$$

where the kernel function is selected as the Gaussian type $G_\upsilon(a) = \exp(-\frac{a^2}{2\upsilon^2})$, and $\upsilon > 0$ represents the kernel bandwidth.

The design of maximum correntropy filter can be formulated into solving the following optimization problem:

$$\hat{x}_{l+1} = \arg\max_{x_{l+1}} F(x_{l+1})$$

where $F(x_{l+1})$ denotes the correntropy-based performance index. As briefly mentioned in [73], there are two mainstream ways in existing literature to define $F(x_{l+1})$.

1) Combining with the idea of weighted least squares method, the kernel function is evaluated at the prediction- and correction-like steps as follows (see e.g., [27], [31], [73]):

$$\begin{aligned} F(x_{l+1}) = {} & G_\upsilon(\|x_{l+1} - \hat{x}_{l+1|l}\|_{\Sigma_{l+1|l}^{-1}}) \\ & + G_\upsilon(\|z_{l+1} - h_{l+1}(x_{l+1})\|_{R_{l+1}^{-1}}) \end{aligned}$$

which usually induces a scalar weight in the filter.

2) Constructing a regression model, the kernel function is evaluated at each dimension of an augmented vector as follows (see e.g., [26], [34], [35]):

$$F(x_{l+1}) = \frac{1}{n_x + n_y} \sum_{k=1}^{n_x + n_y} G_\upsilon(e_{l+1}^k)$$

where e_{l+1}^k denotes the kth component of Ξ_{l+1}, and Ξ_{l+1} is defined as $\Xi_{l+1} = [(\bar{\Sigma}_{l+1|l}^{-1}(x_{l+1} - \hat{x}_{l+1|l}))^T \ (\bar{R}_{l+1}^{-1}(z_{l+1} - h_{l+1}(x_{l+1})))^T]^T$ satisfying $\bar{\Sigma}_{l+1|l}\bar{\Sigma}_{l+1|l}^T = \Sigma_{l+1|l}$ and $\bar{R}_{l+1}\bar{R}_{l+1}^T = R_{l+1}$. Based on the (statistical) linearization, another form of the performance index falling into this group can be found in [29], [32]. Note that such schemes would bring weight matrices in the filter.

The distinct features of these three types of sample-based nonlinear filters are displayed in Fig. 2. It should be mentioned that in existing literature, these filters are usually combined to play to their respective strengths, thereby enhancing the filtering performance. For example, the unscented particle filtering method has been proposed in [74], where the unscented Kalman filter has been exploited to generate the proposal density with the consideration of new measurements. In [32], the unscented Kalman filter has been combined with the maximum correntropy criterion to build a maximum correntropy unscented filter in order to enhance the robustness against the heavy-tailed impulsive noises. Recently, the unscented particle filter has also been integrated with the maximum correntropy criterion in [75] to deal with the measure-

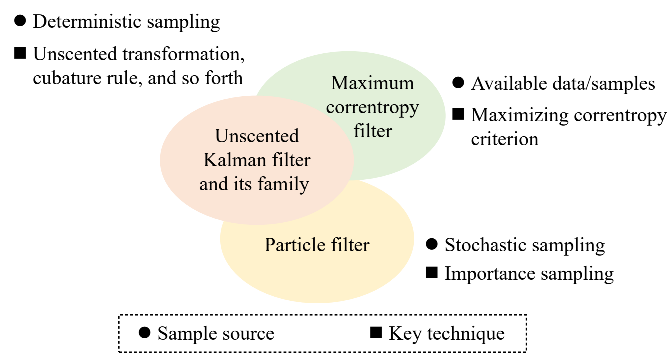

Fig. 2. Features of three types of sample-based nonlinear filters.

ment outliers encountered in the cooperative navigation of autonomous underwater vehicles.

III. Sample-Based Networked Nonlinear Filters Under Communication Constraints

There is no doubt that the popularity of networked systems has immensely promoted the development of modern industries. Nevertheless, the communication-dependent networked systems have also posed a series of additional challenges to the design of networked nonlinear filtering strategies due primarily to the presence of inevitable communication constraints, such as incomplete/imperfect information, limited resources, and cyber security. The schematic diagram of a typical networked nonlinear filtering problem is depicted in Fig. 3. In this section, we are going to survey the recent advances on the sample-based networked nonlinear filtering algorithms under three representative communication constraints. Frankly speaking, it is usually the case in existing literature that some of the above communication constraints are simultaneously taken into consideration. In such a case, the corresponding literature would only be classified into one of these categories for brevity.

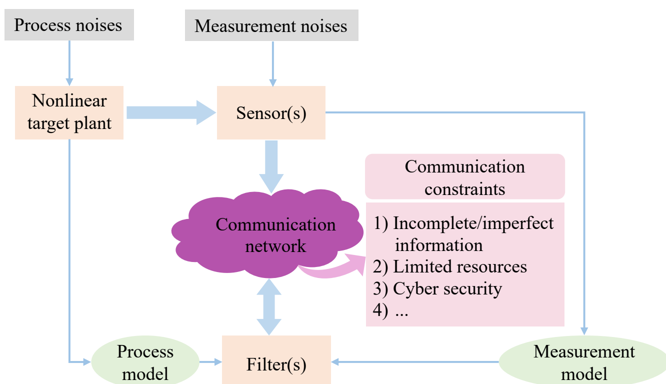

Fig. 3. Schematic diagram of a typical networked nonlinear filtering problem.

A. *Incomplete/Imperfect-Information-Compensated Filtering Schemes*

In practical networked environments, the phenomenon of incomplete/imperfect information is ubiquitous due to a diversity of factors which include, but are not limited to, restricted communication resources, device aging, intermittent sensor failures, noisy transmission surroundings, network traffic congestion as well as deliberate signal jamming. Such a kind of phenomenon, together with the inherent complexity of nonlinear systems, renders it a nontrivial task to design an effective networked nonlinear filtering scheme. Accordingly, much research attention has been focused on this topic. Some common types of incomplete or imperfect information are shown in Fig. 4.

As one of the frequently encountered phenomena in real-world applications, the so-called missing measurement (or packet dropout) constitutes a major source for causing the performance penalty or even mission failure. The unscented Kalman filtering problem has been investigated for nonlinear systems with intermittent observations characterized by the

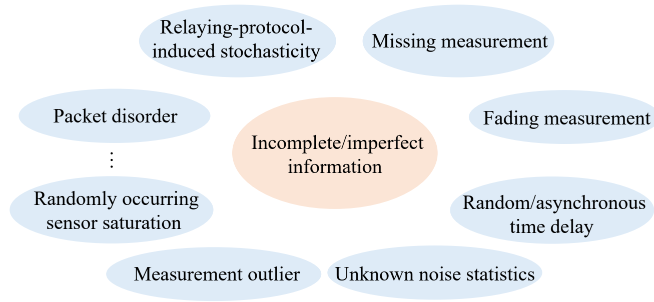

Fig. 4. Common types of incomplete or imperfect information.

Bernoulli process in [76] and binary Markov process in [77], where feasible frameworks have also been provided for stability analysis of the modified unscented Kalman filters. Thereafter, an event-triggered unscented Kalman filter has been proposed in [78] with Bernoulli-process-described packet dropouts. For the case of non-Gaussian noises, the modified particle filtering methods have been put forward for systems subject to Bernoulli-process-described packet dropouts in [79] and Markovian packet dropouts in [80]. Meanwhile, the corresponding conditional Cramér-Rao lower bound and Markovian Cramér-Rao lower bound have also been established to analyze the boundedness of error covariance. In [81], a maximum correntropy unscented Kalman filter with intermittent measurements has been proposed to improve not only the filtering performance, but also the robustness against non-Gaussian noises and intermittent measurements. To better verify the effectiveness of the designed filter, several demonstration simulations have been conducted based on a gravity-aided inertial navigation system.

In the context of distributed state estimation, by embedding a new credibility evaluation and weight design method, a consensus-based cubature information filtering scheme has been proposed in [82] to deal with the network-induced unknown noise statistics and interfered/missing measurements. In [83], a consensus-based filtering algorithm has been developed in the framework of cubature information filtering for heterogeneous mobile sensor networks, where the measurement loss occurs in a component-wise manner. When it comes to the diffusion-based distributed paradigm, the diffusion cubature information filtering problem has been considered in [84] in the presence of intermittent observations, where the final estimate of each node has been obtained by calculating a convex combination of its neighbors' local estimates. Based on the diffusion strategy and covariance intersection method, a distributed unscented Kalman filtering algorithm has been developed in [85] for target tracking affected by intermittent measurements, where the unknown correlations among multiple sensors have been considered and the filtering error has been proven to be exponentially bounded in the mean-square sense.

Apart from cases where the measurement is either completely lost or successfully received, considerable research attention has recently been devoted to a more general phenomenon called fading measurements. In [86], the unscented Kalman filtering problem has been investigated over the noisy fading (possibly failed) transmission channel, where each component of the channel fading gain has been characterized by the product of a Bernoulli distributed variable and a nonzero stochastic variable (with continuous distribution functions). Such a model has been utilized in [87] for the coal mine personnel positioning problem with unknown noise statistics. In [88], a modified unscented Kalman filtering scheme has been proposed for a class of nonlinear systems with both deterministic and stochastic nonlinearities, where the phenomenon of multiple fading measurements has been characterized by introducing a random diagonal matrix whose elements are mutually independent random variables with known statistics. In addition to filter design, certain sufficient conditions have been derived in [86], [88] to ensure the stochastic stability of the proposed algorithms. For the case of non-Gaussian noises, a two-stage particle filtering strategy has been put forward in [89], where the first stage is to restore the raw measurements from faded version and the second stage is to generate state estimate based on restored measurements. The proposed multipath-propagation-induced channel fading model is quite general that contains the one-step delayed transmission and probabilistic sensor failure as special examples.

The communication time delay, primarily caused by the finite speed of signal propagation, is another root for potential instability of real-world networked systems. In [90], a modified Bayesian filtering algorithm (realized via cubature quadrature Kalman filter) has been introduced and a series of independent Bernoulli random variables have been utilized to characterize the randomly delayed measurements. Such a multi-step delay model has also been considered in [91] by employing the particle filtering framework, where the unknown latency probability has been identified under the maximum likelihood criterion. In [92], by using two mutually independent Bernoulli random variables, the particle filtering problem has been investigated in the presence of one-step random delays and missing measurements. A novel particle filter has been proposed in [93] to deal with the multi-step randomly delayed measurements, where the independence of measurements (conditioned on state trajectories) might no longer be satisfied due to the utilized consecutive transmission mechanism. To avoid the difficulty in determining the maximum delay, a new measurement model has been reformulated in [94] consisting of a Bernoulli random variable and a geometric random variable, and has later been applied to the existing Gaussian filters (e.g., cubature Kalman filter). In the context of multiple sensors, the multi-sensor particle filtering fusion problem has been studied in [95] with multi-step yet asynchronous random delays, and an online estimation scheme of delay probability (if unknown) has also been provided.

Considering the complicated operating environments and adverse communication conditions, it might be arduous to determine the accurate noise statistics and avert the occurrence of abnormal measurements called outliers. To this end, some initial research attention has been concentrated on the design of filtering schemes with adaptivity (to unknown noise statistics) and robustness (against measurement outliers). In particular, the variational Bayesian method has been widely utilized to realize the joint estimation of the state and noise statistics by exploiting an analytical approximation to the joint posterior distribution. On the other hand, there are mainly two approaches to handling the measurement outliers. The first one is the active outlier detection (e.g., [96], [97]) and the second one is the passive rejection via certain robust schemes (e.g., [98]). For example, by resorting to a residual χ^2 outlier detector and the pseudo states generated by Gaussian process regression, an improved unscented Kalman filter (combined with interacting multiple models and variational Bayesian strategies) has been proposed in [99] to enhance the accuracy and robustness of the autonomous underwater vehicle navigation. By modeling the heavy-tailed measurement noise (usually formed by outliers) as a Student's t-distributed one, a novel outlier-robust cubature Kalman filtering algorithm has been proposed in [100] for underwater gravity matching navigation. In [101], a novel cubature Kalman filtering scheme has been established based on variational Bayesian method and maximum correntropy criterion, which is able to online identify the unknown measurement noise covariance and automatically suppress the effect of outliers.

In the recent literature, there have been some other types of incomplete/imperfect information such as packet disorder and randomly occurring sensor saturation. For example, in [102], by using the average value and nearest-neighbor strategies, the multi-sensor fusion estimation problem has been considered in the cubature Kalman filtering framework with both packet disorder and loss. Considering the energy-constrained nature of practical sensors, a modified particle filtering algorithm has been parameterized in [24] for nonlinear/non-Gaussian systems with energy harvesting sensors (which harvest the energy from surrounding environments following a first-order Markov process), and the impacts of randomly occurring sensor saturation and missing measurement induced by inadequate energy have been fully taken into account. Under the redundant communication channels, a particle-filter-based state estimation algorithm has been derived in [103] for a class of artificial neural networks (suffering from randomly occurring time delays and saturation constraints) to reduce the occurrence of missing measurement and improve the reliability of data transmission. Under the amplify-and-forward and decode-and-forward relaying protocols, both the centralized and consensus-based distributed auxiliary particle filtering problems have been investigated in [104] in view of the constrained long-distance transmission capability of practical communication channels, where the original measurements have been reinvented by the additive channel noises and random multiplicative channel gains.

For ease of reference, Table II is provided herein to summarize the recent works on sample-based networked nonlinear filtering with common incomplete/imperfect information.

B. Resource-Saving Filtering Schemes

It has been well recognized in engineering practice that the network resources (e.g., communication bandwidth and energy amount) are usually limited, and this is particularly true for large-scale and long-term deployed networked systems. In this regard, it makes practical sense to develop effective yet easy-to-implement resource-saving strategies with aim

TABLE II
BRIEF SUMMARY OF RECENT WORKS ON INCOMPLETE/IMPERFECT-INFORMATION-COMPENSATED FILTERING SCHEMES

Reference	Incomplete/imperfect information	Filtering scheme	Main purpose
[78]	Bernoulli-process-described missing measurement	Unscented Kalman filter	Event-triggered state estimation
[79]	Bernoulli-process-described missing measurement	Particle filter	Non-Gaussian state estimation
[80]	Markovian missing measurement & time delay	Particle filter	Non-Gaussian state estimation
[81]	Bernoulli-process-described missing measurement	Maximum correntropy filter	Non-Gaussian state estimation
[82]	Missing measurement & unknown noise statistics	Cubature information filter	Consensus-based distributed state estimation
[83]	Component-wise measurement loss	Cubature information filter	Consensus-based distributed state estimation
[84]	Bernoulli-process-described missing measurement	Cubature information filter	Diffusion-based distributed state estimation
[85]	Bernoulli-process-described missing measurement	Unscented Kalman filter	Diffusion-based distributed state estimation
[86]	Fading measurement	Unscented Kalman filter	State estimation
[87]	Fading measurement & unknown noise statistics	Unscented Kalman filter	Coal mine personnel positioning
[88]	Multiple fading measurements	Unscented Kalman filter	State estimation with stochastic nonlinearities
[89]	Multipath-propagation-induced fading measurement	Particle filter	Measurement recovery & state estimation
[90]	Randomly occurring multi-step time delay	Cubature quadrature Kalman filter	Bayesian state estimation
[91]	Randomly occurring multi-step time delay	Particle filter	State estimation & parameter identification
[92]	One-step random delay & missing measurement	Particle filter	Non-Gaussian state estimation
[93]	Randomly occurring multi-step time delay	Particle filter	State estimation with dependent measurements
[94]	Randomly occurring multi-step time delay	Cubature Kalman filter	State estimation with unfixed delay bound
[95]	Multi-step yet asynchronous random delays	Particle filter	Multi-sensor fusion estimation
[99]	Unknown noise statistics & measurement outliers	Unscented Kalman filter	Multi-model state estimation
[100]	Unknown noise statistics & measurement outliers	Cubature Kalman filter	Outlier-robust state estimation
[101]	Unknown noise statistics & measurement outliers	Maximum correntropy filter	Outlier-robust state estimation
[102]	Packet disorder and loss	Cubature Kalman filter	Multi-sensor fusion estimation
[24]	Randomly occurring sensor saturation	Particle filter	Energy-aware state estimation
[103]	Probabilistic saturation & redundant channels	Particle filter	State estimation for delayed neural networks
[104]	Relaying-protocol-induced stochasticity	Auxiliary particle filter	Consensus-based distributed state estimation

to prolong the lifetime of networked systems. Up to now, a great many investigations have been directed towards the design of sample-based networked nonlinear filtering schemes with resource-saving properties. The existing schemes can roughly be grouped into three categories: 1) Lower the frequency of data transmission; 2) Decrease the number of components/nodes that have access to the communication network; and 3) Reduce the size of data to be transmitted. Fig. 5 gives an intuitive illustration of the difference among these schemes.

A representative resource-saving strategy belonging to the first category is the so-called event-triggered transmission mechanism, whose primary principle is to only retain the necessary data transmission and discard the less informative data according to certain predefined triggering conditions, thereby alleviating the waste of limited communication resources. By utilizing the traditional “send-on-delta” mechanism, an event-triggered cubature Kalman filtering scheme has been introduced in [105] to realize the state estimation of a synchronous generator with fourth-order dynamics. In [106], the distributed fusion estimation issue has been investigated for a class of multi-sensor systems and an event-triggering module has been utilized to determine the time instants when the fused estimate should be fed back to the local unscented Kalman filters.

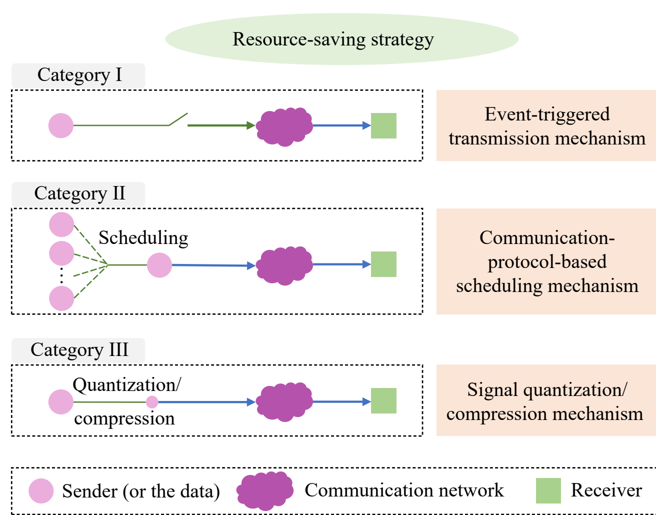

Fig. 5. An intuitive illustration of the resource-saving strategies.

In [107], an innovation-level-based event-triggered filter has been first constructed by using the third-degree spherical-radial cubature rule and then applied to the remote attitude monitoring of unmanned aerial vehicles (UAVs). Moreover, this work has also shed some lights on the relationship among the estimation accuracy, communication burden and designable parameter.

To estimate the states of synchronous generators with phasor measurement units, an improved regularized particle filtering method has been developed in [108] under the event-triggered transmission mechanism. When it comes to the sensor networks, an event-triggered cooperative unscented Kalman filtering scheme has been proposed in [109], where multiple UAVs have been considered to track a moving ground target. After that, in [110], a novel event-triggered distributed cubature Kalman filtering method has been developed based on flooding communication and variational Bayesian approximation to avoid the calculation of upper bound on the error covariance by introducing a pseudo measurement noise (satisfying Student's-*t* distribution) at the non-triggered time instants. For a more complicated scenario, a ternary-event-based transmission strategy has been established in [111], based on which a modified particle filtering scheme has been proposed by jointly considering the point, quantized, and set-valued measurement information. Even though such a scheme is developed for linear systems, the extension to the nonlinear systems is quite straightforward due to the mild requirement of particle filters on system profiles.

It should be pointed out that the triggering threshold is usually determined in advance in the above-mentioned literature, which belongs to the static event-triggered case. On the contrary, the so-called dynamic event-triggered mechanism can dynamically adjust the triggering thresholds with the help of a dynamic auxiliary variable so as to better economize the constrained network resources. A resilient distributed unscented Kalman filtering fusion scheme has been parameterized in [112] based on the dynamic event-triggered transmission strategy, where hardware experiments based on multiple UAVs have been conducted to verify the effectiveness in a practical target tracking scenario. In the context of non-Gaussian noises, both centralized and distributed auxiliary particle filtering schemes have been proposed in [113] under the scheduling of the dynamic event-triggered transmission mechanism, and the non-triggered measurements have been fully exploited to enhance the filtering performance. In [114], the distributed maximum correntropy filtering problem has been investigated under an adaptive event-triggered scheme, and the filter gains have been parameterized in terms of the upper bounds on filtering error covariances. To guarantee the desired communication rate, an event-triggered particle filter has been designed in [115] for the real-time state estimation of smart grids via an information-centric networking, where the weighted particles have been employed to form an approximate distribution of the innovation distances. Hence, the measurement arrival rate (in statistical sense) can be designed as required. Similarly, an event-triggered particle filtering scheme with desired transmission rate has been proposed in [116] based on the Kullback-Leibler (KL) divergence, in which both the particle representation and spline approximation have been utilized to find an explicit form of the KL-divergence-based triggering condition. Recently, such a scheme has been considered in the box particle filtering framework to reduce the computational cost [117].

Apart from the above kinds of event-triggered mechanisms, the stochastic event-triggered mechanism (originally proposed in [118] to guarantee the Gaussianity of the innovation process) has also received considerable research attention in the nonlinear filtering realm. For example, the stochastic event-triggered unscented Kalman filtering problem has been studied in [119], where the stability and convergence of the proposed unscented Kalman algorithm have been analyzed. Moreover, the distributed unscented Kalman filtering problem has been investigated in [120] under a mixed event-triggered mechanism, which is composed of the open-loop stochastic event-triggered scheme for the sensor-to-estimator communication and the covariance-discrepancy-based event-triggered scheme for the estimator-to-estimator communication.

When it comes to the second category of resource-saving strategy, the so-called communication protocol has appeared as a powerful tool to schedule the transmission order of multiple components/nodes. To be more specific, only partial components/nodes are granted the access to a shared communication network at each time instant, thereby reducing the consumption of limited resources and the occurrence of network congestion. Motivated by the distinct engineering insights, the sample-based nonlinear filtering problem with various communication protocols has begun to draw the attention of many researchers, and some advances have been made in very recent years. Among others, the Round-Robin protocol (with fixed cyclic transmission order), weighted try-once-discard protocol (with weight-related priority competition) and stochastic communication protocol (with stochastic-process-described scheduling behavior) have gained particular research attention. For instance, in [121], the Round-Robin protocol and weighted try-once-discard protocol have been, respectively, embedded in the unscented Kalman filtering paradigm to handle the state estimation problem subject to stochastic uncertainties. The protocol-based unscented Kalman filters have been parameterized by quantifying the impacts of regulated transmissions. The two communication protocols have been combined with particle filters in [122] to solve non-Gaussian state estimation problems with reduced communication burden. The stochastic communication protocol with imprecise statistics has been analyzed in [123] under the unscented Kalman filtering scheme. Very recently, the protocol-based distributed state estimation problem has been investigated in [124] by adopting the unscented Kalman filtering method.

As for the third resource-saving strategy, the main idea is to lessen the amount of transmitted bits. In practical engineering, the signals are usually quantized or compressed prior to being transmitted over the communication networks with limited bandwidths. In this sense, the signal quantization can be regarded as an effective mean to accommodate the bandwidth constraints [125], [126]. In case of quantized measurements, the particle-filter-based tracking methods with channel awareness have been developed in [127] for multi-hop multi-sensor systems, where both known and unknown instantaneous fading channel gains have been considered and the corresponding posterior Cramér-Rao lower bounds have also been analyzed. In [128], a novel quantized particle filtering method has

TABLE III
BRIEF SUMMARY OF RECENT WORKS ON RESOURCE-SAVING FILTERING SCHEMES

Reference	Resource-saving mechanism	Filtering scheme	Main purpose
[105]	Measurement-based event-triggered mechanism	Cubature Kalman filter	State estimation for synchronous generators
[106]	State-based event-triggered feedback mechanism	Unscented Kalman filter	Distributed fusion estimation with feedback
[107]	Innovation-level-based event-triggered mechanism	Cubature Kalman filter	Remote attitude monitoring of UAVs
[108]	Measurement-based event-triggered mechanism	Regularized particle filter	State estimation for synchronous generators
[109]	Measurement-based event-triggered mechanism	Unscented Kalman filter	Consensus-based distributed state estimation
[110]	Measurement-based event-triggered mechanism	Cubature Kalman filter	Flooding-based distributed state estimation
[111]	Ternary-event-based mechanism	Particle filter	State estimation with hybrid measurements
[112]	Dynamic event-triggered mechanism	Unscented Kalman filter	Resilient distributed fusion estimation
[113]	Dynamic event-triggered mechanism	Auxiliary particle filter	Diffusion-based distributed state estimation
[114]	Adaptive event-triggered mechanism	Maximum correntropy filter	Consensus-based distributed state estimation
[115]	Innovation-level-based event-triggered mechanism	Particle filter	State estimation with desired communication rate
[116]	KL-divergence-based event-triggered mechanism	Particle filter	State estimation with desired communication rate
[117]	KL-divergence-based event-triggered mechanism	Box particle filter	Non-Gaussian state estimation
[119]	Stochastic event-triggered mechanism	Unscented Kalman filter	State estimation with open- and closed-loop schemes
[120]	Mixed event-triggered mechanism	Unscented Kalman filter	Distributed state estimation with event-triggered fusion
[121]	Round-Robin and weighted try-once-discard protocols	Unscented Kalman filter	State estimation with stochastic uncertainties
[122]	Round-Robin and weighted try-once-discard protocols	Particle filter	Non-Gaussian state and divergence estimation
[123]	Stochastic communication protocol	Unscented Kalman filter	State estimation with imprecise scheduling probability
[124]	Round-Robin and stochastic communication protocols	Unscented Kalman filter	Consensus-based distributed state estimation
[127]	Measurement quantization	Particle filter	State estimation with channel awareness
[128]	Measurement quantization	Particle filter	State estimation with multiple degrading sensors
[130]	Binary measurements	Unscented-Kalman-like filter	State estimation with binary sensors
[131]	Binary proximity measurements	Particle filter	Indoor positioning with proximity reports

been proposed in the presence of multiple degrading sensors, where the Wiener-process-described degradation variables and system state have been augmented into a new state vector and the measurement signals have been quantized by resorting to the uniform quantizers.

Considering an extreme case where the signal size is quantized/compressed into one bit, the estimation problem with binary observations has stirred noticeable attention due to the minimal communication requirement [129]. For example, both linear and nonlinear filtering issues with binary sensors have been investigated in [130] by taking full advantages of the innovation information produced by the binary sensors, and particularly, the unscented transform has been utilized to calculate the predicted statistics. In [131], a low-cost indoor positioning scheme has been established in the particle filtering and smoothing frameworks by using the binary proximity measurements, where the received-signal-strength measurement is considered and the proximity report is triggered only when the binary value of the proximity measurement switches.

In what follows, a brief summary is given in Table III to showcase the latest progress on the sample-based networked nonlinear filtering schemes from the resource-saving perspective.

C. Security-Guaranteed Filtering Schemes

With the surge of interaction between real-world systems and communication networks, the cyber vulnerability has been an increasingly noticeable issue that potentially poses severe threats to strategic facilities and human life. Therefore, one of the recent research focuses has been turned to the cyber security. Relevant directions include, but are not limited to, modelling/detection/prevention of cyber-attacks, design of filtering and control schemes under various attacks, and design of privacy preserving techniques against eavesdroppers. It should be pointed out that, in comparison to the rich literature on the aforementioned nonlinear filtering schemes with incomplete/imperfect information and limited resources, the corresponding results with cyber security consideration are relatively few due probably to the analytical difficulties jointly induced by the inherent system nonlinearity and the complexity/unpredictability of malicious attacks. As depicted in Fig. 6, the existing security-guaranteed nonlinear filtering schemes will be surveyed from the standpoints of handling cyber-attacks and privacy preservation.

Recently, by considering the normalized additive or multiplicative false data (injected by adversaries), the modified nonlinear Gaussian filters (e.g., the unscented Kalman filter and cubature Kalman filter) have been derived in [132] and the Bernoulli random variables with known statistics have been utilized to characterize the random occurrence of false data injection attack. As for the non-Gaussian setting, a secure particle filtering algorithm has been proposed in [133] for cyber-physical systems with a group of binary sensors, where

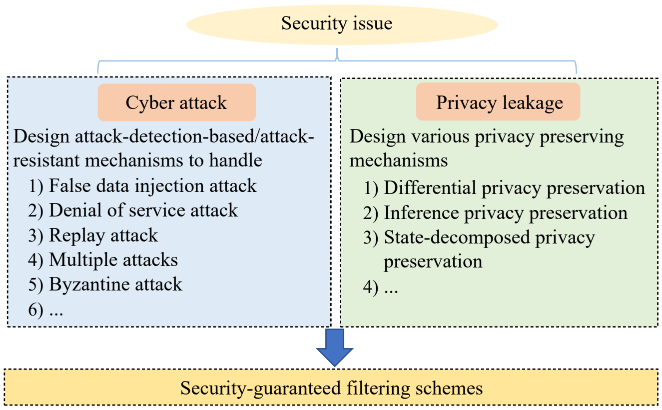

Fig. 6. Taxonomy of the surveyed security issues.

the modified likelihood function has been parameterized by incorporating the characteristics of randomly occurring denial-of-service attacks, deception attacks and flipping attacks.

Considering the distributed state estimation issue, a consensus-based distributed maximum correntropy filtering scheme has been developed in [134] for systems undergoing deterministic and stochastic nonlinearities, where a set of Bernoulli random variables has been exploited to describe whether or not the deception attack is successfully initiated during the internode communication. An adaptive cubature Kalman filter with variational Bayesian approximation has been considered in [135] to relax the requirements on the statistical knowledge of random occurrence probabilities and deception signals of the injection attacks, where the conjugate prior corresponding to the random occurrence probability has been chosen as the Beta distribution and the deception signal has been characterized by a Gaussian mixture distribution with unknown parameters (including the weight, mean and covariance).

To uncover the behavior of launched attacks, the attack detection and state estimation have been jointly taken into account in [136] by modifying the proposal density, and conditioned on the detected attack, the proposed particle filtering method can realize the unbiased estimation. In [137], an attack detection method has been constructed with the aid of Dempster-Shafer theory, based on which a consensus-based distributed filter has been proposed in the unscented Kalman filtering framework with convergency analysis also provided. With aim to cater for the maneuvering target tracking scenario, a diffusion-based distributed unscented Kalman filter (with credibility evaluation and state/covariance clustering) has been put forward in [138], where the neighbors of a non-secure node has been grouped into trusted cluster and non-trusted cluster, and the information owned by the latter has been neglected in data fusion. In [139], by adopting the two-stage particle filtering scheme, a cloud-based sandboxing framework has been proposed for some safety-conscious applications of connected and automated vehicles, which possesses the ability to realize data fusion (for cooperative localization) and attack detection (for the identification and isolation of attacked vehicles). In the presence of Byzantine nodes that deliberately disrupt the collective task, a target tacking scheme with an unscented Kalman filter has been established in [140], where the Byzantine data attack has been reflected by transmitting misleading quantized measurements (manipulated in a probabilistic way) to the fusion center, and the attack effect on the tracking performance has also been analyzed.

On another research frontier, the privacy concern has begun to capture special attention in recent years since daily life and modern industries cannot be divorced from the (possibly sensitive) data sharing, giving rise to the risk of being wiretapped by the third party with ulterior motives. In this regard, several privacy-aware filtering schemes have been reported in the literature, see [141], [142] and the references therein. Particularly, a novel sharing framework of time-series data has been proposed in [143] with the differential privacy guarantees, where both the Kalman filtering and particle filtering methods have been considered to estimate the raw data from perturbed one. After that, the differential privacy aware unscented Kalman filter and square root unscented Kalman filter have been, respectively, established in [144] and [145] to protect the streaming data and process parameters from information leakage in Internet of Things and industrial cyber-physical systems. The inference privacy issue has been discussed in [146] whose focus is to prevent the accurate inference from excess information by the third party (e.g., eavesdropper). Specifically, a data sharing strategy considering both privacy and utility has been proposed in [146] for space situational awareness by resorting to the ensemble/unscented Kalman filter. The privacy-utility tradeoff problem (including utility-aware privacy and privacy-aware utility) have been formulated as two optimization problems with linear matrix inequalities. In consideration of distributed state estimation, a state-decomposed privacy-preserving distributed cubature information filtering method has been developed in [147] based on the push-sum average consensus strategy, and the theoretical analyses (in terms of convergence, privacy, and stability) have also been conducted.

Table IV offers a brief overview of the recent developments on the sample-based networked nonlinear filtering schemes with security concerns.

Remark 2: Up to now, we have made great efforts to review the latest advances on the sample-based nonlinear filtering algorithms from the perspectives of incomplete/imperfect information compensation, resource saving, and security preservation. It is worthwhile to emphasize that the system property plays a crucial role in determining the specific sample-based nonlinear filtering schemes. When the systems of interest suffer from the Gaussian noises, a computationally cheap yet effective way is to employ the filtering scheme within the family of unscented Kalman filter. If the noises are non-Gaussian, it would be preferred to choose the particle filtering and the maximum correntropy filtering schemes, and the latter might be a better choice when the computational burden constitutes a major concern. The distinct features of these three schemes would also give rise to different difficulties in designing the filtering algorithms under the constrained communication. For example, it is not easy to investigate how to consider/attenuate the impacts of the encountered communication constraints onto the calculation of covariance

TABLE IV
BRIEF SUMMARY OF RECENT WORKS ON SECURITY-GUARANTEED FILTERING SCHEMES

Reference	Security issue	Filtering scheme	Main purpose
[132]	False data injection attack	Nonlinear Gaussian filter	Attack-resistant state estimation
[133]	Multiple malicious attacks	Particle filter	Attack-resistant state estimation with binary sensors
[134]	Deception attack	Maximum correntropy filter	Attack-resistant distributed state estimation
[135]	False data injection attack	Cubature Kalman filter	Attack-resistant adaptive state estimation
[136]	False data injection attack	Particle filter	Attack-detection-based state estimation
[137]	Deception/replay/denial of service attack	Unscented Kalman filter	Attack-detection-based distributed state estimation
[138]	Random/replay/false data injection attack	Unscented Kalman filter	Attack-resistant distributed state estimation
[139]	False data injection attack	Particle filter	Attack detection for connected and automated vehicles
[140]	Byzantine data attack	Unscented Kalman filter	Target tracking & attacker strategy analysis
[143]	Differential privacy preservation	Kalman/particle filter	Privacy-aware sharing of real-time aggregate statistics
[144]	Differential privacy preservation	Unscented Kalman filter	Privacy-aware sharing of streaming data
[145]	Differential privacy preservation	Square root unscented Kalman filter	Privacy protection of process parameters
[146]	Inference privacy and utility tradeoff	Ensemble/unscented Kalman filter	Data sharing for space situational awareness
[147]	State-decomposed privacy preservation	Cubature information filter	Privacy-aware distributed state estimation

matrices (in the unscented Kalman filter), the selection of proposal density and the calculation of weights (in the particle filter), and the design of correntropy-based performance index (in the maximum correntropy filter).

IV. CONCLUSION AND CHALLENGING ISSUES

In this paper, we have launched a timely survey on the cutting-edge progress of sample-based networked nonlinear filtering problem from the viewpoint of communication constraints. To begin with, we have briefly introduced the practical backgrounds of communication-related networked nonlinear filtering problem and revisited the main ideas of three representative types of sample-based filtering paradigms including the unscented Kalman filter (and its family), particle filter, and maximum correntropy filter. Subsequently, some relatively recent works have been reviewed and summarized on the design and analysis of sample-based networked nonlinear filters in accordance with the specific category of communication constraints, namely, incomplete/imperfect information, limited resources, and cyber security. This kind of categorization, together with the summary of adopted filtering schemes and main purposes, can assist the practitioners in finding a possibly feasible solution to the practical state estimation/filtering problem with specific system configurations and networked environments. Admittedly, a plethora of theoretical and methodological insights have been recently shed on the design and performance analysis of the sample-based networked nonlinear filters. However, it is still difficult (if not impossible) to establish a universal rule that parameterizes the corresponding design and performance analysis due basically to the complexity or diversity of the target plant, networked environment, and task goal. In what follows, we endeavor to point out some promising yet challenging directions/issues for future research.

1) Considering More Comprehensive Models to Cater for the Engineering Reality: The exact characterization of physical phenomenon is not only a premise of designing the networked filtering schemes, but also a pivotal factor of applying the proposed schemes. In most of the existing literature, the considered models (in terms of system setups, scheduling protocols, malicious attacks, and so forth) are customized and relatively simple, which might fail to describe the increasingly complicated engineering reality. For example, in order to increase the success rate of cyber-attacks and maximize the attack effects, the adversaries tend to simultaneously launch different kinds of malicious (and advanced) attacks. In this case, the existing secure filtering or detection methods (developed on a single type of attack) would be no longer applicable, and such a situation has placed new demands and challenges on the modelling of attack behaviors. Therefore, a possible research topic would be developing novel sample-based networked nonlinear filtering algorithms based on the engineering-oriented comprehensive models.

2) Reducing the Manual Parameter Adjustment to Enhance the Flexibility/Adaptability of Algorithms: It should be mentioned that many parameters have been involved in the foregoing sample-based networked nonlinear filtering algorithms, such as the threshold-related parameters in (dynamic) event-triggered mechanisms, the artificial noise level in certain privacy-preserving strategies, the scaling parameters in deriving the upper bounds of error covariances, and the kernel bandwidth in maximum correntropy filter. In most cases, these parameters are manually determined by resorting to the usual experience or the trial-and-error approach. Nevertheless, such manual methods might not meet the practical engineering requirements since the networked environment and other external factors are usually unpredictable due to their changes over time. To improve the flexibility/adaptability of networked filtering algorithms, it is of great significance to reduce the manual effort in parameter adjustment as much as possible. In this regard, the evolutionary computation or machine learning methods would be the possible options.

3) Designing the Data-Driven Networked Nonlinear Filtering Methodologies: The vast majority of existing networked nonlinear filtering schemes are actually model-based ones, which largely depend on the accurate knowledge/model of the physical systems and environmental conditions. Nevertheless, as the increase of system scale and the complication of operating conditions and external factors (e.g., various cyber-attacks and disturbances), it becomes more and more difficult to establish an accurate mathematical model for the completion of state estimation/filtering tasks. Instead, only some data sets collected from similar scenarios or previous implementations are available. For such a case, it is of paramount importance to develop the data-driven networked nonlinear filtering methodologies. In addition, since the model-based and data-driven techniques have their respective merits, it would be really interesting to investigate how to construct a filtering framework combining these two types of techniques so as to achieve better performance. It is worth mentioning that inspired by the capability of the famed Gaussian processes in terms of approximating the unknown functions/dynamics via mean function and covariance function, a seemly natural idea is to utilize such processes to learn the system dynamics and the measurement models based on the historical data [148]. In other words, the Gaussian processes might be one of the effective tools to develop the data-driven networked nonlinear filtering algorithms.

4) Extending the Existing Results to the Multi-Sensor Multi-Target Tracking Scenarios: It has been well recognized that the nonlinear filtering technique plays an important role in the target tracking applications. Naturally, a great many elegant filtering algorithms have been published in the literature regarding the traditional single target tracking problem. Nevertheless, these algorithms might not be applicable to the nowadays complicated application scenarios where multiple targets are present in the regions of interest and likely to exhibit complex behaviors such as birth and death (disappearance). A large number of data-association-based and random-finite-set-based methods have been developed to tackle such (multi-sensor) multi-target tracking issues, see [56] and the references therein. When the communication constraint becomes a concern, the corresponding research has begun to receive attention in very recent years [149], [150]. In this sense, a prospective direction might be studying how to design multi-sensor multi-target tracking schemes under the communication constraints identified in this survey.

5) Establishing an Easy-to-Verify Theoretical Framework for the Performance Analysis: Performance analysis is one of the most basic problems in the control and signal processing areas, based on which the engineers can choose proper schemes with certain reliability guarantees. As for the sample-based networked nonlinear filtering schemes, it remains an arduous task to conduct the theocratical performance analysis (e.g., stability, boundedness, and robustness) due primarily to the mathematical complexities induced by the underlying system nonlinearity, sample-based approximation, and various communication constraints. It is worth mentioning that in most existing literature, the performance analysis has been carried out by making assumptions on the boundedness of some (unknown) matrices or the system observability, which are, sometimes, difficult to verify in practical applications. As such, it is necessary to establish a proper yet easy-to-verify theoretical analysis framework for the sample-based networked nonlinear filtering algorithms.

6) Exploring the Practical Engineering Applications of Theoretical Algorithms: In recent years, considerable research attention has been concentrated on the sample-based networked nonlinear filtering problems with various communication constraints. However, very few results have been available in terms of the real-world applications owing to the gap between engineering practices and assumption/simplification-based theoretical algorithms. For example, the existing attack models, established on certain assumptions, might not fully characterize the highly sophisticated and stealthy attack behaviors in some scenarios, which unavoidably impedes the practical applications of related secure filtering schemes. In addition, it should also be pointed out that most experimental verifications in existing works are carried out in relatively ideal indoor environments. As such, there is still a long way to go before successfully applying these works to practical scenarios, such as the cooperative detection and target tracking in highly uncertain and antagonistic environments.

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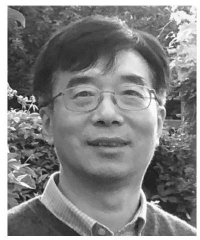

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