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DISTRIBUTED FILTERING OF NETWORKED DYNAMIC SYSTEMS WITH NON-GAUSSIAN NOISES OVER SENSOR NETWORKS: A SURVEY

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Sensor networks are regarded as a promising technology in the field of information perception and processing owing to the ease of deployment, cost-effectiveness, flexibility, as well as reliability. The information exchange among sensors inevitably suffers from various network-induced phenomena caused by the limited resource utilization and complex application scenarios, and thus is required to be governed by suitable resource-saving communication mechanisms. It is also noteworthy that noises in system dynamics and sensor measurements are ubiquitous and in general unknown but can be bounded, rather than follow specific Gaussian distributions as assumed in Kalman-type filtering. Particular attention of this paper is paid to a survey of recent advances in distributed filtering of networked dynamic systems with non-Gaussian noises over sensor networks. First, two types of widely employed structures of distributed filters are reviewed, the corresponding analysis is systematically addressed, and some interesting results are provided. The inherent purpose of adding consensus terms into the distributed filters is profoundly disclosed. Then, some representative models characterizing various network-induced phenomena are reviewed and their corresponding analytical strategies are exhibited in detail. Furthermore, recent results on distributed filtering with non-Gaussian noises are sorted out in accordance with different network-induced phenomena and system models. Another emphasis is laid on recent developments of distributed filtering with various communication scheduling, which are summarized based on the inherent characteristics of their dynamic behavior associated with mathematical models. Finally, the state-of-the-art of distributed filtering and challenging issues, ranging from scalability, security to applications, are raised to guide possible future research.

Keywords: distributed filtering, sensor networks, non-Gaussian noises, network-induced phenomena, communication protocols

Classification: 93E11, 93C55, 93A15

1. INTRODUCTION

Sensor networks represent one of the most cornerstone technologies in the era of Industry 4.0 and have broad applications in the areas of military sensing, physical security, environment monitoring as well as industrial and manufacturing automation. Spatially deployed sensing devices (i. e. sensor nodes) are usually small, power-constrained and

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low-cost, and perform various predetermined tasks in a collaborative manner. The information exchange among these devices commonly leverages a distributed communication network with self-organization, whose topologies could be bus, tree, star, ring, mesh, circular, grid and so forth. In the past few decades, various communication protocols are specifically designed to adapt efficient, fast, and resource-friendly requirements.

As an interdisciplinary topic, the distributed filtering over sensor networks has persistently attracted increasing research interest in recent years due to the flexibility of the parallel processing, the reliability of distributed implementation and the robustness of estimated results[8]. To be specific, in comparison with traditionally centralized filtering, each sensor node in a distributed setting is equipped with a filter that employs both local and neighboring information to obtain the true estimates [45]. In other words, a key idea of distributed filtering is to decentralize the function of the fusion center to each intelligent sensor in such a way that the calculation and communication burden are significantly alleviated. On the other hand, the distributed fusion of neighboring information in this process is generally realized by making use of iterative consensus algorithms or constructed consensus terms in the designed filter structures. Although offering computation and communication advantages, the resultant distributed filtering schemes in practical engineering often result in several inherent challenges ranging from design cost, resource constraints, external disturbances and communication protocols to cyber-attacks. For example, network-induced phenomena inevitably encounter because of the limited bandwidth of the communication channel, and sparse measurements could artificially occur due to the usage of scheduling protocols to ease communication burden. As such, it is not surprising that the desired performance of the filtering algorithm could not be ensured if these factors are not adequately handled. Over the past decade, a rich body of literature has appeared on this topic and a great number of filtering algorithms are proposed by resorting to the technologies of Kalman consensus filtering, H_∞ consensus filtering, set-membership filtering, or recursive least squares, see, e. g., the recent surveys [7, 25] for more details.

As one of the most fashionable approaches, consensus Kalman filtering usually depends on the assumption of accurate statistics of Gaussian noises. The latest research developments have been systematically surveyed in [7]. However, such an assumption is not true in practical engineering. Noises existed could be unknown-but-bounded or energy bounded, from which the effect can be evaluated by the hard bound or the H_∞ performance of the filtering error dynamics. As such, it is desirable to survey what results have been developed in the field of distributed filtering over sensor networks subject to non-Gaussian noises, and further identify what challenging issues need to be dealt with. Recently, some interesting reviews about distributed filtering have been reported in accordance with network-induced phenomena, event-triggered protocols and so forth. However, there is a lack of comprehensive reviews and summaries of distributed filtering focusing on the dynamic systems subject to non-Gaussian noises. For this purpose, this paper attempts to provide an overview of the state-of-the-art of distributed filtering dealing with non-Gaussian noises, especially when the concerned sensor network are subject to various network-induced phenomena or communication scheduling protocols. Specifically, we first outline two typical structures of distributed filters and particularly expound the corresponding analysis procedures. According to network-induced phenomena and communication scheduling protocols, their representative models are systematically reviewed, the inherent characteristics of their dynamic behavior are profoundly identified, and recent results in these two topics are sorted out. Finally, several challenging issues are provisioned to guide possible future research.

The remainder of this paper is organized as follows (see also Figure 1). In Section 2, typical analysis frameworks for both stability-based and set-membership-based distributed filtering are summarized in light of Lyapunov-function-based techniques. In Section 3, distributed filtering with network-induced phenomena are presented. An overview with communication scheduling is summarized in Section 4 from the aspect of the categories on protocol modeling, typical analysis approaches, and corresponding results. Latest developments and challenging issues are raised in Section 5 to guide the future research.

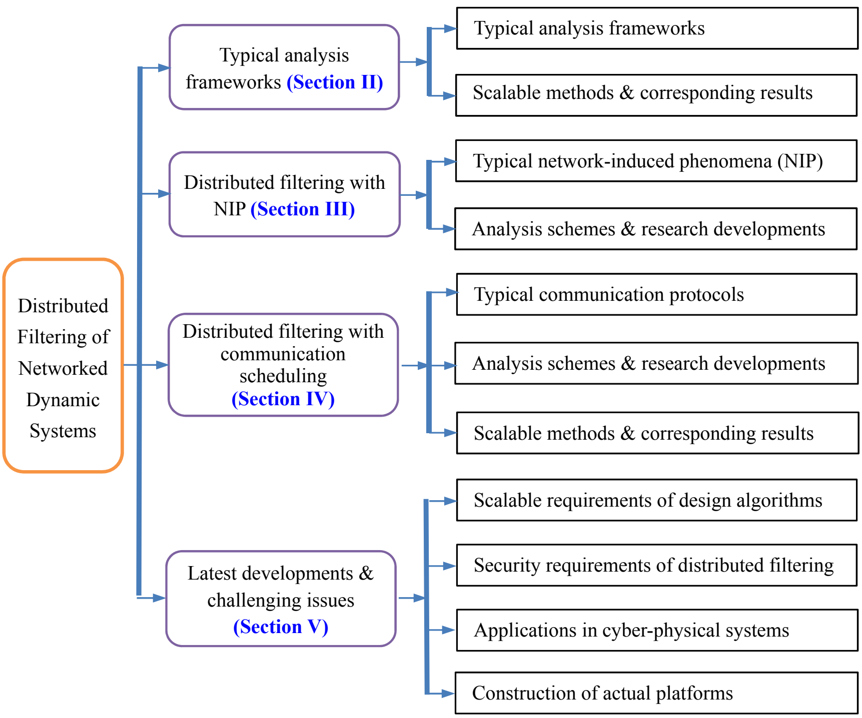

Fig. 1. Main structure of this survey.

2. THE TYPICAL ANALYSIS FRAMEWORK OF DISTRIBUTED FILTERING

2.1. The typical analysis frameworks

It is assumed that the sensor network consists of n sensor nodes which connect with each other according to a topology represented by a weighted digraph $\mathscr{G} = (\mathscr{V}, \mathscr{E}, \mathscr{W})$ with the set of nodes $\mathscr{V}$ $=\{1, 2, \ldots, n\}$, the set of edges $\mathscr{E} \in \mathscr{V} \times \mathscr{V}$, and the weighted adjacency matrix $\mathscr{W} = [w_{ij}]$ with nonnegative adjacency element w_{ij}. The set of neighbors of node $i \in \mathscr{V}$ is denoted by $\mathcal{N}_i = \{j \in \mathscr{V} : (i, j) \in \mathscr{E}\}$.

Consider a physical system modeled by the following nonlinear state-space equation

$$x^+ = Ax(t) + f(x(t)) + Bv(t) \tag{1}$$

with n sensors

$$y_i(t) = C_i x(t) + D_i v(t), \quad i = 1, 2, \ldots, n, \tag{2}$$

where $x(t) \in \mathbb{R}^{n_x}$ is the state of the target that cannot be observed directly, $y_i(t) \in \mathbb{R}^{n_y}$ is the measurement output from sensor i, $f(x(t)) \in \mathbb{R}^{n_x}$ is a vector-valued function, and $v(t)$ denotes the noise (or disturbance or modeling error) input. In this paper, a uniform notation x^+ is exploited to stand for $\dot{x}(t)$ for continuous-time systems or $x(t+1)$ for discrete-time systems. Of course, the nonlinear function $f(x(t))$ impacts the filtering performance, and its some certain information should be reflected in sufficient conditions to handle the filter design. In the literature, the assumption is widely adopted as follows.

Assumption. The vector-valued function in (1) satisfies the constraint

$$(f(x(t)) + \delta) - f(x(t)))^T H\delta \leq 0$$

or

$$(f(x(t) + \delta) - f(x(t)))^T H(f(x(t) + \delta) - f(x(t))) \leq \theta\|\delta\|,$$

where H is a known matrix, and θ is a known positive scalar.

In the networked setting, the noise $v(t)$ can be described by an ellipsoid $\{v(t) : v^T(t)Qv(t) \leq 1\}$ with a shape matrix $Q > 0$, or modeled as an energy bounded signal $v(t) \in l_2[0,\ \infty)$ i.e. $\sum_{t=0}^{\infty} \|v(t)\|^2 < \infty$. The corresponding filtering approaches are mainly set-membership filtering, $l_2 - l_\infty$ filtering or H_∞ filtering. Compared with the H_∞ performance, the $l_2 - l_\infty$ criterion generally guarantees the energy-to-peak bound. Furthermore, the desired filter gain can be easily obtained in terms of linear matrix inequalities (LMIs) guaranteeing some tractable design criteria.

In comparison with centralized filtering, one of the main characteristics of distributed filtering is that the filtering performance can be improved by fusing the neighbor information, which can be realized by two information fusion approaches: *the measurement fusion approach* [7, 64] and *the estimate fusion approach* [25, 58, 87]. More specifically, the two approaches above generally lead to the following distributed filter structures:

$$\hat{x}_i^+ = A\hat{x}_i(t) + f(\hat{x}_i(t)) + K_i(y_i(t) - C_i\hat{x}_i(t)) + L_i \sum_{j\in\mathcal{N}_i} w_{ij}(y_j(t) - C_j\hat{x}_j(t)) \tag{3}$$

or

$$\hat{x}_i^+ = A\hat{x}_i(t) + f(\hat{x}_i(t)) + K_i(y_i(t) - C_i\hat{x}(t)) + \varepsilon \sum_{j\in\mathcal{N}_i} w_{ij}(\hat{x}_j(t) - \hat{x}_i(t)), \tag{4}$$

where $\hat{x}_i(t) \in \mathbb{R}^{n_z}$ is the estimated state on sensor node i, the scalar ε is the coupled strength, and K_i and L_i are the filter gain matrices to be determined.

Note that the term "$\varepsilon\sum_{j\in\mathcal{N}_i} w_{ij}(\hat{x}_j(t)-\hat{x}_i(t))$" in (4) is usually called the consensus term which is first introduced by Reza Olfati-Saber in [56]. Since then, the consensus-based ditributed filtering has received an intensive research interest. Usually, the local filtering algorithm on each node (sensor/estimator) cannot guarantee the so-called consensus of filtering, and therefore the role of added consensus term is to reduce the disagreement potential $\sum_{(i,j)\in\mathcal{E}}\|\hat{x}_j-\hat{x}_i\|^2$, see [56] for more details. Furthermore, both the optimality and the stability are extensively discussed in [57], while the optimized filter gains are dependent on the cross-variance of neighboring filtering errors, which, unfortunately, limits the scope of the practical application. Similar results can also be found in [72] by utilizing the H_∞ filtering approach combined with the theory of vector dissipativeness. From the viewpoint of system performance, the disagreement potential is actually a constraint that is more stringent the traditional minimum covariance or the stability. In other words, the larger the coupling strength ε is, the more complex the dynamic behavior is. Furthermore, such a parameter can provide a trade-off between the traditional filtering performance and the consensus performance. There is no doubt that the selection of coupling strength ε has a considerable effect on the convergence of the filtering errors, which lies in the range of $(0,1/\Delta)$ ($\Delta=\max_i\lfloor\mathcal{N}_i\rfloor$) where $\lfloor\mathcal{N}_i\rfloor$ is the number of in-neighbors, see Theorem 3.1 in [89]. Finally, compared with the structure (4), one can find that the term $\sum_{j\in\mathcal{N}_i} w_{ij}(y_j(t)-C_j\hat{x}_j(t))$ in (3) can be rewritten as

$$\sum_{j\in\mathcal{N}_i} w_{ij}(y_j(t)-C_j\hat{x}_j(t))=\sum_{j\in\mathcal{N}_i} w_{ij}(y_j(t)-C_j\hat{x}_i(t))-\sum_{j\in\mathcal{N}_i} w_{ij}C_j(\hat{x}_j(t)-\hat{x}_i(t)).$$

Obviously, the fist term on the right-hand side of the above equation can be utilized to guarantee the union observability, which plays a critical role in the filter design, and the second one is employed to evaluate the consensus performance among estimates.

In what follows, denoting $e_i(t)=x(t)-\hat{x}_i(t)$ and $\tilde{f}(e_i(t))=f(x(t))-f(\hat{x}_i(t))$, one has, respectively, from (1), (3) and (4) that

$$e_i^+=(A-K_iC_i)e_i(t)+\tilde{f}(e_i(t))-\sum_{j\in\mathcal{N}_i} w_{ij}L_iC_je_j(t)-K_iD_iv(t)-\sum_{j\in\mathcal{N}_i} w_{ij}L_iD_jv(t)$$

or

$$e_i^+=(A-K_iC_i)e_i(t)+\tilde{f}(e_i(t))+\varepsilon\sum_{j\in\mathcal{N}_i} w_{ij}(e_j(t)-e_i(t))-K_iD_iv(t). \tag{5}$$

In light of the Kronecker product, the augmented error dynamics is then written as

$$e^+=\big(\mathcal{A}-\big(\mathcal{K}+\mathcal{L}(\mathcal{W}\otimes I)\big)\mathcal{C}\big)e(t)+F(e(t))-\big(\mathcal{K}+\mathcal{L}(\mathcal{W}\otimes I)\big)\mathcal{D}\mathcal{I}_nv(t) \tag{6}$$

or

$$e^+=\big(\mathcal{A}-\mathcal{K}\mathcal{C}+\varepsilon(\mathcal{W}-\bar{\mathcal{W}})\otimes I\big)e(t)+F(e(t))-\mathcal{K}\mathcal{D}\mathcal{I}_nv(t), \tag{7}$$

where

$$
\begin{aligned}
&e(t) = [\ e_1^T(t) \quad e_2^T(t) \quad \cdots \quad e_n^T(t)\ ]^T,\\
&F(e(t)) = [\ \tilde{f}^T(e_1(t)) \quad \tilde{f}^T(e_2(t)) \quad \cdots \quad \tilde{f}^T(e_n(t))\ ]^T,\\
&\mathcal{A} = I \otimes A,\ \mathcal{C} = \mathrm{diag}_n\{C_i\},\ \mathcal{D} = \mathrm{diag}_n\{D_i\},\ \mathcal{K} = \mathrm{diag}_n\{K_i\},\\
&\mathcal{L} = \mathrm{diag}_n\{L_i\},\ \bar{\mathcal{W}} = \mathrm{diag}_n\Big\{\sum_{j=1}^{n} w_{ij}\Big\},\ \mathcal{I}_n = [\ I \quad I \quad \cdots \quad I\ ]^T.
\end{aligned}
$$

The filtering issue is then transformed into the analysis of stability, the noise rejection as well as the ellipsoid estimation of the filtering error dynamics above. Obviously, the stability is determined by the system matrix $\mathcal{A} - \big(\mathcal{K} + \mathcal{L}(\mathcal{W} \otimes I)\big)\mathcal{C}$ (or $\mathcal{A} - \mathcal{K}\mathcal{C} + \varepsilon(\mathcal{W} - \bar{\mathcal{W}}) \otimes I$) and the nonlinear function $F(e(t))$. In the framework of LMIs, one can construct a suitable Lyapunov function candidate $V(t) = e^T(t)\mathcal{P}e(t)$ for the filtering error dynamics (6) and then calculate its derivative or difference, resulting in

$$
\begin{aligned}
V^+ = {} & e^T(t)\mathcal{P}\big(\mathcal{A} - \big(\mathcal{K} + \mathcal{L}(\mathcal{W} \otimes I)\big)\mathcal{C}\big)e(t) + e^T(t)\mathcal{P}F(e(t))\\
& - e^T(t)\mathcal{P}\big(\mathcal{K} + \mathcal{L}(\mathcal{W} \otimes I)\big)\mathcal{D}\mathcal{I}_n v(t)\\
& + e^T(t)\big(\mathcal{A} - \big(\mathcal{K} + \mathcal{L}(\mathcal{W} \otimes I)\big)\mathcal{C}\big)^T\mathcal{P}e(t) + F^T(e(t))\mathcal{P}e(t)\\
& - v^T(t)\mathcal{I}_n^T\mathcal{D}^T\big(\mathcal{K} + \mathcal{L}(\mathcal{W} \otimes I)\big)^T\mathcal{P}e(t)
\end{aligned}
$$

for a continuous-time case or

$$
\begin{aligned}
V^+ = {} & e^T(t)\big(\mathcal{A} - \big(\mathcal{K} + \mathcal{L}(\mathcal{W} \otimes I)\big)\mathcal{C}\big)^T\mathcal{P}\big(\mathcal{A} - \big(\mathcal{K} + \mathcal{L}(\mathcal{W} \otimes I)\big)\mathcal{C}\big)e(t)\\
& + 2e^T(t)\big(\mathcal{A} - \big(\mathcal{K} + \mathcal{L}(\mathcal{W} \otimes I)\big)\mathcal{C}\big)^T\mathcal{P}F(e(t))\\
& - 2e^T(t)\big(\mathcal{A} - \big(\mathcal{K} + \mathcal{L}(\mathcal{W} \otimes I)\big)\mathcal{C}\big)^T\mathcal{P}\big(\mathcal{K} + \mathcal{L}(\mathcal{W} \otimes I)\big)\mathcal{D}\mathcal{I}_n v(t)\\
& + F^T(e(t))\mathcal{P}F(e(t)) - 2F^T(e(t))\mathcal{P}\big(\mathcal{K} + \mathcal{L}(\mathcal{W} \otimes I)\big)\mathcal{D}\mathcal{I}_n v(t)\\
& + v^T(t)\mathcal{I}_n^T\mathcal{D}^T\big(\mathcal{K} + \mathcal{L}(\mathcal{W} \otimes I)\big)^T\mathcal{P}\mathcal{L}(\mathcal{W} \otimes I)\big)\mathcal{D}\mathcal{I}_n v(t) - e^T(t)\mathcal{P}e(t)
\end{aligned} \tag{8}
$$

for a discrete-time case. Furthermore, considering the nonlinear function $f(x(t))$ and letting $V^+ < 0$, one can obtain the desired condition on the stability, the input-to-state stability or the H_∞ performance, by adding the following constraints

$$
-\rho F^T(e(t))(I \otimes H)e(t) \geq 0 \tag{9}
$$

or

$$
\rho\theta e^T(t)e(t) - \rho F^T(e(t))(I \otimes H)F(e(t)) \geq 0, \tag{10}
$$

where ρ is a positive scalar which is commonly regarded as a decision variable to adjust the solvability of the corresponding LMIs.

On the other hand, when the set-membership performance [24, 25] is a concern, the desired recursive conditions can be readily obtained via replacing

- "$-e^T(t)Pe(t)$" by "-1" in (8)
- "$e(t)$" by "$e(t) = \Theta\eta(t)$" in (8) and (9) (or (10)),

where the auxiliary variable $\eta(t)$ satisfies $\|\eta(t)\| < 1$ and the matrix Θ guarantees $e^T(t)\Theta\Theta^T e(t) < 1$, which depends on the estimated ellipsoid set at the time instant t. Similar results on the filtering error dynamics (7) can be derived, see, e. g., [10, 24, 47, 50] and the references therein.

2.2. Some scalable methods and corresponding results

Inspired by [36], authors in [11] select a Lyapunov function as follows:

$$V(t) = \sum_{i=1}^{n} e_i^T(t) P e_i(t). \tag{11}$$

Denote $\eta_i(t) = [\ e_i^T(t) \quad \tilde{f}^T(e_i(t)) \quad v^T(t)]^T$ and assume $\|v(t)\|^2 \leq \varsigma$. Along the error dynamics (5), one can easily calculate that

$$\begin{aligned}
\Delta V(t) &= V(t+1) - V(t) \\
&= \sum_{i=1}^{n} \Big\{ e_i^T(t+1) P e_i(t+1) - \chi_i e_i^T(t) P e_i(t) \Big\} \\
&\quad + (\chi_i - 1) \sum_{i=1}^{n} \Big\{ e_i^T(t) P e_i(t) \Big\} \\
&\leq \pi e^T(t) e(t) + \sum_{i=1}^{n} \eta_i^T(t) \Pi_{1i} \eta_i(t) \\
&\quad + (\chi_i - 1) \sum_{i=1}^{n} \Big\{ e_i^T(t) P e_i(t) \Big\} + \varrho\varsigma,
\end{aligned}$$

where

$$\begin{aligned}
\Pi_{1i} &= \begin{bmatrix} \Pi_{11i} & \Pi_{12i} & \Pi_{13i} \\ * & \Pi_{22i} & \Pi_{23i} \\ * & * & \Pi_{33i} \end{bmatrix}, \\
\Pi_{11i} &= (1 + \sigma_{1i})(A - K_i C_i)^T P (A - K_i C_i) + \rho\theta I - \chi_i I, \\
\Pi_{12i} &= (A - K_i C_i)^T P, \ \Pi_{13i} = -(A - K_i C_i)^T P K_i D_i \\
\Pi_{22i} &= (1 + \sigma_{2i}) P - \rho H, \ \Pi_{23i} = -P K_i D_i \\
\Pi_{33i} &= (1 + \sigma_{3i}) D_i^T K_i^T P K_i D_i - \varrho I.
\end{aligned}$$

Here, the introduced scalars ρ and θ come from the second assumptions about nonlinear function $\tilde{f}(e_i(t))$, and ϱ is any positive scalar induced by $\varrho\|v(t)\|^2 \leq \varrho\varsigma$. Based on the above analysis, we have the following simplified result.

Theorem 2.1. Consider the discrete-time nonlinear system (1) with the measurement (2). For given scalars $\mu > 1$ and ε as well as matrices K_i $(i = 1, 2, \ldots, n)$, the estimation error dynamics (5) is input-to-state stable, if there exist a positive-definite matrix P and positive scales ρ, ϱ, χ_i and σ_{ji} $(j = 1, 2, 3)$ such that the following inequalities

$$\Pi_{1i} < 0, \quad \varpi_i = 1 - \chi_i - \pi > 0 \tag{12}$$

hold, where

$$\pi = \varepsilon^2(1+\sigma_{1i}^{-1}+\sigma_{2i}^{-1}+\sigma_{3i}^{-1})\lambda_{\max}(P)\lambda_{\max}((\mathcal{W}-\bar{\mathcal{W}})^T(\mathcal{W}-\bar{\mathcal{W}})).$$

In what follows, let us provide a recursive filtering with a similar Kalman-type framework based on set-membership approaches [10, 48]. Assume $Bv(t)\in\mathcal{E}(0,BVB^T)$ and denote the current estimated state as $\hat{x}^*_{i,t|t}$ on filter i. The well-known Lagrange remainder $r_{i,t}$ along the system dynamics (1) is

$$r_{i,t} = \frac{1}{2}\mathrm{diag}(x(t)-\hat{x}^*_{i,t|t})^T\frac{\partial^2 f(x)}{\partial x^2}\Big|_{x=\varphi_{i,t}}(x(t)-\hat{x}^*_{i,t|t}). \tag{13}$$

Here, $\varphi_{i,t}$ is a vector taking some suitable value over an interval $X_{i,t}=[-p_{i,t},\ p_{i,t}]$ with

$$p_{i,t} = \Big[\sqrt{P^{*1,1}_{i,t|t}},\ \sqrt{P^{*2,2}_{i,t|t}},\ \dots,\ \sqrt{P^{*n,n}_{i,t|t}}\ \Big]^T,$$

where $P^{*m,m}_{i,t|t}$ stands for the (m,m) element of the shape matrix $P^*_{i,t|t}$ on instant t. In addition, extending (13) to all states yields

$$\bar{\mathcal{R}}_{i,t} = \frac{1}{2}\mathrm{diag}_n(X^T_{i,t})\frac{\partial^2 f(x)}{\partial x^2}\Big|_{x\in X_{i,t}+\hat{x}^*_{i,k|k}}X_{i,t}, \tag{14}$$

where $\bar{\mathcal{R}}_{i,t}$ is an interval vector that can be determined via interval mathematics.

The Lagrange remainder $r_{i,t}$ can be bounded by an ellipsoid $\mathcal{E}(0,\bar{W}_{i,t})$ with minimal volume:

$$[\bar{W}_{i,t}]_{m,n} = \begin{cases} 2(\bar{\mathcal{R}}^{n+}_{i,t}-\bar{\mathcal{R}}^{n-}_{i,t})^2, & m=n; \\ 0 & \text{otherwise}, \end{cases} \tag{15}$$

where $[\bar{W}_{i,t}]_{m,n}$ stands for the (m,n) element of the matrix $\bar{W}_{i,t}$ and the subscripts "+" and "−" denote, respectively, the maximum and minimum values of the interval $\bar{\mathcal{R}}_{i,t}$. Next, taking the process disturbances and the linearization error into account, one has

$$\tilde{\omega}_{i,t} = Bv(t)+r_{i,t}\in\mathcal{E}(0,BVB^T)\oplus\mathcal{E}(0,\bar{W}_{i,t})\subseteq\mathcal{E}(0,\hat{W}_{i,t}), \tag{16}$$

where $\hat{W}_{i,t}=\frac{BVB^T}{\alpha_{i,t}}+\frac{\bar{W}_{i,t}}{1-\alpha_{i,t}}$.

In light of the above preparation, we have the following result, whose proof is omitted for simplicity of presentation.

Theorem 2.2. Let $\pi^i_{j,t+1}>0$ and $\beta_{i,t}\in(0,\ 1)$ be given. Suppose that the system state $x(t)$ lies in the ellipsoid $\mathcal{E}(\hat{x}^*_{i,t|t},P^*_{i,t|t})$. The system state $x(t+1)$ derived by (1) involves in the ellipsoid $\mathcal{E}(\hat{x}^*_{i,t+1|t+1},P^*_{i,t+1|t+1})$ with parameters:

$$\begin{aligned} P^*_{i,t+1|t+1} &= \Big(\sum_{j\in\mathcal{N}_i\cup\{i\}}\lambda^i_{j,t+1}(P^i_{j,t+1|t+1})^{-1}\Big)^{-1}, \\ \Upsilon^i_{j,t+1} &= \lambda^i_{j,t+1}(P^i_{j,t+1|t+1})^{-1}\hat{x}^i_{j,t+1|t+1}, \\ \hat{x}^*_{i,t+1|t+1} &= \sum_{j\in\mathcal{N}_i\cup\{i\}}P^*_{i,t+1|t+1}\Upsilon^i_{j,t+1}, \end{aligned} \tag{17}$$

in which the positive scalar $\lambda^i_{j,k+1}$ satisfies

$$\hat{x}^{*T}_{i,t+1|t+1}(P^*_{i,t+1|t+1})^{-1}\hat{x}^*_{i,t+1|t+1} + \sum_{j\in\mathscr{N}_i\cup\{i\}} \lambda^i_{j,t+1} - 1 - \sum_{j\in\mathscr{N}_i\cup\{i\}} \lambda^i_{j,t+1}\hat{x}^{iT}_{j,t+1|t+1}(P^i_{j,t+1|t+1})^{-1}\hat{x}^i_{j,t+1|t+1} \le 0,$$

where

$$\begin{aligned}
&\hat{x}^i_{i,t+1|t+1} = A\hat{x}^*_{i,t|t} + f(\hat{x}^*_{i,t|t}) + \mathcal{K}^i_{j,t+1}\xi^i_{j,t+1},\\
&P^i_{j,t+1|t+1} = \sigma^i_{j,t+1}\big(I - \mathcal{K}^i_{j,t+1}C_j\big)P^i_{j,t+1|t},\\
&\hat{x}^i_{j,t+1|t} = A\hat{x}^*_{i,t|t} + f(\hat{x}^*_{i,t|t}), \quad \hbar^i_{j,t+1} = y_j(t+1) - C_j\hat{x}^i_{j,t+1|t},\\
&P^i_{j,t+1|t} = (1-\beta_{i,t})^{-1}(A + A_{i,t})P^*_{i,t|t}(A + A_{i,t})^T + \beta^{-1}_{i,t}\hat{W}_{i,t},\\
&\mathcal{O}^i_{j,t+1} = (\pi^i_{j,t+1})^{-1}D_jVD_j^T + C_jP^i_{j,t+1|t}C_j^T,\\
&\mathcal{K}^i_{j,t+1} = P^i_{j,t+1|t}C_j^T(\mathcal{O}^i_{j,t+1})^{-1}, A_{i,t} = \frac{\partial f(x)}{\partial x}\Big|_{x=\hat{x}^*_{i,t|t}},\\
&\sigma^i_{j,t+1} = 1 + \pi^i_{j,t+1} - \hbar^{iT}_{j,t+1}(\mathcal{O}^i_{j,t+1})^{-1}\hbar^i_{j,t+1}.
\end{aligned}$$

3. DISTRIBUTED FILTERING WITH NETWORK-INDUCED PHENOMENA

In this section, some typical network-induced phenomena will be discussed according to their mathematical models and analytic strategies. Furthermore, recent developments in this regard are systematically summarized based on various system dynamics with different network-induced phenomena.

3.1. Typical network-induced phenomena

Communication conditions cannot reach the ideal state in an end-to-end setting due to both the large scale of sensor networks and the limited communication resources, and therefore various network-induced phenomena could occur in a random way. These phenomena include, but not limited to, quantization, signal fadings, packet dropout as well as time-delays, see Table 1 for their mathematical models and some representative references. In this table, $\tilde{y}_{ij}(t)$ is the received measurement of filter i from sensor j; each stochastic variable $\alpha^i_{s,t}$ $(s = 0, 1, \ldots, l)$ takes a value on the interval $[0,\ 1]$; β^i_t is a binary stochastic variable taking the value in set $\{0, 1\}$; $q(\cdot)$ is a quantization function with a predetermined quantization level; π_t stands for a time delay which could be time-varying with known upper- and lower-bound information; and $\varepsilon(t)$ is a channel noise.

It is worth noting that the proposed packet dropout model above represents the *successive packet dropouts*, which includes the traditional model $\tilde{y}_{ij}(t) = \beta^i_t y_j(t)$ as a special case. Furthermore, the received signal $\tilde{y}_{ij}(t)$ with zero-order-hold compensation, denoted as $\tilde{y}_{ij}(t) = \beta^i_t y_j(t) + (1-\beta^i_t)\tilde{y}_{ij}(t-1)$, is naturally adopted for various control and filtering issues. On the other hand, the time-delayed model $\tilde{y}_{ij}(t) = \beta^i_t y_j(k-\pi_t)$ is regarded as the *randomly occurring time-delays*. Furthermore, the quantizer $q(\cdot)$ is

Types	Models	References
Quantization	$\tilde{y}_{ij}(t) = q(y_j(t)) + \epsilon(t)$	[13, 19, 82]
Fadings	$\tilde{y}_{ij}(t) = \alpha^i_{0,t} y_j(t) + \sum_{s=1}^{l} \alpha^i_{s,t} y_j(t-s)$	[5, 14, 45]
Packet dropout	$\tilde{y}_{ij}(t) = \beta^i_t y_j(t) + (1-\beta^i_t)\beta^i_{t-1} y_j(t-1) + \cdots$	[19, 41, 63, 91]
Time-delays	$\tilde{y}_{ij}(t) = y_j(k-\pi_t)$ or $\tilde{y}_{ij}(t) = \beta^i_t y_j(k-\pi_t)$	[15, 18, 21, 55]

Tab. 1. Mathematical models of typical network-induced phenomena.

generally a symmetrical piecewise function with respect to the origin, and maps input values to output values with an infinite countable number of levels. Typical quantizers involve *uniform quantizers* and *logarithmic quantizers*. Additionally, the *dynamic quantizer* with function $q_u(\cdot) = uq(\cdot/u)$ has recently attracted an ever-increasing research attention, where u is a dynamic variable named as a "zoom" variable. There is no doubt that the received data by distributed filters could be incomplete or non-real-time because of these phenomena and therefore the filtering performance may be deteriorated for the designed distributed filters if they are not appropriately considered.

3.2. Basic analysis schemes and research developments

From the technical perspective, the challenge from quantization is trivial due to the mathematical transformation. Specifically, the uniform quantizer can be denoted as the traditional measurement with a bounded noise

$$q(y_j(t)) = y_j(t) + \zeta_j(t)$$

where the quantization error $\zeta_j(t)$ is determined by the number of bits of digital sensors, and the quantization error of logarithmic quantizers can be transformed into a norm uncertainty or a sector-bounded nonlinearity

$$q(y_j(t)) = (1 + \Delta_j(t))y_j(t), \text{ or } q(y_j(t)) = y_j(t) + \zeta_j(t)$$

where the quantization error $\Delta_j(t)$ or $\zeta_j(t)$ satisfies $\|\Delta_j(t)\| \leq \kappa$ or $\zeta_j^T(t)(\zeta_j(t) - 2\kappa y_j(t)) \leq 0$, respectively. Here, the parameter κ is determined by the adopted quantization level, see [103] for more details.

A unified framework is developed in [19] by two mutually independent sets of Bernoulli distributed white sequences to describe the phenomena of both quantization and successive packet dropouts, where quantization errors are regarded as bounded noises. Based on such a model, a set of distributed finite-horizon filters are designed to ensure the redescribed average filtering performance over lossy sensor networks. A similar mixed model is constructed in [95] for a class of nonlinear systems described by T-S fuzzy models over sensor networks with switching topologies, where quantization errors are modeled as norm-bounded uncertainties. With the help of the average dwell time, the desired gains of distributed filters and the permitted noise rejection level are obtained. Furthermore, a similar result by resorting to a Lur'e-type Lyapunov function can be found in

[107] for discrete-time Markov jump Lur'e systems, where the transmitted model has the capability of describing quantization and randomly occurring packet dropouts under redundant channels. Besides, a more generally switched system subject to quantization effect is discussed in [94], where the switches come from both the varying sampling period and the varying communication topologies to govern the sensor scheduling. The designed filters guarantee that the filtering error system is exponentially stable with a determined decay rate and achieves the H_∞ performance with a solution-dependent attenuation level. Finally, as a class of special switching topologies, sensor networks with M-periodic topologies are considered in [38] for discrete-time stochastic periodic systems with topology-dependent logarithmic quantizers. A sufficient condition with M-periodic LMIs is derived to deal with the design of distributed H_∞ state estimators with the help of a topology-dependent Lyapunov function and the well-known robust control approach.

When the sequences of stochastic variables $\alpha_{s,t}^i$ or β_t^i are unknown in accordance with the adopted communication coding, the error dynamics is impossibly autonomous even if omitting noises, that is, dependent on the system state. In other words, the error dynamics and the system are coupled with each other and therefore should be augmented together for the purpose of performance analysis and gain design. In what follows, we will employ the simplest model $\tilde{y}_{ij}(t) = \beta_t^i y_j(t)$ as a special case to show the analysis procedure.

Denote the probability of $P\{\beta_t^i = 1\}$ as $\bar{\beta}^i$ and therefore the received measurements can be written as

$$\begin{aligned}\tilde{y}_{ij}(t) &= \bar{\beta}^i y_j(t) + (\beta_t^i - \bar{\beta}^i) y_j(t)\\ &= \bar{\beta}^i C_j x(t) + \bar{\beta}^i D_j v(t) + (\beta_t^i - \bar{\beta}^i)(C_j x(t) + D_j v(t)).\end{aligned} \tag{18}$$

Then, the desired filter structure is given as

$$\hat{x}_i^+ = A\hat{x}_i(t) + f(\hat{x}_i(t)) + K_i(y_i(t) - C_i\hat{x}_i(t)) + L\sum_{j\in\mathcal{N}_i} w_{ij}(\tilde{y}_{ij}(t) - \bar{\beta}^i C_j \hat{x}_j(t)),$$

which results in the following modified error dynamics

$$\begin{aligned}e^+ = {}&\big(\mathcal{A} - \big(\mathcal{K} + \mathcal{L}((\bar{\Phi}_\beta \mathcal{W}) \otimes I)\big)\mathcal{C}\big)e(t) + F(e(t)) - \big(\mathcal{K} + \mathcal{L}((\bar{\Phi}_\beta \mathcal{W}) \otimes I)\big)\mathcal{D}\mathcal{I}_n v(t)\\ &- \mathcal{L}((\Phi_\beta(t)\mathcal{W}) \otimes I)\mathcal{C}\mathcal{I}_n x(t) - \mathcal{L}((\Phi_\beta(t)\mathcal{W}) \otimes I)\mathcal{D}\mathcal{I}_n v(t),\end{aligned} \tag{19}$$

where

$$\mathcal{L} = I \otimes L,\ \bar{\Phi}_\beta = \mathrm{diag}_n\{\bar{\beta}^i\},\ \Phi_\beta(t) = \mathrm{diag}_n\{\beta_t^i - \bar{\beta}^i\}.$$

It is not difficult to see from the equation above that the main challenge comes from the last two terms of the right hand side of the equation. When the performance analysis is a concern, the expectations of the products of these two terms and the other terms are zero, which, therefore, does not obstruct the utilization of the Schur complement lemma for handling the results of the first three terms. Furthermore, their variances are not zero and can be derived by selecting a special matrix in the Lyapunov function. In particular, this function usually takes the following form

$$V(t) = e^T(t)(I \otimes P)e(t) + x^T(t)Qx(t).$$

Then, by resorting to the property of Kronecker product, one has the $(I \otimes P)$-weighted variance of $\mathcal{L}((\Phi_\beta(t)\mathcal{W}) \otimes I)\mathcal{C}\mathcal{I}_n x(t)$ as

$$\begin{aligned}
&\mathbb{E}\{x^T(t)\mathcal{I}_n^T\mathcal{C}^T((\Phi_\beta(t)\mathcal{W}) \otimes I)^T\mathcal{L}^T(I \otimes P)\mathcal{L}((\Phi_\beta(t)\mathcal{W}) \otimes I)\mathcal{C}\mathcal{I}_n x(t)\}\\
=\,&\mathbb{E}\{x^T(t)\mathcal{I}_n^T\mathcal{C}^T((\mathcal{W}^T\Phi_\beta^T(t)\Phi_\beta(t)\mathcal{W}) \otimes (L^TPL))\mathcal{C}\mathcal{I}_n x(t)\}\\
=\,&\mathbb{E}\{x^T(t)\mathcal{I}_n^T\mathcal{C}^T((\mathcal{W}^T\tilde{\Phi}_\beta\mathcal{W}) \otimes (L^TPL))\mathcal{C}\mathcal{I}_n x(t)\}\\
=\,&\mathbb{E}\{x^T(t)\mathcal{I}_n^T\mathcal{C}^T((\tilde{\Phi}_{d,\beta}\mathcal{W}) \otimes I)^T\tilde{\mathcal{L}}^T(I \otimes P^{-1})\tilde{\mathcal{L}}((\tilde{\Phi}_{d,\beta}\mathcal{W}) \otimes I)\mathcal{C}\mathcal{I}_n x(t)\}
\end{aligned}$$

with $\tilde{\Phi}_\beta = \mathrm{diag}_n\{\bar{\beta}^i(1-\bar{\beta}^i)\}$, $\tilde{\Phi}_{d,\beta} = \mathrm{diag}_n\{\sqrt{\bar{\beta}^i(1-\bar{\beta}^i)}\}$ and $\tilde{\mathcal{L}} = I \otimes (PL)$.

In comparison with the analysis in Section 2, the main differences are summarized from three aspects: (i) *a uniform gain* L and *an adjust estimation* $\bar{\beta}^i C_j \hat{x}_j(t)$ are, respectively, utilized to replace L_i and $C_j\hat{x}_j(t)$ in the filter structure; (ii) a *diagonal matrix* $I \otimes P$ is adopted to substitute a general matrix $\mathcal{P}$ in the employed Lyapunov function; and (iii) there exist some *additional terms* on $\tilde{\Phi}_{d,\beta}$ in the derived quadratic polynomial, which impacts the solvability of the obtained LMIs.

Inspired by the analysis process above, distributed sampled-data filtering is addressed in [100] for sensor networks with nonuniform sampling periods, where a switching signal with average dwell-time is adopted to govern the aperiodic sampled-data filtering system. A similar approach is adopted in [85] to discuss the distributed filtering with time-varying switching topologies and packet losses, and in [86] for repeated scalar nonlinear systems with asynchronous switching. Compared with the filter structure [85] with the standard Luenberger type, all matrices of filter dynamics in [86] have to be designed because asynchronous switching causes the indeterminacy of system matrices. It should be pointed out that a co-positive Lyapunov function with the form $e^T(t)\mathcal{P}$ ($\mathcal{P}$ is a positive vector) should be selected for distributed filtering issue of positive systems although other process are similar. In order to evaluate the capability of noise attenuation, the H_∞ performance is usually replaced by the average l_∞ performance index, see [77] for more details.

Benefiting from the merit of linear systems, the distributed nonlinear filtering can be investigated by means of the celebrated T-S fuzzy models, under which the challenges on the approximation accuracy and the calculation burden are still open issues. For example, a distributed fuzzy filter is designed in [69], where the mathematic models of the considered random link failures are the same as the ones of packet dropouts. Recently, a distributed Luenberger-type fuzzy filter is developed in [80] for nonlinear multirate networked double-layer industrial processes, where the measurements are subject to both random packet dropouts and time delays. It should be pointed out that the well-known lifting technology is utilized to transform the multi-rate system into a traditional analysis framework. In the results above, the packet dropout rate is assumed to be known, which may be unrealistic in many engineering practice due to the variable network states as well as inadequate statistical tests. For this purpose, the effect from random packet dropouts with uncertain packet dropout rate is verified in [98] by employing a scalar small gain theorem. In comparison with existing results, matrix dimensions of the obtained LMIs are smaller and not dependent on the scale of senor networks.

Note that the phenomena of both fading and time-delays occurred in communication will result in that the dynamics of filtering errors is essentially a time-delayed system, and therefore the performance analysis can be performed by adding some time-related terms in the Lyapunov function in order to disclose the impact from time-delays. These added terms do not cause additional difficulties when the design conservatism based on various integral inequalities or free weight matrices is not a concern. For instance, a full-order channel-dependent estimator is deployed in [90] to provide accurate state estimates against the channel switching and the transmission delays, and a distributed H_∞ filter is designed in [5] by means of the convex optimization, which is obtained via a multiple Lyapunov functional approach. We refer readers to [101, 102, 104, 105] for some most recent results on various time-delayed systems.

4. DISTRIBUTED FILTERING WITH COMMUNICATION SCHEDULING

In this section, some latest and representative results on distributed filtering with various communication scheduling protocols will be reviewed and summarized based on different mathematical models, and the inherent characteristics of their dynamical behavior will also be identified to provide an insight of the analysis procedures.

4.1. Typical communication protocols

Communication scheduling is regarded as one of the most effective schemes to reduce the resource consumption. Consequently, the network congestion could be greatly alleviated and the serve life of sensor nodes could be prolonged. Scheduling can be carried out in a periodic manner, an aperiodic manner or a random manner while the transmission is only activated when some specific events occur [93]. Representative protocols involve event-triggered (ET) protocols, try-once-discard (TOD) protocols, Round-Robin (RR) protocols, as well as stochastic communication (SC) protocols. It should be noted that the first one could be performed in application layers and the other three ones, typical time-division multiple access (TDMA) protocols, could be implemented in physical layers. Table 2 provides their mathematical models with zero-order-holders (ZOHs) and some representative references.

Types	Models	References
TOD protocol	$\tilde{y}_i(t) = \begin{cases} y_i(t), & i = \phi_{1,t} \\ \tilde{y}_i(t-1), & \text{otherwise} \end{cases}$	[78, 108]
RR protocol	$\tilde{y}_i(t) = \begin{cases} y_i(t), & i = \phi_{2,t} \\ \tilde{y}_i(t-1), & \text{otherwise} \end{cases}$	[12, 73, 76, 84, 110, 111]
SC protocol	$\tilde{y}_i(t) = \begin{cases} y_i(t), & i = \phi_{3,t} \\ \tilde{y}_i(t-1), & \text{otherwise} \end{cases}$	[9, 75, 109]
ET protocol	$\tilde{y}_i(t) = \begin{cases} y_i(t_k), & \phi_{4,t} < 0 \\ y_i(t), & \text{otherwise} \end{cases}$	[10, 11, 23, 24, 99]

Tab. 2. Mathematical models of communication protocols.

In Table 2, $\tilde{y}_i(t)$ is the received measurement by each neighbor of sensor i via broadcasting, $\phi_{s,t}$ ($\forall\ s = 1, 2, 3, 4$) denotes the scheduling functions usually predetermined on the basis of some practical requirements, $y_i(t_k^i)$ is the broadcast measurement at the latest time (or latest event time) t_k^i, $\xi_i(t)$ is the gap and generally defined as $\xi_i(t) = y_i(t) - y_i(t_k^i)$. More specifically, the access token in the first three protocols is, respectively, $\phi_{1,t} = \arg\max_{i\in\{1,\ldots,n\}} \|y_i(t) - y_i(t_k^i)\|^2$, $\phi_{2,t} = \mathrm{mod}(t-1, n) + 1$, and the stochastic variable $\phi_{3,t} \in \{1, 2, \ldots, n\}$ with $\sum_{i=1}^n \mathbf{P}\{\phi_3(t) = i|\phi_3(t-1) = j\} = 1$. If a weighted parameter W is adopted in $\|y_i(t) - y_i(t_k^i)\|_W^2$, the corresponding protocol is referred as a *weighted TOD protocol*. For the fourth protocol, the event generator $\phi_{4,t} = g(y_i(t), \xi_i(t), \kappa_i) : \mathbb{R}^{n_y} \times \mathbb{R}^{n_y} \times \mathbb{R} \mapsto \mathbb{R}$ determines whether or not the current measurements $y_i(t)$ need to be broadcasted via the comparison with the broadcast measurement $y_i(t_k^i)$. If the threshold κ_i is time-varying, the corresponding protocol is called as *a dynamic event-triggered one* [20, 22]. Finally, if the filter structure (4) is employed, the received signal and the broadcast signal will be denoted as $\hat{x}_{r,i}(t)$ and $\hat{x}_i(t)$, and the function $\phi_{4,t}$ will be $g(\hat{x}_i(t), \xi_i(t), \kappa_i)$ with $\xi_i(t) = \hat{x}_i(t) - \hat{x}_i(t_k^i)$.

It is not difficult to see that the communication burden is almost the same for TOD, RR and SC protocols, because only one sensor is authorized to access the shared network. However, when a certain sensor is investigated, the ratio of obtaining the token is the same with the others under RR protocols, and is predetermined according to the given probabilities under SC protocols. Obviously, the TOD and ET protocols reflect the conception of on-demand transmission, and their transmission ratios usually cannot be determined in theory.

4.2. Basic analysis schemes and research developments

Define the matrix $\Xi(s) = \mathrm{diag}\{\delta(1-s)I, \delta(2-s)I, \ldots, \delta(n-s)I\}$, where $\delta(a)$ is a binary function taking a value of 1 for $a = 0$ and 0 otherwise. By this definition, one can rewrite the received measurements as

$$\tilde{y}_i(t) = \delta(i - \phi_{s,t})y_i(t) + (1 - \delta(i - \phi_{s,t}))\tilde{y}_i(t-1),\ s = 1, 2, 3.$$

Furthermore, the received measurements $\tilde{y}_i(t)$ under the ET protocol can be transformed into

$$\tilde{y}_i(t) = y_i(t) + \xi_i(t),$$

where, obviously, the gap $\xi_i(t)$ satisfies the nonlinear constraint $\phi_4(y_i(t), \xi_i(t), \kappa_i) < 0$.

In what follows, taking the modes above into consideration, one has the desired filter via replacing

- "$y_j(t) - C_j\hat{x}_j(t)$" by "$\tilde{y}_j(t) - \delta(j - \phi_{s,t})C_j\hat{x}_j(t)$" for $s = 1, 2, 3$ or "$\tilde{y}_j(t) - C_j\hat{x}_j(t)$" for $s = 4$ in (3),

- "$\hat{x}_j(t) - \hat{x}_i(t)$" by "$\hat{x}_{r,j}(t) - \delta(j - \phi_{s,t})\hat{x}_i(t)$" for $s = 1, 2, 3$ or "$\hat{x}_{r,j}(t) - \hat{x}_i(t)$" for $s = 4$ in (4).

In the following, we only consider the filtering structure (3) and then have the following modified error dynamics

$$\begin{cases} e^{+} = \big(\mathcal{A} - \big(\mathcal{K} + \mathcal{L}(\mathcal{W} \otimes I)\Xi(\phi_{s,t})\big)\mathcal{C}\big)e(t) + F(e(t)) \\ \qquad - \mathcal{L}(\mathcal{W} \otimes I)(I - \Xi(\phi_{s,t}))\tilde{y}(t-1) - \big(\mathcal{K} + \mathcal{L}(\mathcal{W} \otimes I)\Xi(\phi_{s,t})\big)\mathcal{D}\mathcal{I}_n v(t) \\ \tilde{y}(t) = \Xi(\phi_{s,t})y(t) + (I - \Xi(\phi_{s,t}))\tilde{y}(t-1) \end{cases} \tag{20}$$

under the first three protocols (i. e. $s = 1, 2, 3$) and

$$\begin{aligned} e^{+} = {} & \big(\mathcal{A} - \big(\mathcal{K} + \mathcal{L}(\mathcal{W} \otimes I)\big)\big)\mathcal{C}\big)e(t) \\ & + F(e(t)) - \mathcal{L}(\mathcal{W} \otimes I)\xi(t) - \big(\mathcal{K} + \mathcal{L}(\mathcal{W} \otimes I)\big)\mathcal{D}\mathcal{I}_n v(t) \end{aligned} \tag{21}$$

under the ET protocol, where

$$\begin{aligned} y(t) &= [\ y_1^T(t) \quad y_2^T(t) \quad \cdots \quad y_n^T(t)\ ]^T, \\ \tilde{y}(t) &= [\ \tilde{y}_1^T(t) \quad \tilde{y}_2^T(t) \quad \cdots \quad \tilde{y}_n^T(t)\ ]^T, \\ \xi(t) &= [\ \xi_1^T(t) \quad \xi_2^T(t) \quad \cdots \quad \xi_n^T(t)\ ]^T. \end{aligned}$$

It follows from (20) and (21) that the error dynamics is enslaved to the system state $x(t)$ hiding in $y(t)$ or $\xi(t)$. Furthermore, (20) is essentially a switching system, in which the switching signal is $\phi_{s,t}$ ($s = 1, 2, 3$). It can be observed that the filtering error system possesses a general switching under the TOD protocol, a periodic switching under the RR protocol as well as a Markov switching under the SC protocol. As such, one can employ the various available analysis tools according to the properties of switching signals and then derive the related results in the different forms of LMIs with ADT, periodic LMIs[12] or probability-dependent LMIs [9]. For the dynamics (21) induced by ET protocols, $\xi(t)$ will be regarded as an external signal and V^{+} is written as

$$V^{+} = [\ e^T(t) \quad F^T(e(t)) \quad \xi^T(t)\ ]M[\ e^T(t) \quad F^T(e(t)) \quad \xi^T(t)\ ]^T,$$

where M is a matrix determined by the corresponding quadratic polynomial. Furthermore, the nonlinear constraint ϕ_4 will be added into V^{+} via a similar scheme on nonlinear function $F(e(t))$ in (9).

In order to avoid the augmented structure of the system state, ZOHs should be omitted in the first three protocols, and the error dynamics (20) will be simplified as

$$\begin{aligned} e^{+} = {} & \big(\mathcal{A} - \big(\mathcal{K} + \mathcal{L}(\mathcal{W} \otimes I)\Xi(\phi_{s,t})\big)\mathcal{C}\big)e(t) \\ & + F(e(t)) - \big(\mathcal{K} + \mathcal{L}(\mathcal{W} \otimes I)\Xi(\phi_{s,t})\big)\mathcal{D}\mathcal{I}_n v(t). \end{aligned} \tag{22}$$

In addition, the event generator function ϕ_4 in the ET protocol should select an absolute form such as $g(y_i(t), \xi_i(t), \sigma_i) = \xi_i^T(t)Q\xi_i(t) - \kappa_i$, see [10] for more details.

In contrast to periodic mechanisms, an event-triggered mechanism offers conspicuous advantages since the sampled data is released after the occurrence of some well-designed event-triggered condition rather than the elapse of a fixed period of time [97]. Recently, various event generator functions are systematically surveyed in [17, 25]. Considering the implementation of event-triggered communication mechanisms, it is necessary to ensure a strictly positive minimal interval time between consecutive twice triggering. In the continuous-time paradigm, some rigorous design should be performed to avoid Zeno behavior, which is still an open yet challenging issue especially for the cases based on measurement outputs. In this case, it is generally difficult to derive a rigorous condition because the measurement matrix C_i is not invertible commonly. At the same time, an inherent requirement for the implementation of ET protocols is real-time monitoring, which could lead to the excessive usage of sensor power. An alternative approach is to design a self-triggered condition [17, 31] so that the next event instant is predicted based on the last triggered data and knowledge of the system dynamics [25]. In the discrete-time paradigm, the event generator is dependent on the sampled data, and therefore the real-time monitoring can be circumvented with the worst case of the inter-event time equivalent to the sampled period.

Extensive studies of event-triggered distributed filtering have been emerging in recent years. For example, a delay-fractioning approach is employed in [34] to deal with the event-triggered distributed state estimation of nonlinear stochastic time-varying delayed systems. In term of the solutions of a series of recursive LMIs, a distributed filter is designed in [79] for a class of stochastic parameter systems such that both the H_∞ requirement and the variance constraint are satisfied over a given finite-horizon against the random parameter matrices, successive missing measurements as well as stochastic noises. A complex event-triggered scheme, related to the general consensus term, the innovation and the estimation-based consensus term, is proposed in [96] to deal with distributed H_∞ filtering for 2-DOF quarter-car suspension systems. At the same time, some distributed filtering schemes are developed for systems subject to saturated constraints, where the state-saturation is transformed as a convex hull [39], sensor saturations are processed into a bounded nonlinear constraint [43, 50, 71], or the saturation level is driven by a dynamical equation which is augmented into the filtering errors [81]. Furthermore, the feasibility of the optimization algorithm is profoundly discussed in [50] for a set of bilinear matrix inequalities in light of the properties of unique ergodicity and irregularity of the series generated by chaos. In [68], the event-triggered Kalman-consensus filtering method is developed to tackle a two-target tracking problem over sensor networks. Based on Lyapunov functional method and matrix theory, sufficient conditions are derived to guarantee the stability of the filtering error system.

Note that the number of transmitted data packets is closely related to thresholds. Some co-design algorithms obtaining both the filter gains and the thresholds are developed in [16, 21] to achieve the trade-off between communication resource utilization and the weighting average H_∞ performance. Note also that the developed co-design is a hierarchical one, where the threshold is determined by simulations over a fixed interval to realize the expected average transmission rate. However, the rigorous theoretical analysis is still demanded. It should be also emphasized that all event-triggered mechanisms specified above are commonly known as static event-triggered mechanisms. Besides, dynamic event-triggered schemes and adaptive event-triggered schemes [23, 24, 40, 42, 97] are two kinds of emergent approaches to further adjust the resource utilization. Specifically, the time-varying thresholds could lie on an interval [23] or be governed by an artificial dynamics [24, 42, 97]. For the first case, the threshold-dependent Lyapunov function is constructed and a polytope-like transformation is performed to make all matrices involve in convex compact sets so as to avoid infinite LMIs. For the second one, the utilization of triggering conditions has no essential difficulties for finite-horizon issues or set-membership filtering [24], but the biggest triggering interval needs to be obtained in order to transform the error system into a time-varying delayed system [42] or a conservative condition dependent on the initial threshold should be employed to bypass the challenge coming from the dynamics of threshold [97].

The RR protocol is another commonly used protocol, which allows only one node to communicate with its neighbors during scheduled time slots and therefore leads to bandwidth savings. Preliminary research on H_∞ consensus filtering can be found in [73] and, subsequently, has gained increasing attention by making use of the time-delay approach [44] as well as the periodic system analysis method [47, 76, 84]. For example, distributed set-membership filtering is addressed in [47] for multi-rate systems which are transformed into a traditional discrete-time system by means of lifting techniques. Distributed state estimation over finite-horizon is investigated in [84], where the index of average stochastic finite-time boundedness is developed to evaluate the estimation performance. It is worth mentioning that the developed LMIs via periodic system analysis have more slack variables which could reduce the design conservatism, whereas LMIs via time-delayed approaches possess higher computational complexity. On the other hand, it should be pointed out that distributed filtering under both SC protocols and TOD protocols has not attracted enough attention, due possibly the fact that issues under SC protocols suffer less essential difficulties in comparison with Markov systems [75] while the existing approaches under TOD protocols cannot profoundly reveal the effect on the system performance from the scheduling rules themselves [78]. Furthermore, there often requires a scheduling center for RR protocols and TOD protocols, which is usually unpractical for filtering issues in a distributed way.

4.3. Some scalable methods and corresponding results

Without loss of generality, the event-triggered function is selected as $\phi_4(y_i(t), \xi_i(t), \kappa_i) = \|\xi_i(t)\|^2 - \kappa_i$. Adopting the same approach in Subsection 2.2 and denoting

$$\eta_i(t) = [\ e_i^T(t) \quad \tilde{f}^T(e_i(t)) \quad \xi_i^T(t) \quad v^T(t)]^T \ ,$$

one has

$$\begin{aligned}
\Delta V(t) &= V(t+1) - V(t) \\
&\leq \pi e^T(t)e(t) + \sum_{i=1}^{n} \eta_i^T(t)\Pi_{2i}\eta_i(t) \\
&\quad + (\chi_i - 1)\sum_{i=1}^{n}\left\{e_i^T(t)Pe_i(t)\right\} + \varrho\varsigma + \sigma\sum_{i=1}^{n}\kappa_i,
\end{aligned}$$

where

$$\Pi_{2i} = \begin{bmatrix} \bar{\Pi}_{11i} & \bar{\Pi}_{12i} & \bar{\Pi}_{13i} & \bar{\Pi}_{14i} \\ * & \bar{\Pi}_{22i} & \bar{\Pi}_{23i} & \bar{\Pi}_{24i} \\ * & * & \bar{\Pi}_{33i} & \bar{\Pi}_{34i} \\ * & * & * & \bar{\Pi}_{44i} \end{bmatrix},$$

$$\begin{aligned}
\bar{\Pi}_{11i} =&(1+2\sigma_{1i})(A-K_iC_i)^TP(A-K_iC_i)+\rho\theta I-\chi_iI,\\
\bar{\Pi}_{12i} =&(A-K_iC_i)^TP,\ \bar{\Pi}_{13i}=(A-K_iC_i)^TP,\\
\bar{\Pi}_{14i} =&-(A-K_iC_i)^TPK_iD_i,\ \bar{\Pi}_{22i}=(1+2\sigma_{2i})P-\rho H,\\
\bar{\Pi}_{23i} =&P,\ \bar{\Pi}_{24i}=-PK_iD_i,\ \bar{\Pi}_{33}=P-\sigma Q,\ \bar{\Pi}_{34}=PK_iD_i,\\
\bar{\Pi}_{44i} =&(1+2\sigma_{3i})D_i^TK_i^TPK_iD_i-\varrho I.
\end{aligned}$$

Now, we have the following theorem.

Theorem 4.1. Consider the discrete-time nonlinear system (1) with the measurement (2) and the event-triggered condition $\|\xi_i(t)\|_Q^2 \geq \kappa_i$. For given scalars $\mu > 1$ and ε as well as matrices K_i ($i = 1, 2, \ldots, n$), the estimation error dynamics (5) is input-to-state stable, if there exist a positive-definite matrix P and positive scales σ, ρ, ϱ, χ_i and σ_{ji} ($j = 1, 2, 3$) such that the following inequalities

$$\Pi_{2i} < 0, \quad \varpi_i = 1-\chi_i-\bar{\pi}_i > 0 \tag{23}$$

hold, where

$$\bar{\pi}_i =\varepsilon^2(1+2\sigma_{1i}^{-1}+2\sigma_{2i}^{-1}+2\sigma_{3i}^{-1})\lambda_{\max}(P)\lambda_{\max}((\mathcal{W}-\bar{\mathcal{W}})^T(\mathcal{W}-\bar{\mathcal{W}})).$$

In what follows, define

$$\begin{aligned}
\mathcal{C}_{ij} &= \begin{cases} w_{ij}C_i, & i\neq j,\\ C_i, & i=j;\end{cases}\\
\mathcal{S}_{j,t+1}^i &= \begin{cases} [w_{ij}I \quad -w_{ij}I], & t\neq t_k^j-1,\\ [w_{ij}I \quad 0], & t=t_k^j-1;\end{cases}\\
\hat{V}_{ij} &= \begin{cases} \mathrm{diag}\{B^TVB, w_{ij}\kappa_iI\} & i\neq j,\\ \mathrm{diag}\{B^TVB, 0\}, & i=j.\end{cases}
\end{aligned}$$

Similar to Theorem 2.2, we have the following result on the set-membership filtering.

Theorem 4.2. Let $\pi_{j,t+1}^i > 0$ and $\beta_{i,t} \in (0,\ 1)$ be given. Suppose that the system state $x(t)$ lies in the ellipsoid $\mathcal{E}(\hat{x}_{i,t|t}^*, P_{i,t|t}^*)$. The system state $x(t+1)$ derived by (1) involves in the ellipsoid $\mathcal{E}(\hat{x}_{i,t+1|t+1}^*, P_{i,t+1|t+1}^*)$ determined by (17), under which the corresponding parameters are

$$\begin{aligned}
&P_{j,t+1|t+1}^i = \sigma_{j,t+1}^i\big(I-\mathcal{K}_{j,t+1}^i\mathcal{C}_{ij}\big)P_{j,t+1|t}^i,\\
&\hbar_{j,t+1}^i = y_j(t+1)-C_j\hat{x}_{j,t+1|t}^i,\\
&\mathcal{O}_{j,t+1}^i = (\pi_{j,t+1}^i)^{-1}\mathcal{S}_{j,t+1}^i\hat{V}_{ij}(\mathcal{S}_{j,t+1}^i)^T+\mathcal{C}_{ij}P_{j,t+1|t}^i\mathcal{C}_{ij}^T,
\end{aligned}$$

and other parameters are the same with ones in Theorem 2.2.

It should be pointed out that the stability-based distributed filtering including the well-known H_∞ filtering will essentially generate some point estimates which provide the desired estimate values on the real states while distributed set-membership filtering provides a confidential set/region which includes the real states within.

5. LATEST DEVELOPMENTS AND CHALLENGING ISSUES

1) Scalable requirements of design algorithms

Sensor networks usually consist of a large number of wireless sensor nodes, and the dimensions of augmented dynamics of filtering errors are directly related to the number of nodes. Obviously, the LMI-based algorithms discussed above meet with the scalability issue that the computational burden usually linearly increases when the number goes larger, and the solvability is dramatically affected by the communication topology which is global information. There is no doubt that such a shortcoming inevitably restricts the application in practical engineering. As such, the distributed filter algorithms must be able to effectively and efficiently overcome the shortcoming and satisfy the requirements of the scalable design.

Two representative strategies can be summarized as follows: the first one is the vector dissipativity method of large-scale systems combined with the small-gain condition, and the other is the decoupling scheme via the basic matrix inequality $2a^T b \leq \kappa a^T a + \kappa^{-1} b^T b$. For instance, an H_∞-consensus metric is firstly proposed in [72] and then expanded in [29, 30] with a finite-time version to evaluate both the filtering accuracy of each node and the consensus among neighbor nodes. In light of missing measurements, the concept of stochastic vector dissipativity is proposed and the dissipation matrix is formulated by a nonsingular substochastic matrix in [30]. Furthermore, a similar substochastic matrix is constructed in [29] to handle filtering issues over networks subject to multiplicative noises and deception attacks. Scalable design algorithms based on the second strategy are recently developed in [36] for nonlinear stochastic systems, where nonlinear functions are bounded by a pseudo-Lipschitz condition and the upper bound of mean-square error is optimized via a presented criterion. A similar idea is employed in [11] to develop a joint estimation of system states and unknown parameters over sensor networks with switching topologies. Under these two strategies, the conservatism of decoupling seems to be relatively large and hence more effective and efficient approaches are demanded.

2) Security requirements of distributed filtering

Due to technological and cost limitations, data transmission among sensors via various communication networks could undergo unavoidable security vulnerabilities. In the realm of sensor networks, typical cyber-attacks include, but not limited to, denial of service attacks, replay attacks as well as false data injection attack [13, 26]. There is no doubt that any successful attacks may lead to a serious impact on system monitoring, which could cause great economic loss and confusion of society. Recently, from the perspective of adversaries, various scheduling strategies on denial of service attacks are developed to realize the attack objective or bypass attack detections by resorting to the stability theory of Kalman filtering, see [6] for more details.

As analyzed in [6], denial of service attacks are similar to packet dropouts in models, and therefore filtering performances can be investigated by employing typical approaches for packet dropouts but the effect from the admissible attack frequency or the maximum number of consecutive attacks are considerable. On the other hand, replay attacks can be modeled by time-varying delays and therefore the admissible maximum upper bounds can be calculated by applying the time-delayed system theory together with some optimization approaches. False data injection attacks, however, are essentially bounded disturbances without any prior about the intensity and the duration. In other words, the developed results are of great conservatism in the frameworks of input-to-state stability or set-membership filtering. For instance, the filtering error is modeled as a switched system in light of a time-delay approach, which characterizes the impact from both event-triggering schemes and nonperiodic DoS jamming attacks [35]. Considering a class of randomly occurring deception attacks, theoretical analysis on finite-time l_1-gain boundedness and the design of desired positive filters are carried out in [83] for a class of positive discrete-time linear system, where sensor networks also suffer from random communication link failures. In [27], a cunning adversary who intentionally launches deception attacks is carefully modeled by considering the simultaneously injected spurious data into both the system state and the exchanged measurements among neighboring sensors, behaving like the true system disturbance and measurement noises. Then, a Krein space-based joint distributed resilient estimation and attack detection approach is developed such that the corrupted system state as well as the unknown attack and/or disturbance signals can be locally estimated, and the effects caused by attacks can be differentiated from the true disturbance and noise. In [49], variance-constrained distributed filtering is discussed for time-varying systems where deception attack signals are assumed to be confined into some ellipsoid sets and the locally filtering performance is optimized via a formulated optimization problem based on the constraints of recursive LMIs. Very recently, additional control inputs are introduced into distributed observers in [74] to suppress biasing misappropriation attacks. It is worth mentioning that, compared with relatively mature techniques under traditional distributed frameworks, distributed filtering with security perspective has not received adequate attention, thus deserving a deeper investigation.

3) Applications in cyber-physical systems

Sensor networks are usually seamlessly integrated into industrial cyber-physical systems to facilitate real-time sensing, monitoring, and control. Typical applications include the supervisory control and data acquisition (SCADA) of both distributed power systems or industrial process control systems, and the tracking of maneuvering targets [3, 4, 7, 53, 88, 92, 99]. It is noteworthy that, different from fashionable distributed filtering of the single system, there are essentially two simultaneous configurations of interactions/connections of a cyber-physical system (CPS): the physical connection among subsystems and cyber connection among units of information processing [3]. This will result in a considerable feature that the dynamics of filtering errors is nonautonomous even if noises are omitted when network-induced phenomena or communication protocols are taken into account. As such, there is an unavoidable stumbling block for practical applications of developed filtering approaches, especially when the scalability is a concern.

In the past few years, applications in the scenarios above have received significant progress in the framework of Kalman filtering, while the stability of developed algorithms still represents an open yet challenging issue due mainly to the utilization of suboptimal strategies during the distributed implementation. Interested readers are referred to the survey papers [2, 7, 25]. Recently, based on LMIs, an application of a distributed set-membership filtering is investigated in [88] for the islanding detection of distributed gird-connected solar PV generation systems. Especially, an intersection between the estimation ellipsoid produced by the system without islanding and the estimation ellipsoid produced by the practical system is proposed to judge whether the islanding fault occurs or not. Furthermore, for large-scale power systems with limited bandwidth constraints, distributed estimators are designed in [46] to predict the needed but no available information by utilizing remote telemetry units. Unfortunately, the conditions on desired gains are almost unsolvable. In summary, the applications of distributed filtering with various network-induced phenomena or communication still remain at an infant stage and thus require further research efforts.

Note that the homogeneous architecture of sensor networks inevitably brings about poor fundamental limits and performance due mainly to the diversity of information in cyber-physical systems. Therefore, the effective information processing dependent on distributed, dynamical and heterogeneous multi-platform measurements is usually an indispensable step in the implementation of collaborative tasks [28, 67, 106]. For instance, the sequential design approach coupled with the minimum principle of Pontryagin and the Lagrange multiplier method has been employed in [106] to deal with the heterogeneity of sensors to realize the unbiasedness and optimality of distributed consensus filtering. For the asynchronization induced by heterogeneous sensors, a stochastic competitive transmission strategy has been developed in [66] to govern sensors' transmissions and then an H_∞ filter has been designed to periodically generate estimates. We should point out how to handle the heterogeneity of sensors to facilitate the filter design still remain largely unexplored.

4) The construction of actual platforms

Actual platforms of sensor networks are also an ever-increasing research area benefiting from the improving capabilities of local processing and computing of both processors and memories [32]. Some representative platforms have been developed in the past few years. According to the embedded microcontrollers, there are (a) MCU-based nodes such as Mica2, MicaZ and TelosB developed by the University of California (UC) at Berkeley, μAMPS proposed by MIT, BTnode developed by ETH Zurich, EARN-PIPE designed by University of Sfax and so forth; (b) sensor nodes based on FPGA/SoPC, such as nodes consisting of a Spartan 3-2000 FPGA and a XEMICS DP-1203 radio transceiver, as well as nodes including nios SOPC cyclone II; (c) nodes based on hybrid architectures, see [37] for more details. For instances, the Mica platform adopts an Atmel Atmega processor running the TinyOS operating system, and microcontrollers utilized in Particle and μNode are, respectively, PIC18f6720 and MSP430, see Figure 2 and Figure 3 for their nodes [33, 52]. The research on sensor platforms is still open despite the diversity and the wealth of the node design. Representative topics include, but are not limited to, the concrete evaluation for power consumption and real field deployments, the development of new useful modules to facilitate the life time of the battery and the capability of nodes. On the other hand, the tests in the above platforms concentrate on Kalman type algorithms and least square based methods. However, the corresponding tests about algorithms with the form of matrix inequalities are very scarce due possibly to their low scalability and high communication burden.

A potential solution is to employ a fog architecture to facilitate the interconnection of sensor nodes with the back-end cloud so that it is able to make self decision for reducing computational time or energy consumption [59]. In this framework, sensor nodes

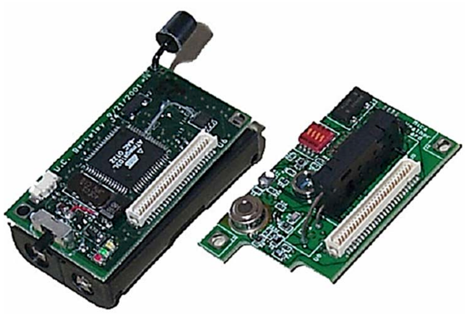

Fig. 2. Mica node.

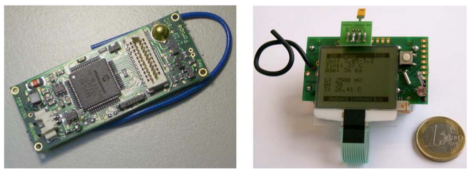

Fig. 3. Sensor node: Particle and μNode.

are utilized to perform some initial operations, such as collection, translation, filtering as well as aggregation, and fog nodes providing enough computing and storage resource deal with complex processing and analysis on the collected data[60]. In essence, fog computing, a geographically distributed computing architecture, composed of heterogeneous connected devices at the edge of the network and not exclusively supported by cloud services [54]. In other words, fog can be regarded as a basic extension of the distant cloud to the edge of the network, closer to sensor networks or other devices accessing it [61]. In summary, the merits of fog computing mainly involve (a) quick response to delay-sensitive requirements, (b) data aggregation from heterogeneous devices, (c) data protection and security for sensitive data applications due to avoiding to send data to the cloud, and (d) avoiding unnecessary communication, see [1] for more details. Recently, some preliminary results on fog computing for sensor networks are published in the literature, such as edge node reconfiguration [51, 60], the choice of the sensing routing [70], as well as network architecture managements [54, 62]. It should be stressed that fog computing, being in its infancy stage, exposes several challenges that need to be further addressed, such as fog-cloud collaboration, service scalability, fog scalability, storage security and communication security, tradeoff between energy consumption and communication efficiency and so forth.

6. CONCLUSIONS

The recent results of distributed filtering have been systematically reviewed for dynamical systems that are operated over sensor networks subject to network-induced phenomena or communication scheduling protocols. The typical models have, respectively, been exhibited with regard to different distributed filter structures, various network-induced phenomena as well as distinct communication protocols. Combing with the inherent characteristics of their dynamic behavior, the corresponding analysis procedures have been disclosed with the help of LMI techniques and set-membership filtering approaches. Some latest and representative results along this line of research have been sorted out. Finally, the state-of-the-art of distributed filtering has been further surveyed and some important and yet challenging issues worthy of further investigations have been suggested in accordance with scalability, security and applications.

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