International Journal of
Network Dynamics and Intelligence (IJNDI)

Scilight

Review

Set-Membership Estimation for Networked Nonlinear Systems under Communication Constraints: A Survey

Zhongyi Zhao [1], Yu-Ang Wang [1], and Jinling Liang [1,2,*]

[1] School of Mathematics, Southeast University, Nanjing 210096, China
[2] School of Automation and Electrical Engineering, Linyi University, Linyi 276005, China
* Correspondence: jinlliang@seu.edu.cn
Received: 1 May 2026; Revised: 23 June 2026; Accepted: 3 August 2026; Published: 17 August 2026

Abstract: Set-membership estimation (SME) has attracted increasing attention in recent years due to its capability of providing guaranteed state bounds for systems subject to unknown-but-bounded uncertainties. Compared with the estimation methods dealing with stochastic noises, SME does not rely on probabilistic assumptions on noises, making it particularly suitable for safety-critical systems and the systems in networked environments with incomplete statistical information. Meanwhile, the rapid development of communication networks has significantly promoted the deployment of networked systems, where communication constraints such as time delays, packet dropouts, communication protocols, quantization effects, event-triggered schemes, and cyber attacks inevitably introduce additional challenges to the state estimation. Motivated by these developments, this paper presents a comprehensive survey on SME for networked nonlinear systems under communication constraints. First, the fundamental concepts and the recursive principles of SME are reviewed. Then, representative set representations and the corresponding SME methods for nonlinear systems are systematically summarized, with particular emphasis on the techniques for handling the nonlinear mappings as well as the ellipsoidal and the zonotopic SME approaches. Subsequently, existing SME methods under various communication constraints are classified and reviewed from a unified perspective according to their influences on the measurement transmission and the estimator design. Finally, several open problems and future research directions are discussed.

Keywords: set-membership estimation (SME); networked systems; communication constraints; nonlinear systems; ellipsoidal SME; zonotopic SME

1. Introduction

State estimation plays a fundamental role in control, signal processing, and fault diagnosis. Among the existing estimation methods, those dealing with the stochastic noises, such as the Kalman filtering, have been extensively investigated over the past decades [1–5]. Such methods usually rely on the probabilistic descriptions of the uncertainties and aim to obtain the optimal estimate in statistical senses, e.g., minimum variance or minimum mean-square error. However, in many practical applications, accurate probabilistic information of the disturbances and noises may be unavailable or difficult to be identified. In such cases, it is often more reasonable to assume that the uncertainties are unknown-but-bounded (UBB) and belong to some prescribed compact sets.

Set-membership estimation (SME), originally proposed in the pioneering works [6,7], provides an alternative estimation framework under the UBB assumption. Instead of computing a point estimate together with its statistical properties, SME aims to recursively construct a set that is guaranteed to contain the true system state. The basic idea is to propagate the feasible set of all states consistent with the system model, measurements, and uncertainty bounds through prediction and correction operations [8–10]. Compared with the methods coping with stochastic noises, SME does not require any probabilistic assumptions on noises, and therefore usually provides stronger robustness guarantees against the modeling uncertainties and external noises. Moreover, SME naturally produces state bounds rather than statistical confidence information, making it particularly suitable for safety-critical applications requiring guaranteed estimation performance [11–13].

The early SME methods mainly employ the ellipsoidal representations due to their compact mathematical forms and favorable compatibility with optimization-based analysis techniques [14–17]. Subsequently, various other set representations have been introduced, including zonotopes [18–21], constrained zonotopes [22], polynomial zonotopes [23], and ellipsoid bundles [24]. Compared with the classical ellipsoids, these set representations may provide tighter outer approximations, reduced conservatism, or improved computational efficiency for specific applications. As a result, SME has gradually evolved into a rich research area involving set propagation, outer approximation, and optimization.

Over the past decades, the SME problems have been extensively investigated for various classes of systems, including the linear systems [10,25], nonlinear systems [26], singular systems [27], distributed systems [28], and two-dimensional systems [29]. Among them, nonlinear systems play a particularly important role in practical engineering applications, as most real-world dynamical processes exhibit inherent nonlinearities arising from physical laws, actuator constraints, and environmental interactions. However, the SME problem for nonlinear systems is significantly more challenging due to the difficulty in propagating uncertainty sets through nonlinear mappings, which generally leads to non-convex and intractable set representations. As a result, much of the existing research focuses on constructing tractable outer-approximations of nonlinear dynamics to enable recursive set propagation within standard SME frameworks. Meanwhile, SME has also found wide applications in many engineering scenarios, such as the target tracking [14,30], fault detection and estimation [31–34], monitoring and supervision [29,35,36], as well as set-based control [37].

Along with the rapid development of the communication and network technologies, increasing attention has been devoted to networked systems, where sensors, estimators, controllers, and actuators exchange information through shared communication networks [38–44]. Compared with the traditional point-to-point systems, the networked systems provide significant advantages in terms of flexibility, scalability, low deployment cost, and resource sharing. However, the introduction of communication networks inevitably gives rise to various communication constraints, which may significantly degrade the estimation performance and even destroy the estimation consistency if not properly addressed [45–51]. Typical communication constraints in networked systems include time delays [52–54], packet dropouts [55,56], quantization effects [57,58], encoding-decoding mechanisms [59–61], encryption-decryption schemes [28], bit rate constraints [62,63], communication protocols [64–67], event-triggered transmission schemes [68–70], and cyber attacks [55,71–74]. Owing to the vast amount of existing literature, only representative references are provided here, while a comprehensive review of the corresponding SME methodologies is presented in the subsequent sections. These communication constraints often lead to incomplete, distorted, delayed, or intermittently available measurements, thereby bringing new challenges to the SME problems. On the other hand, the recursive propagation of feasible sets becomes more challenging due to the interaction between network-induced effects and set-based uncertainty propagation.

Motivated by the above observations, this survey aims to provide a systematic overview of the SME methods for networked nonlinear systems under communication constraints. In particular, we focus on nonlinear systems and investigate how different set representations and nonlinearity handling techniques are combined with the communication-constrained estimation framework. The main works of this survey are summarized as follows:

(1) The fundamental concepts and principle of SME are reviewed in a unified framework.
(2) Representative set representations and corresponding SME methods for nonlinear systems are systematically summarized and compared.
(3) The existing SME approaches under various communication constraints are classified and reviewed from a network-oriented perspective.
(4) Several open problems and promising future research directions are discussed.

The organization of this paper is illustrated in Figure 1. Specifically, Section 2 introduces some basic concepts and recursive principles of SME. Section 3 reviews the representative set representations and SME methods for nonlinear systems. Section 4 summarizes the SME approaches for networked nonlinear systems under various communication constraints. Section 5 concludes this survey and discusses several future research directions.

2. Foundations of SME

In this section, we briefly review the fundamental concepts and principles of SME, which will serve as the basis for subsequent developments under communication constraints.

2.1. Problem Formulation

Consider the following discrete-time nonlinear system:

$$x(k+1) = f(x(k)) + w(k), \tag{1}$$

$$y(k) = g(x(k)) + v(k), \tag{2}$$

where $x(k) \in \mathbb{R}^n$ is the system state, $y(k) \in \mathbb{R}^m$ is the measurement ouput, $f(\cdot)$ and $g(\cdot)$ are known nonlinear functions, and $w(k)$ and $v(k)$ denote the process and the measurement noises, respectively.

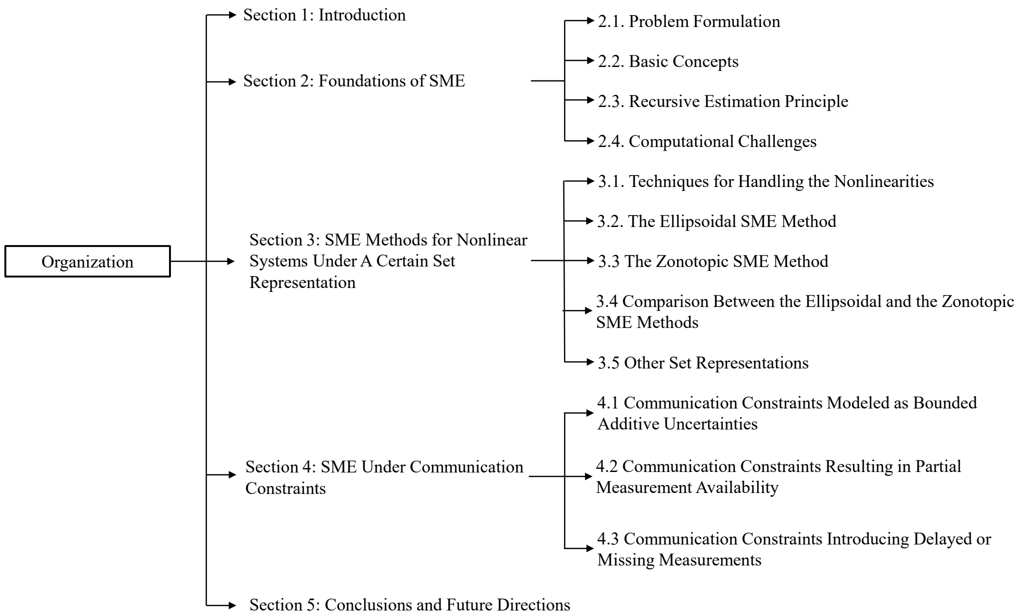

Figure 1. The organization of the survey.

In the SME framework, the noises and the initial system state are all assumed to be UBB:

$$w(k) \in \mathcal{W}(k), \quad v(k) \in \mathcal{V}(k), \quad x(0) \in \mathcal{X}(0), \tag{3}$$

where $\mathcal{W}(k)$, $\mathcal{V}(k)$, and $\mathcal{X}(0)$ are known compact sets.

The objective of SME is to determine, at each time instant k, a set $\mathcal{X}(k)$ that contains the system state $x(k)$, where the set is typically computed in a recursive manner.

Remark 1. *The nonlinear system model (1)–(2) is adopted as a general framework to facilitate the presentation and classification of the existing SME methodologies. It encompasses a broad class of nonlinear systems encountered in practical applications. This model serves as a unified basis for discussing the main ideas, technical developments, and research trends in SME for networked nonlinear systems.*

2.2. Basic Concepts

In the framework of SME, the state estimate is derived/represented by a set rather than a point. The following sets are central to the recursive estimation procedure.

(1) *Feasible Set:* The feasible set $\mathcal{X}(k)$ is defined as the set of all possible states that are consistent with the state Equation (1), the measurement Equation (2), and the sets given in (3) enclosing the noises and the initial state.

(2) *Prediction Set:* Given the set $\mathcal{X}(k-1)$ at moment $k-1$, the prediction set $\mathcal{X}(k|k-1)$ is the set obtained by propagating $\mathcal{X}(k-1)$ through the state Equation (1):

$$\mathcal{X}(k|k-1) \triangleq \{x \in \mathbb{R}^n : x = f(\xi) + w,\ \xi \in \mathcal{X}(k-1),\ w \in \mathcal{W}(k-1)\}. \tag{4}$$

(3) *Update Set:* The update set $\mathcal{X}(k)$ is the set obtained by intersecting the prediction set with the set of states consistent with the measurement signal $y(k)$:

$$\mathcal{X}(k) \triangleq \{x \in \mathcal{X}(k|k-1) : y(k) = g(x) + v, v \in \mathcal{V}(k)\}. \tag{5}$$

Equivalently, the set $\mathcal{X}(k)$ can be written as

$$\mathcal{X}(k) = \mathcal{X}(k|k-1) \cap \mathcal{Y}(k), \tag{6}$$

where $\mathcal{Y}(k)$ denotes the measurement-consistent set as follows:

$$\mathcal{Y}(k) = \{x(k) : y(k) - g(x(k)) \in \mathcal{V}(k)\}.$$

(4) *Outer Approximation:* In general, the exact computation of $\mathcal{X}(k|k-1)$ and $\mathcal{X}(k)$ is intractable for nonlinear systems. Therefore, one needs to compute outer-approximations $\bar{\mathcal{X}}(k|k-1)$ and $\bar{\mathcal{X}}(k)$ such that

$$\mathcal{X}(k|k-1) \subseteq \bar{\mathcal{X}}(k|k-1), \;\; \mathcal{X}(k) \subseteq \bar{\mathcal{X}}(k). \tag{7}$$

2.3. Recursive Estimation Principle

In the process of SME, deriving the exact prediction set $\mathcal{X}(k|k-1)$ and the update set $\mathcal{X}(k)$ is, in general, computationally intractable for nonlinear systems. To address this issue, a common method is to propagate the outer-approximations of these sets, which will ensure the recursive computability at the expense of introducing certain conservatism. Within this framework, the recursive estimation procedure consists of two fundamental operations, namely, prediction and correction.

(1) *Prediction:* Given an outer-approximation $\bar{\mathcal{X}}(k-1)$ of the feasible set at time instant $k-1$, the predicted set is over-approximated as

$$\bar{\mathcal{X}}(k|k-1) \supseteq \Big\{ f(x) + w : x \in \bar{\mathcal{X}}(k-1), w \in \mathcal{W}(k) \Big\}, \tag{8}$$

which corresponds to the case of propagating the uncertainty through dynamics of the system.

(2) *Correction:* With the measurement $y(k)$, the set $\bar{\mathcal{X}}(k|k-1)$ can be further corrected by incorporating the constraint of the measurement consistency, leading to

$$\bar{\mathcal{X}}(k|k) \supseteq \bar{\mathcal{X}}(k|k-1) \cap \{x : y(k) - g(x) \in \mathcal{V}(k)\}. \tag{9}$$

2.4. Computational Challenges

During the SME procedure, there are several computational challenges:

(1) *Nonlinear Projection:* The image of a set under a nonlinear mapping is generally difficult to be characterized.
(2) *Sets Intersection:* In the update step, complex or non-convex sets might be introduced.
(3) *Growth of the Complexity:* Exact set representations often lead to an exponential growth in the complexity over the time.

The above challenges motivate the use of structured set representations, such as ellipsoids and zonotopes, which allows an efficient implementation of the outer-approximation schemes. These representations and their associated estimation algorithms will be discussed in detail in the next section.

3. SME Methods for Nonlinear Systems under A Certain Set Representation

In this section, we discuss the principle of how the states of a nonlinear system are bounded by a given set representation. To this end, we first introduce some handling techniques frequently used for continuously differentiable nonlinearities. Then, we will introduce how the sets $\bar{\mathcal{X}}(k|k-1)$ in (8) and $\bar{\mathcal{X}}(k)$ in (9) are recursively calculated using ellipsoidal and zonotopic representations. Finally, we will briefly review some other set representations that have been employed in SME. Here, consideration of the nonlinear systems is motivated by the fact that many practical dynamical systems exhibit inherent nonlinear behaviors, and linear models are often under simplifying assumptions.

3.1. Techniques for Handling the Nonlinearities

In the process of SME, the main difficulty brought by the nonlinear systems lies in the computation of the image set under nonlinear mappings. Specifically, given a set $\mathcal{X} \subset \mathbb{R}^n$ and a nonlinear function $h(\cdot) : \mathbb{R}^n \mapsto \mathbb{R}^n$, it is generally difficult to obtain the exact set

$$h(\mathcal{X}) \triangleq \{h(x) : x \in \mathcal{X}\}.$$

Therefore, it is urgent to construct a tractable outer-approximation for $h(\mathcal{X})$. To this end, various handling techniques have been developed, which are briefly reviewed as follows.

- *Sampling-Based Method:* This method approximates the image of a set by evaluating the nonlinear function at a sufficiently large number of sampled points within the set $\mathcal{X}$. The outer boundary of $h(\mathcal{X})$ is then approximated using images of these sampled points. This approach is conceptually simple and widely applicable, but its accuracy depends heavily on the sampling density and the computational burden may become significant for high-dimensional systems.

- *Taylor-Expansion-Based Method:* For continuously differentiable nonlinear functions, Taylor expansion provides a systematic way to approximate the nonlinear mapping and construct the outer bound of the set image. The existing/relating methods in the literature can be broadly classified into two categories. The first one is based on the Lagrange mean value theorem, which yields an incremental representation with an implicit Jacobian matrix evaluated at an unknown point. The second one relies on the first-order Taylor expansion with an explicit linearization at the nominal point, together with a bounded higher-order remainder term. These two approaches provide different trade-offs between the tightness and the computational tractability, and are widely adopted in the field of SME.
  When using the Lagrange mean value theorem, the nonlinear function $h(\cdot)$, which is assumed to be continuously differentiable, is tackled using the following incremental form:
  $$h(x) = h(\bar{x}) + J_h(x - \bar{x}), \tag{10}$$
  where x is a given point, $\bar{x}$ is the estimate of x, and J_h is defined as
  $$J_h = \begin{bmatrix} \left(J_h^{(1)}\right)^T & \left(J_h^{(2)}\right)^T & \cdots & \left(J_h^{(n)}\right)^T \end{bmatrix}^T$$
  with $J_h^{(i)} = \frac{\partial h^{(i)}}{\partial x}\big|_{\bar{x}+\theta_i(x-\bar{x})}$ for $i = 1, 2, \ldots, n$. Here, $h^{(i)}$ denotes the i-th component of $h(\cdot)$, and $\theta_i \in [0, 1]$ is an unknown scalar. Such a form allows the derivation of certain bound for $h(x)$ based on the assumption that $x - \bar{x}$ always resides in a compact set.
  On the other front, when $h(\cdot)$ is twice continuously differentiable, the first-order Taylor expansion can be employed. In this case, the function $h(\cdot)$ can be approximated by a linear term plus a bounded remainder term as follows:
  $$\begin{aligned} h(x) = {} & h(\bar{x}) + J(\bar{x})(x - \bar{x}) \\ & + \frac{1}{2}\begin{bmatrix} (x-\bar{x})^T\mathcal{H}^{(1)} \\ (x-\bar{x})^T\mathcal{H}^{(2)} \\ \vdots \\ (x-\bar{x})^T\mathcal{H}^{(n)} \end{bmatrix}(x - \bar{x}), \end{aligned} \tag{11}$$
  where
  $$J(\bar{x}) = \frac{\partial h}{\partial x}\Big|_{\bar{x}}, \;\; \mathcal{H}^{(i)} = \frac{\partial^2 h^{(i)}}{\partial x^2}\Big|_{\bar{x}+\vartheta_i(x-\bar{x})}; \;\; \vartheta_i \in [0, 1], \;\; i = 1, 2, \ldots, n.$$
  The expression in (11) provides another way to bound the nonlinear function $h(x)$ when $h(x)$ is twice continuously differentiable.
- *Neural-Network-Based and Takagi-Sugeno (T-S) Fuzzy-Model-Based Methods:* In this class of approaches, the nonlinear function is approximated by a weighted combination of local models. To be more specific, neural-network-based methods are employed to learn a global approximation of the nonlinear mapping from data, where the approximation error is typically assumed to be bounded or can be characterized within a known uncertainty set. This allows the original nonlinear system to be represented as an approximate model with additive or parametric uncertainties, which can then be incorporated into the SME framework. In contrast, T-S fuzzy modeling represents the nonlinear system as a convex combination of multiple linear subsystems, where the weighting functions depend on measurable premise variables. This convex representation enables the nonlinear dynamics to be embedded into a polytopic linear system structure. Based on these approximations, the original nonlinear system can be reformulated into structures that are amenable to set propagation, thereby facilitating the construction of outer-bounding sets with standard SME methodologies.

To provide a more clear comparison of the aforementioned techniques for handling the nonlinear mappings, a summary is presented in Table 1. This table highlights their main ideas, advantages and limitations, and representative references.

The above techniques provide different ways to construct tractable outer-approximations for the nonlinear mappings. Once such approximations are obtained, the prediction and the update sets in the SME procedure can then be recursively propagated using specific set representations. In the following, we will focus on the ellipsoidal method and show how these outer-approximations can be characterized/computed within an ellipsoidal framework.

Table 1. Comparison of the techniques for handling the nonlinear mappings in SME.

Method	Main Idea	Characteristics	References
Sampling-based method	Approximate the image of a set via function evaluations over the sampled points	Simple and broadly applicable; free of the explicit approximation model; computationally expensive in the high dimension cases; the accuracy depends on the sampling density	[75,76]
Taylor expansion-based method	Approximate the nonlinear mappings using Taylor expansions of a given order	Analytical and approximation-based; compatible with the set-propagation and LMI-based techniques; potentially conservative due to the Jacobian uncertainty or the remainder bounding; the accuracy depends on the local region	[12,16,26,77,78]
Neural-network-based method and T-S fuzzy-model-based method	Approximate the nonlinear mappings using data-driven models or convex combinations of the local linear subsystems	Flexible and powerful for complex nonlinearities; enabling the structured representations; requiring model training or identification; prone to the approximation errors	[79–81]

3.2. The Ellipsoidal SME Method

To begin with, we introduce the definition and measures of the ellipsoids.

Definition 1 ([82])**.** *An ellipsoid $\mathcal{E}(c,P)\subset\mathbb{R}^n$ with center $c\in\mathbb{R}^n$ and shape matrix $P>0$ is defined as*

$$\mathcal{E}(c,P)=\left\{x\in\mathbb{R}^n:(x-c)^TP^{-1}(x-c)\le 1\right\}. \tag{12}$$

The size of an ellipsoid $\mathcal{E}(c,P)$ can be quantified by measures such as $\mathrm{Tr}(P)$ or $\ln\det(P)$, which are commonly used as optimization criteria in the ellipsoidal SME.

In the ellipsoidal SME, the sets $\mathcal{W}(k)$, $\mathcal{V}(k)$, and $\mathcal{X}(0)$ in (3) are assumed to be ellipsoidal:

$$\mathcal{W}(k)=\mathcal{E}(0,Q),\ \ \mathcal{V}(k)=\mathcal{E}(0,R),\ \ \mathcal{X}(0)=\mathcal{E}(c(0),P(0)),$$

where $c(0)$ is a known vector, and Q, R, and $P(0)$ are positive-definite matrices.

In the following, we first review the classical ellipsoidal SME methods for linear system, and then extend the discussion to nonlinear systems.

Consider the linear system corresponding to (1) and (2) as follows:

$$x(k+1)=Ax(k)+w(k), \tag{13}$$
$$y(k)=Cx(k)+v(k), \tag{14}$$

where A and C are known matrices. For notational convenience, denote $\mathcal{E}(c(k+1|k),P(k+1|k))$ and $\mathcal{E}(c(k+1),P(k+1))$ as the ellipsoids that bound the state at the prediction and the correction steps, respectively.

For linear systems, the existing ellipsoidal SME methods can be broadly classified into two categories according to the way that the recursive ellipsoidal bounds are constructed. The first category is based on the geometric properties of the ellipsoids and the set operations. A representative work is [6], where the support function techniques have been employed to derive the optimal outer ellipsoidal approximation of the Minkowski sum of ellipsoids in the sense of minimum volume or minimum sum of the squared semi-axes. Based on these results, the prediction ellipsoid $\mathcal{E}(c(k+1|k),P(k+1|k))$ is recursively obtained from $\mathcal{E}(c(k),P(k))$. Furthermore, an outer ellipsoid is constructed to enclose the intersection between $\mathcal{E}(c(k+1|k),P(k+1|k))$ and the measurement-consistent set $\mathcal{Y}(k+1)$, thereby yielding the correction ellipsoid $\mathcal{E}(c(k+1),P(k+1))$. The second category formulates the ellipsoidal set propagation within an optimization framework based on the linear matrix inequalities (LMIs). For example, the work in [9] has computed the ellipsoid $\mathcal{E}(c(k+1),P(k+1))$ recursively by solving an optimization problem under the LMI constraints, where the objective function is typically chosen as $\mathrm{Tr}(P(k+1))$ or $\ln\det(P(k+1))$. Moreover, a decoupling technique has also been proposed therein to separate the computation of the center $c(k+1)$ and the shape matrix $P(k+1)$, leading to analytical solutions for both parameters. These linear-system-oriented SME techniques provide the fundamental building blocks for many nonlinear SME methods.

In particular, once suitable outer approximations of the nonlinear mappings are constructed, the resulting set propagation and ellipsoidal bounding problems can often be transformed into forms that can be addressed using the aforementioned methodologies for linear systems.

We now turn to the ellipsoidal SME method for nonlinear systems in (1) and (2). The main challenge lies in constructing tractable outer-approximations for the nonlinear mappings $f(\cdot)$ and $g(\cdot)$. The existing methods mainly differ in the way that the nonlinear remainder terms are bounded, including the interval analysis, the norm-bounded uncertainty modeling, the semi-infinite programming (SIP) technique, and the state-dependent coefficient (SDC) parameterization approach.

In [83], the first-order Taylor expansion has been adopted to linearize the nonlinear mappings at both the prediction and the correction steps. The interval analysis techniques in [84] have then been employed to bound the corresponding remainders by interval vectors, which are subsequently enclosed by the optimal outer ellipsoids. As a result, the nonlinear system can be transformed into a linear-like system with bounded uncertainties, allowing the ellipsoidal SME method in [6] to be applied.

Instead of the interval analysis, the work in [16] has modeled the remainder terms as norm-bounded uncertainties that can be conveniently handled within an LMI framework. For instance, the remainder term in the prediction step is represented as

$$R_f(k) = L_f(k)\Delta_1(k)(x(k) - c(k)), \tag{15}$$

where $L_f(k) \in \mathbb{R}^{n\times n}$ is some derived matrix, and the uncertainty associated with $\Delta_1(k)(x(k) - c(k))$ satisfies

$$(x(k) - c(k))^T \Delta_1^T(k)\Delta_1(k)(x(k) - c(k)) \leq z^T(k)(P^{1/2}(k))^T P^{1/2}(k)z(k), \ \ \|z(k)\| \leq 1.$$

Here, $P^{1/2}(k)$ denotes the principal matrix square root of the positive-definite matrix $P(k)$. Such a formulation enables the recursive ellipsoidal bounds to be derived systematically via LMIs.

To further reduce the conservatism caused by the remainders of the Taylor expansion, the SIP technique has also been incorporated into the ellipsoidal SME. In [77], the first-order Taylor expansion and SIP are combined to derive some tighter ellipsoidal bounds for the remainder terms. The resulting SIP problem is approximated by the sampling technique and converted into a tractable semi-definite programming (SDP) problem. The obtained remainder-bounding ellipsoids are then incorporated into the LMI-based recursive framework in [9].

Different from the Taylor-expansion-based approaches, the work in [75] has directly constructed the tight ellipsoidal bound for the nonlinear mapping $f(\cdot)$ through sampling-based SIP. The prediction ellipsoid has been subsequently obtained using the ellipsoidal propagation method employed in [6]. For the correction step, under the assumption that the nonlinear measurement function $g(\cdot)$ is invertible, a similar SIP technique has been utilized to linearize the measurement equation [6].

Beyond the above mentioned techniques, alternative nonlinear approximation techniques have also been investigated. For example, the work in [15] has employed the SDC parameterization to transform the nonlinear system into a pseudo-linear form. Then, the matrix Taylor expansion has been applied to the SDC matrices around the current estimate, while sampling-based technique is utilized to bound the spectral norm of the resulting remainder terms. Finally, recursive ellipsoidal bounds have been derived within an LMI framework.

Remark 2. *The aforementioned methods exhibit different trade-offs between the computational complexity and the estimation conservatism. The Taylor-expansion-based approaches are computationally efficient but may introduce significant conservatism due to the bounding of the higher-order remainder terms. LMI-based methods with norm-bounded uncertainty provide a systematic framework with convex optimization guarantees, at the cost of increased computational burden. The sampling-based techniques can yield tighter ellipsoidal bounds by directly approximating the nonlinear mappings, but their performance depends on the sampling strategy and may lead to a higher computational complexity. In contrast, the SDC-based methods offer a structured way to represent the nonlinear systems in a pseudo-linear form, potentially improving the estimation accuracy, while requiring additional efforts in the parameterization and the remainder bounding.*

3.3. The Zonotopic SME Method

Definition 2 ([13])**.** *An m-order zonotope with center $c \in \mathbb{R}^n$ and generator matrix $G \in \mathbb{R}^{n\times m}$, denoted as $\langle c, G\rangle$, is defined as $\langle c, G\rangle \triangleq \{c + Gz : z \in \mathbb{R}^m, \|z\|_\infty \leq 1\}$.*

The size of a zonotope can be characterized by measures such as the volume [26,85]. Compared with the volume, the F_W-radius (or F-radius) is more widely adopted in the literature due to its computational simplicity.

Definition 3 ([10]). *Let $W \in \mathbb{R}^{m\times m}$ be a given positive-definite matrix. For zonotope $\langle c, G\rangle$, its weighted F_W-radius is defined as $\sqrt{\mathrm{Tr}(GWG^T)}$. Specifically, the F-radius of zonotope $\langle c, G\rangle$ is defined as its F_W-radius when $W = I$.*

The following lemma gives some useful properties of zonotopes.

Lemma 1 ([86]). *For two zonotopes $\langle c_1, G_1\rangle, \langle c_2, G_2\rangle \subset \mathbb{R}^n$ and a matrix $Z \in \mathbb{R}^{m\times n}$, the following properties hold:*

$$\begin{aligned} \langle c_1, G_1\rangle \oplus \langle c_2, G_2\rangle &= \big\langle c_1 + c_2, \begin{bmatrix} G_1 & G_2 \end{bmatrix} \big\rangle, \\ Z \odot \langle c_1, G_1\rangle &= \langle Zc_1, ZG_1\rangle, \\ \langle c_1, G_1\rangle &\subseteq \langle c_1, \mathrm{rs}(G_1)\rangle, \end{aligned}$$

where '$\oplus$' and '$\odot$' represent the Minkowski sum and the linear image operations of sets, and $\mathrm{rs}(G_1) \triangleq |G_1|\mathbf{1}$ with $|G_1|$ being the element-wise absolute value of matrix G_1 and $\mathbf{1}$ being a column vector whose entries are all equal to 1.

Remark 3. *The properties in Lemma 1 constitute the fundamental operations in the zonotopic set propagation. The first equality shows that the zonotopic operation is closed under the Minkowski sum, while the second equality indicates that the image of a zonotope under a linear transformation remains to be a zonotope. The third inclusion corresponds to an order reduction operation, where the original zonotope is over-approximated by an interval vector generated via $\mathrm{rs}(\cdot)$. Although such an approach is computationally efficient, it may introduce significant conservatism. To address this issue, various tighter order reduction techniques have been developed, see e.g., [87].*

In the zonotopic SME, the sets $\mathcal{W}(k)$, $\mathcal{V}(k)$, and $\mathcal{X}(0)$ in (3) are often set to be zonotopes as follows:

$$\mathcal{W}(k) = \langle 0, Q\rangle, \;\; \mathcal{V}(k) = \langle 0, R\rangle, \;\; \mathcal{X}(0) = \langle c(0), G(0)\rangle,$$

where $c(0)$ is a known vector, and Q, R, and $G(0)$ are often positive diagonal matrices.

Let $\langle c(k), G(k)\rangle$ be a zonotope enclosing $x(k)$. For the linear system in (13)–(14), the recursion between $\langle c(k+1), G(k+1)\rangle$ and $\langle c(k), G(k)\rangle$ can be derived by using Lemma 1. For example, in [10], the zonotope bounding $x(k)$ is given as

$$c(k+1) = (A - K(k)C)c(k) + K(k)y(k), \tag{16}$$

$$G(k+1) = \begin{bmatrix} (A - K(k)C)G(k) & Q & -K(k)R \end{bmatrix}, \tag{17}$$

where $K(k)$ is the estimator parameter to be designed. Note that the above estimator is essentially a one-step predictor. The case of filter can be seen in [88].

For linear systems, the existing zonotopic SME methods can be broadly classified into two categories according to the design strategy of the estimator parameter $K(k)$. The first category determines $K(k)$ online by minimizing the size of the resulting zonotope at each time instant, where the optimization objective is typically chosen as the volume or the F-radius [27,89,90]. The second category adopts a constant estimator gain and designs it by means of the LMI technique such that certain steady-state performance requirements are satisfied [91,92]. The above methods for linear systems also form the basis of many nonlinear zonotopic SME problems. By constructing suitable outer approximations of the nonlinear mappings, the resulting set propagation problem can often be handled within the same zonotopic SME framework.

The existing zonotopic SME methods for nonlinear systems mainly differ in the way that the nonlinear mappings are outer-approximated. Representative techniques include the Lagrange mean value theorem based approach, the first-order Taylor expansion method, the SIP-based method, the T-S fuzzy modeling approach, and the higher-order polynomial approximation method.

In [26], the Lagrange mean value theorem has been employed to transform the nonlinear mappings into the form in (10), after that interval analysis techniques have been utilized to derive appropriate zonotopic bounds for the remainder terms. Building upon such an idea, the first-order Taylor expansion together with the interval analysis has been utilized in [93] to handle the nonlinear functions arising in complex networks. Furthermore, both the Lagrange mean value theorem and the first-order Taylor expansion techniques have been employed in [94], where different approximation strategies are exploited in order to improve the estimation accuracy.

To reduce the conservatism introduced by the interval-based remainder bounding, SIP technique has been introduced into the zonotopic SME problem. For example, outer-approximation zonotopes are directly constructed in [76] for the nonlinear mappings through SIP, thereby yielding some tighter set representations. Besides the approximation-based methods, model transformation techniques have been investigated too. In [79], the original nonlinear model has been transformed into a T-S fuzzy system, based on which a zonotopic SME method guaranteeing the ℓ_∞ performance has been proposed.

Higher-order approximation techniques have also been explored in the zonotopic SME problems. In [12], a polynomial SME framework based on the Carleman linearization has been proposed for nonlinear systems. By incorporating the higher-order partial derivatives information, the obtained zonotopic bounds can potentially achieve improved estimation accuracy compared with conventional the first-order approximation method. Overall, compared with the ellipsoidal methods, the zonotopic SME approaches usually provide tighter set representations and exhibit favorable properties under the Minkowski sum operation. However, the dimension number of the generator matrix may increase rapidly during the recursive propagation, making the order reduction technique an essential component in the zonotopic SME researches.

Remark 4. *In this survey, we mainly focus on the SME of nonlinear networked systems with continuously differentiable nonlinearities, since such nonlinearities are widely encountered in practical systems and have motivated various nonlinear mapping approximation techniques. It is worth mentioning that the nonlinearities satisfying the sector-bounded condition can also be incorporated into the SME framework, particularly within the LMI-based formulation, by directly utilizing the corresponding sector-bounded condition, see e.g., [95]. Therefore, such a topic is not discussed separately in this survey.*

3.4. Comparison Between the Ellipsoidal and the Zonotopic SME Methods

The ellipsoidal and the zonotopic set representations are two of the most widely used frameworks in the field of SME. Although both of these two approaches aim to recursively propagate the outer-approximation sets for the system states, they exhibit different characteristics in terms of the geometric representation capability, computational complexity, and analytical tractability. A qualitative comparison between these two representations is summarized in Table 2.

Table 2. Comparison between the ellipsoidal and the zonotopic SME methods.

Aspect	**Ellipsoidal SME**	**Zonotopic SME**
Elements of the set representation	Center vector and shape matrix	Center vector and generator matrix
Minkowski sum	Outer-approximation generally required	Closed under the Minkowski sum operation
Set approximation	Relatively conservative for the complex set shapes	Relatively tight for the complex set shapes
Computational complexity	Relatively low and fixed-dimensional	Increasing with the dimension of the generator matrix
Order reduction	Unnecessary	Frequently required
Optimization methods	Convenient for LMI- and SDP-based analysis	Less convenient for optimization-based analysis
Real-time implementation	Suitable for online computation	Dependent on the order reduction
Main advantages	Simple representation and mature optimization tools	Tight set propagation and exact Minkowski sum computation
Main limitations	Conservatism caused by ellipsoidal approximation	Computational burden caused by the increasing dimension of the generator matrix

Remark 5. *The ellipsoidal and the zonotopic SME methods exhibit complementary characteristics. The ellipsoidal approaches possess strong analytical tractability and are naturally compatible with the optimization-based tools such as LMI and SDP, making them attractive for theoretical analysis and real-time implementation. In contrast, the zonotopic methods generally could provide tighter set approximations and enjoy favorable closure properties under the Minkowski sum operation. However, the dimension of the generator matrix may increase rapidly during*

the recursive propagation, thereby requiring additional order reduction techniques to control the computational complexity. Therefore, the specific choice between the ellipsoidal and the zonotopic representations should depend on the trade-offs among the estimation accuracy, the computational complexity, and the application requirements.

3.5. Other Set Representations

Ellipsoids and zonotopes constitute two of the most widely used set representations in SME, primarily due to their favorable trade-offs between the analytical tractability and the computational efficiency. In addition to these two classical frameworks, other set representations have also been explored in the literature to further enhance the modeling flexibility or reduce the conservatism. A basic example is the polytopes [96]. Over the past decade, more structured and computationally efficient representations have also been developed. Representative examples include the ellipsoid bundles [24,97–99], constrained zonotopes [100–104], sparse polynomial zonotopes [23], constrained polynomial zonotopes [105], ellipsotopes [106], and line zonotopes [107]. These representations can be viewed as extensions of the classical ellipsoidal and zonotopic frameworks, designed to improve their representation capability while balancing the estimation accuracy and the computational complexity.

4. SME under Communication Constraints

In practical networked systems, the measurement information is transmitted through shared and bandwidth-limited communication networks before reaching the estimator. As a result, the received measurement signals are often affected by various communication constraints, such as transmission delays, packet dropouts, scheduling of protocols, quantization effects, and network attacks. They may degrade the estimation performance, enlarge the feasible set, or even invalidate the recursive estimation procedure if not properly addressed.

From the viewpoint of SME, the key challenge brought by the communication constraints lies in utilizing the modified measurement information to obtain the feasible update set. In general, in the framework of SME, the communication constraints can be roughly classified into three categories according to the available measurement information: (1) communication constraints modeled as bounded additive uncertainties; (2) communication constraints resulting in partial measurement availability; and (3) communication constraints introducing delayed or missing measurements. In the following, we will review these representative communication constraints and the corresponding SME techniques under those three categories.

4.1. Communication Constraints Modeled as Bounded Additive Uncertainties

For many communication mechanisms, influence of the communication constraints on transmitted measurements can be modeled as additional bounded disturbances. Consequently, the received measurement equation can still be represented in a form similar to the standard measurement model:

$$\tilde{y}(k) = y(k) + \delta(k),$$

where $\delta(k)$ denotes the bounded uncertainty induced by communication constraints. Under this framework, the communication effect can be incorporated into the update set construction in a unified manner, and many existing SME techniques discussed in Section 3 remain applicable.

A representative example is the event-triggered mechanism [17], where the estimator receives transmitted measurements only when certain triggering conditions are satisfied. The resulting transmission error is usually characterized as a bounded uncertainty determined by the triggering threshold. Such an idea has then been extended to the dynamic event-triggered schemes [57, 108], where additional dynamic variables are introduced into the triggering conditions in order to improve the communication efficiency.

Quantization effects can also be handled within the bounded-uncertainty framework. For uniform quantization, the quantization error can be directly modeled as a UBB noise [58]. Building upon this idea, a variety of communication mechanisms based on finite-bit information transmission have been investigated in the SME literature. Among them, encoding-decoding mechanisms constitute a fundamental framework, where the measured data are first encoded into finite-bit representations before transmission and subsequently reconstructed at the estimator side [80,109–111]. The encoding process inevitably introduces quantization and reconstruction errors, which can usually be characterized by bounded uncertainties and incorporated into the set-membership estimation procedure.

Based on the encoding-decoding architecture, more sophisticated communication schemes have also been developed. For instance, encryption-decryption mechanisms introduce reversible transformations to the encoded data in order to guarantee communication security [112]. Meanwhile, bit-rate-allocation strategies explicitly consider the limited communication resources by optimally distributing the available bits among different sensors or channels [81,113]. Despite their different implementation objectives, these schemes are all closely related to the underlying encoding-decoding process, and their impacts on the transmitted measurements are commonly represented as bounded additive uncertainties or bounded reconstruction errors within the SME framework.

A similar modeling approach has been adopted for cyber attacks. For deception attacks [52,95,114–118], the maliciously corrupted signals are frequently modeled as UBB noises acting on the measurement channel. As a result, feasible set propagation can still be performed by enlarging the uncertainty sets accordingly.

4.2. Communication Constraints Resulting in Partial Measurement Availability

Another important class of communication constraints arises from scheduling of the network protocols, where only partial measurement components are allowed to access the communication channel at each transmission instant. In this case, the estimator cannot utilize the complete measurement information, and therefore suitable equivalent measurement models need to be established.

Frequently used protocols in the SME framework include the try-once-discard protocol [58,119–121], the round-robin protocol [122,123], and the FlexRay protocol [124,125]. Under these protocols, only selected sensor nodes or measurement components are transmitted through the communication network. To cope with the effects of these protocols, two commonly used strategies are the zero-input strategy and the zero-order-hold strategy. The former replaces the unavailable measurements with zero values, whereas the latter uses the most recently received measurements to compensate for unavailable data. Based on these strategies, equivalent measurement equations can be established, thereby enabling the recursion between the prediction set and the update set within the SME framework.

4.3. Communication Constraints Introducing Delayed or Missing Measurements

Time delays and packet dropouts constitute another important category of communication constraints in networked SME. Different from the previously discussed communication effects, these constraints directly affect the temporal availability of the measurements.

For transmission delays [54], the received measurement corresponds to the previous system states rather than the current state. To handle such delayed measurements, one commonly adopted approach is the augmented system technique, where delayed states are incorporated into an augmented state vector. In this way, the delayed discrete-time system can be transformed into an equivalent delay-free model, thereby allowing the standard SME techniques to be applied.

For packet dropouts, the measurement updates can only be carried out when valid measurements are successfully received [126]. Consequently, the recursive SME procedure alternates between the prediction-only steps and the prediction-correction steps according to the packet reception status. The resulting feasible sets are therefore generally enlarged due to missing measurement information.

5. Conclusions and Future Directions

In this paper, a comprehensive survey on SME for networked nonlinear systems under communication constraints has been presented. Fundamental concepts and recursive mechanisms of SME have been first reviewed. Subsequently, representative set representations and corresponding SME methods for nonlinear systems, including the ellipsoidal and the zonotopic SME approaches, have been systematically summarized. In particular, different techniques for handling the nonlinear mappings, such as Taylor expansion based methods, sampling-based methods, T-S fuzzy modeling approaches, and higher-order approximation techniques, have been discussed. Furthermore, the existing SME methods under various communication constraints, including the communication delays, packet dropouts, communication protocols, quantization effects, event-triggered schemes, and cyber attacks, have been reviewed from a unified perspective according to their influences on the measurement transmission and the set-membership estimator design.

Although significant progress has been achieved in recent years, SME for networked systems under communication constraints still faces many open challenges. Several promising future research directions are summarized as follows.

(1) *Low-Conservatism SME Methods for Nonlinear Systems:* Compared with the linear systems, SME for nonlinear systems usually suffers from increased conservatism caused by the nonlinear outer-approximation procedures. Although various approximation techniques have been developed, deriving tight outer bounds for nonlinear mappings while maintaining an acceptable computational complexity remains a challenging problem. The development of less conservative set representations and nonlinear approximation techniques deserves further investigation.

(2) *Steady-State Performance Analysis for Nonlinear SME:* For SME of linear systems, considerable progress has been made in establishing recursive estimation algorithms and steady-state performance analysis framework [127,128]. In particular, tractable sufficient conditions guaranteeing boundedness or convergence of the feasible sets

are often derived within the optimization-based framework. However, for nonlinear systems, the obtained steady-state performance criteria, such as those based on the assumption that the size of the prediction set is uniformly bounded, are usually difficult to be verified. Developing low-conservatism steady-state analysis methods for nonlinear SME remains an important yet open problem.

(3) *SME under Emerging Communication Constraints:* Although various communication constraints have been investigated in the existing SME literature, many practically relevant network phenomena still remain unexplored. For example, some communication scheduling mechanisms such as token bucket protocol [129] have not yet been systematically studied within the SME framework. In addition, compared with the deception attacks, other types of cyber attacks, such as replay attack [130, 131], have received very limited attention in the field of SME. Moreover, relay-aided transmission schemes, which are widely used in wireless sensor and multi-hop communication networks to enhance transmission reliability [44, 132–137], have not been adequately investigated from the perspective of SME. In such systems, intermediate relay nodes forward or process measurement information before it reaches the estimator, which introduces additional delays, channel uncertainties, and structural coupling effects that complicate the recursive propagation of feasible sets. Since these communication constraints and cyber threats may significantly affect the recursive propagation of feasible sets, developing proper SME methods capable of handling such phenomena represents a promising future research direction.

(4) *Distributed and Large-Scale SME:* With the increasing complexity of cyber-physical systems and sensor networks, distributed SME methods for large-scale interconnected systems have attracted growing attention [138–145]. However, fully distributed set propagation and fusion may significantly increase the computational complexity and the communication burden. Developing scalable distributed SME frameworks with reduced conservatism and limited communication requirements is still a challenging issue.

(5) *Data-Driven and Learning-Based SME:* Recent advances in machine learning and data-driven modeling (see e.g., [146–149]) provide new opportunities for SME of complex nonlinear systems. Combining the learning-based approximation techniques with the set-based uncertainty propagation may improve the estimation accuracy for systems with unknown or partially known dynamics. Nevertheless, how to preserve the guaranteed inclusion property of SME within the data-driven framework remains an open yet important problem.

(6) *SME for Safety-Critical Autonomous Systems:* As the autonomous driving, intelligent manufacturing, and robotic systems continue to develop rapidly, there is an increasing demand for reliable estimation techniques with rigorous safety guarantees [150–152]. Since the SME naturally provides guaranteed state bounds, it has significant potential in the safety-critical applications. Future research may further investigate the integration of SME with safety verification, resilient control, fault diagnosis, and secure autonomous decision-making.

Author Contributions: Z.Z.: conceptualization, investigation, writing—original draft preparation, writing—reviewing and editing; Y.-A.W.: investigation, writing—reviewing and editing; J.L.: conceptualization, supervision, writing—reviewing and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported in part by the Natural Science Foundation of Jiangsu Province of China under Grant BK20241286; in part by the Jiangsu Funding Program for Excellent Postdoctoral Talent of China under Grant 2024ZB601, in part by the Jiangsu Provincial Scientific Research Center of Applied Mathematics of China under Grant BK20233002, and in part by the National Natural Science Foundation of China under Grants 62373103 and 62403130.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies: No AI tools were utilized for this paper.

References

1. Li, J.X.; Wang, Z.D.; Hu, J.; et al. Cubature Kalman Fusion Filtering under Amplify-and-Forward Relays with Randomly Varying Channel Parameters. *IEEE/CAA J. Autom. Sin.* **2025**, *12*, 356–368. https://doi.org/10.1109/JAS.2024.124590.
2. Li, J.X.; Wang, Z.D.; Hu, J. Cubature Kalman Fusion Filtering under Stochastic Communication Protocol: Tackling Dynamical Bias, Scheduling Probability and Channel Noise. *Inf. Fusion* **2025**, *113*, 102610. https://doi.org/10.1016/j.inffus.2024.102610.
3. Feng, X.L.; Wu, C.S.; Ge, Q.B. Sequential Fusion Filtering Based on Minimum Error Entropy Criterion. *Inf. Fusion* **2024**, *104*, 102193. https://doi.org/10.1016/j.inffus.2023.102193.
4. Caballero-Águila, R.; Hu, J.; Linares-Pérez, J. Filtering and Smoothing Estimation Algorithms from Uncertain Nonlinear

Observations with Time-Correlated Additive Noise and Random Deception Attacks. *Int. J. Syst. Sci.* **2024**, *55*, 2023–2035. https://doi.org/10.1080/00207721.2024.2328781.

5. Sun, J.; Shen, B.; Wen, C.B.; et al. Recursive State-Fault Filtering for Stochastic Nonlinear Systems over Sensor Networks with Sensor Resolution and Time-Correlated Fading Channels. *J. Franklin Inst.* **2025**, *362*, 108020. https://doi.org/10.1016/j.jfranklin.2025.108020.
6. Schweppe, F.C. Recursive State Estimation: Unknown but Bounded Errors and System Inputs. *IEEE Trans. Autom. Control* **1968**, *13*, 22–28. https://doi.org/10.1109/TAC.1968.1098790.
7. Witsenhausen, H.S. Sets of Possible States of Linear Systems Given Perturbed Observations. *IEEE Trans. Autom. Control* **1968**, *13*, 556–558. https://doi.org/10.1109/TAC.1968.1098995.
8. Li, Y.D.; Cong, Y.R.; Zhou, X.Y.; et al. Optimal Set-Membership Smoothing. *IEEE Trans. Autom. Control* **2026**, *71*, 3327–3334. https://doi.org/10.1109/TAC.2025.3632158.
9. El Ghaoui, L.; Calafiore, G. Robust Filtering for Discrete-Time Systems with Bounded Noise and Parametric Uncertainty. *IEEE Trans. Autom. Control* **2001**, *46*, 1084–1089. https://doi.org/10.1109/9.935060.
10. Combastel, C. Zonotopes and Kalman Observers: Gain Optimality under Distinct Uncertainty Paradigms and Robust Convergence. *Automatica* **2015**, *55*, 265–273. https://doi.org/10.1016/j.automatica.2015.03.008.
11. Han, F.; Wang, Z.D.; Liu, H.J.; et al. Local Design of Distributed State Estimators for Linear Discrete Time-Varying Systems over Binary Sensor Networks: A Set-Membership Approach. *IEEE Trans. Syst. Man Cybern. Syst.* **2024**, *54*, 5641–5654. https://doi.org/10.1109/TSMC.2024.3409611.
12. Zhao, Z.Y.; Wang, Z.D.; Liang, J.L.; et al. Zonotopic Polynomial Set-Membership Fusion Estimation for Nonlinear Systems via Carleman Approximation: An Encoding-Decoding Scheme. *IEEE Trans. Autom. Control* **2026**, *71*, 2466–2481. https://doi.org/10.1109/TAC.2025.3627100.
13. Le, V.T.H.; Stoica, C.; Alamo, T.; et al. *Zonotopes: From Guaranteed State-Estimation to Control*; ISTE Ltd: Philadelphia, PA, USA, 2013. https://doi.org/10.1002/9781118761588.
14. Bai, X.Z.; Wang, Z.D.; Zou, L.; et al. Target Tracking for Wireless Localization Systems Using Set-Membership Filtering: A Component-Based Event-Triggered Mechanism. *Automatica* **2021**, *132*, 109795. https://doi.org/10.1016/j.automatica.2021.109795.
15. Bhattacharjee, D.; Subbarao, K. Set-Membership Filter for Discrete-Time Nonlinear Systems Using State-Dependent Coefficient Parameterization. *IEEE Trans. Autom. Control* **2022**, *67*, 894–901. https://doi.org/10.1109/TAC.2021.3082504.
16. Calafiore, G. Reliable Localization Using Set-Valued Nonlinear Filters. *IEEE Trans. Syst. Man Cybern. Part A Syst. Hum.* **2005**, *35*, 189–197. https://doi.org/10.1109/TSMCA.2005.843383.
17. Ding, D.R.; Wang, Z.D.; Han, Q.L. A Set-Membership Approach to Event-Triggered Filtering for General Nonlinear Systems over Sensor Networks. *IEEE Trans. Autom. Control* **2020**, *65*, 1792–1799. https://doi.org/10.1109/TAC.2019.2934389.
18. Zhang, Z.; He, X.; Zhou, D.H. Active Fault Diagnosis for Uncertain LPV Systems: A Zonotopic Set-Membership Approach. *IEEE Trans. Autom. Sci. Eng.* **2024**, *21*, 5110–5120. https://doi.org/10.1109/TASE.2023.3308576.
19. Lan, L.; Wei, G.L.; Ding, D.R.; et al. Zonotopic Distributed Fusion over Binary Sensor Networks with Bit Rate Allocation: A Coding-Decoding Approach. *IEEE Trans. Cybern.* **2024**, *54*, 6855–6866. https://doi.org/10.1109/TCYB.2024.3419033.
20. Lan, L.; Wei, G.L. Zonotopic Distributed Fusion for 2-D Nonlinear Systems under Binary Encoding Schemes: An Outlier-Resistant Approach. *Inf. Fusion* **2025**, *120*, 103103. https://doi.org/10.1016/j.inffus.2025.103103.
21. Combastel, C.; Zolghadri, A. A Distributed Kalman Filter with Symbolic Zonotopes and Unique Symbols Provider for Robust State Estimation in CPS. *Int. J. Control* **2020**, *93*, 2596–2612. https://doi.org/10.1080/00207179.2019.1707278.
22. Zhang, Z.; He, X.; Zhou, D.H. Active Fault Diagnosis for LPV Systems Based on Constrained Zonotopes. *IEEE Trans. Autom. Control* **2024**, *69*, 7893–7900. https://doi.org/10.1109/TAC.2024.3401271.
23. Kochdumper, N.; Althoff, M. Sparse Polynomial Zonotopes: A Novel Set Representation for Reachability Analysis. *IEEE Trans. Autom. Control* **2021**, *66*, 4043–4058. https://doi.org/10.1109/TAC.2020.3024348.
24. Tang, W.T.; Zhang, Q.H.; Wang, Z.H.; et al. Ellipsoid Bundle and Its Application to Set-Membership Estimation. *IFAC-PapersOnLine* **2020**, *53*, 13688–13693. https://doi.org/10.1016/j.ifacol.2020.12.871.
25. Chen, A.; Dinh, T.N.; Raïssi, T.; et al. Outlier-Robust Set-Membership Estimation for Discrete-Time Linear Systems. *Int. J. Robust Nonlinear Control* **2022**, *32*, 2313–2329. https://doi.org/10.1002/rnc.5948.
26. Alamo, T.; Bravo, J.M.; Camacho, E.F. Guaranteed State Estimation by Zonotopes. *Automatica* **2005**, *41*, 1035–1043. https://doi.org/10.1016/j.automatica.2004.12.008.
27. Wang, Y.; Puig, V.; Cembrano, G. Set-Membership Approach and Kalman Observer Based on Zonotopes for Discrete-Time Descriptor Systems. *Automatica* **2018**, *93*, 435–443. https://doi.org/10.1016/j.automatica.2018.03.082.
28. Hu, J.; Li, J.X.; Jia, C.Q.; et al. A Recursive Method to Encryption-Decryption-Based Distributed Set-Membership Filtering for Time-Varying Saturated Systems over Sensor Networks. *IEEE/CAA J. Autom. Sin.* **2025**, *12*, 1047–1049. https://doi.org/10.1109/JAS.2023.123915.
29. Zhao, C.Y.; Zhang, X.K.; Xu, C.Y.; et al. Set-Membership State Estimation for 2-D Roesser Systems Based on Zonotope Radius and Its Application. *IEEE Trans. Circuits Syst. II Express Briefs* **2024**, *71*, 465–469. https://doi.org/10.1109/TCSII.2023.3300733.

30. Zhao, Z.Y.; Wang, Z.D.; Liang, J.L.; et al. Distributed Polynomial Set-Membership Fusion Estimation for Target Tracking Systems under a Binary Encoding Scheme. *IEEE Trans. Ind. Inform.* **2026**, *22*, 418–428. https://doi.org/10.1109/TII.2025.3610212.
31. Mousavinejad, E.; Ge, X.H.; Han, Q.L.; et al. An Ellipsoidal Set-Membership Approach to Distributed Joint State and Sensor Fault Estimation of Autonomous Ground Vehicles. *IEEE/CAA J. Autom. Sin.* **2021**, *8*, 1107–1118. https://doi.org/10.1109/JAS.2021.1004015.
32. Li, Y.; Dong, J.X. Fault Detection for Discrete-Time Interval Type-2 Takagi-Sugeno Fuzzy Systems Using H_{-}/L_{∞} Unknown Input Observer and Zonotopic Analysis. *IEEE Trans. Fuzzy Syst.* **2024**, *32*, 846–858. https://doi.org/10.1109/TFUZZ.2023.3305456.
33. Ju, Y.M.; Wei, G.L.; Ding, D.R.; et al. A Novel Fault Detection Method under Weighted Try-Once-Discard Scheduling over Sensor Networks. *IEEE Trans. Control Netw. Syst.* **2020**, *7*, 1489–1499. https://doi.org/10.1109/TCNS.2020.2980362.
34. Pourasghar, M.; Combastel, C.; Puig, V.; et al. FD-ZKF: A Zonotopic Kalman Filter Optimizing Fault Detection Rather Than State Estimation. *J. Process Control* **2019**, *73*, 89–102. https://doi.org/10.1016/j.jprocont.2018.12.003.
35. Wang, Z.X.; Zhang, Y.L.; Xu, W.M.; et al. Set-Membership Global Estimation for Multi-Sensor Asynchronous Sampling Systems: A Soft Actor-Critic-Based Approach. *IEEE Trans. Autom. Sci. Eng.* **2026**, *23*, 587–599. https://doi.org/10.1109/TASE.2025.3640208.
36. Chen, W.; Wang, Z.D.; Hu, J.; et al. Distributed Resilient State Estimation for Cyber-Physical Systems Against Bit Errors: A Zonotopic Set-Membership Approach. *IEEE Trans. Netw. Sci. Eng.* **2023**, *10*, 3922–3932. https://doi.org/10.1109/TNSE.2023.3276851.
37. Ge, X.H.; Han, Q.L.; Yang, F.W. Event-Based Set-Membership Leader-Following Consensus of Networked Multi-Agent Systems Subject to Limited Communication Resources and Unknown-But-Bounded Noise. *IEEE Trans. Ind. Electron.* **2017**, *64*, 5045–5054. https://doi.org/10.1109/TIE.2016.2613929.
38. Sun, J.; Shen, B.; Zou, L. Ultimately Bounded State Estimation for Nonlinear Networked Systems with Constrained Average Bit Rate: A Buffer-Aided Strategy. *IEEE Trans. Signal Process.* **2024**, *72*, 1865–1876. https://doi.org/10.1109/TSP.2024.3382404.
39. Han, F.; Wang, Z.D.; Liu, H.J.; et al. A Recursive Matrix Inequality Approach to Distributed Filtering over Binary Sensor Networks: Handling Amplify-and-Forward Relays. *IEEE Trans. Netw. Sci. Eng.* **2024**, *11*, 1347–1362. https://doi.org/10.1109/TNSE.2023.3322378.
40. Sun, L.; Ding, D.R.; Dong, H.L.; et al. Distributed Economic Dispatch of Microgrids Based on ADMM Algorithms with Encryption-Decryption Rules. *IEEE Trans. Autom. Sci. Eng.* **2025**, *22*, 8427–8438. https://doi.org/10.1109/TASE.2024.3485922.
41. Xu, C.; Wang, H.; Shen, Y.X.; et al. Neural-Network-Based Finite-Horizon Estimation for Complex Networks with Probabilistic Quantizations and Sensor Faults. *Int. J. Robust Nonlinear Control* **2025**, *35*, 604–616. https://doi.org/10.1002/rnc.7669.
42. Hu, J.; Yang, S.; Caballero-Águila, R.; et al. Mixed Static-Dynamic Protocol-Based Tobit Recursive Filtering for Stochastic Nonlinear Systems Against Random False Data Injection Attacks. *IEEE Trans. Signal Inf. Process. Netw.* **2024**, *10*, 445–459. https://doi.org/10.1109/TSIPN.2024.3388953.
43. Yang, Y.P.; Shen, B.; Ge, X.H.; et al. Dynamic Event-Triggered Cluster Consensus of Multi-Agent Systems via PSO-GA Co-Design. *IEEE Trans. Autom. Sci. Eng.* **2025**, *22*, 11505–11518. https://doi.org/10.1109/TASE.2025.3536076.
44. Zhang, N.; Liang, J.L. Distributed Interval Fusion Filtering for Multirate Nonlinear Positive Systems under Amplify-and-Forward Relay: The Finite-Horizon Case. *Inf. Fusion* **2026**, *129*, 104061. https://doi.org/10.1016/j.inffus.2025.104061.
45. Yao, L.; Wang, Z.; Huang, X.; et al. Stochastic Sampled-Data Exponential Synchronization of Markovian Jump Neural Networks with Time-Varying Delays. *IEEE Trans. Neural Netw. Learn. Syst.* **2023**, *34*, 909–920. https://doi.org/10.1109/TNNLS.2021.3103958.
46. Bai, X.Z.; Wang, Z.D.; Zou, L.; et al. Target Tracking for Wireless Localization Systems with Degraded Measurements and Quantization Effects. *IEEE Trans. Ind. Electron.* **2018**, *65*, 9687–9697. https://doi.org/10.1109/TIE.2018.2813982.
47. Yao, M.; Wei, G.L.; Ding, D.R.; et al. Reset PI Controller Design of Cyber-Physical Systems under Constrained Bit Rate and DoS Attacks: A Hybrid System Framework. *IEEE Trans. Syst. Man Cybern. Syst.* **2025**, *55*, 1298–1308. https://doi.org/10.1109/TSMC.2024.3495833.
48. Caballero-Águila, R.; Hu, J.; Linares-Pérez, J. Distributed Estimation for Uncertain Systems Subject to Measurement Quantization and Adversarial Attacks. *Inf. Fusion* **2025**, *120*, 103044. https://doi.org/10.1016/j.inffus.2025.103044.
49. Zhao, P.F.; Ding, D.R.; Dong, H.L.; et al. Secure Distributed State Estimation for Microgrids with Eavesdroppers Based on Variable Decomposition. *IEEE Trans. Circuits Syst. I Regul. Pap.* **2024**, *71*, 3307–3316. https://doi.org/10.1109/TCSI.2024.3357523.
50. Wang, C.X.; Yang, Y.P.; Zou, L.; et al. Predictive Containment Control for Multi-Agent Systems Subject to Denial-of-Service Attacks. *IEEE Trans. Autom. Sci. Eng.* **2025**, *22*, 23177–23189. https://doi.org/10.1109/TASE.2025.3626377.
51. Fu, H.J.; Shen, B.; Zou, L. Covert Attack Detection for Cyber-Physical Systems Using Input-Associated Watermarking Mechanism. *Automatica* **2025**, *182*, 112516. https://doi.org/10.1016/j.automatica.2025.112516.
52. Bao, S.G.; Li, J.; Liu, C.; et al. Distributed Set-Membership Estimation over Delayed and Attacked Sensor Networks.

IEEE Trans. Ind. Cyber-Phys. Syst. **2026**, *4*, 25–33. https://doi.org/10.1109/TICPS.2025.3632249.

53. Zhao, Z.Y.; Wang, Z.D.; Zou, L.; et al. Finite-Time State Estimation for Delayed Neural Networks with Redundant Delayed Channels. *IEEE Trans. Syst. Man Cybern. Syst.* **2021**, *51*, 441–451. https://doi.org/10.1109/TSMC.2018.2874508.
54. Cheng, C.C.; Bai, X.Z.; Zhang, Q.Q.; et al. Set-Membership Filtering for Generator Dynamic State Estimation with Delayed Measurements. *Syst. Sci. Control Eng.* **2018**, *6*, 35–43. https://doi.org/10.1080/21642583.2018.1531794.
55. Caballero-Águila, R.; Linares-Pérez, J. Centralized Fusion Estimation in Networked Systems: Addressing Deception Attacks and Packet Dropouts with a Zero-Order Hold Approach. *Int. J. Netw. Dyn. Intell.* **2024**, *3*, 100021. https://doi.org/10.53941/ijndi.2024.100021.
56. Li, Y.Y.; Liang, J.L.; Wang, F.; et al. Robust Fusion Filtering for 2-D Multi-Sensor Systems with Measurement Censoring and Redundant Channels. *Inf. Fusion* **2026**, *129*, 104048. https://doi.org/10.1016/j.inffus.2025.104048.
57. Li, G.H.; Wang, Z.D.; Bai, X.Z.; et al. Dynamic Event-Triggered State Estimation for Power Harmonics with Quantization Effects: A Zonotopic Set-Membership Approach. *IEEE Trans. Sustain. Comput.* **2024**, *9*, 803–813. https://doi.org/10.1109/TSUSC.2024.3391733.
58. Liu, S.; Wei, G.L.; Song, Y.; et al. Set-Membership State Estimation Subject to Uniform Quantization Effects and Communication Constraints. *J. Franklin Inst.* **2017**, *354*, 7012–7027. https://doi.org/10.1016/j.jfranklin.2017.08.012.
59. Ju, Y.M.; Chen, Y.K.; Ding, D.R.; et al. Neural-Network-Based Distributed State Estimation under Encoding-Decoding Schemes: Probabilistic-Constrained Cases. *IEEE Trans. Syst. Man Cybern. Syst.* **2025**, *55*, 5332–5344. https://doi.org/10.1109/TSMC.2025.3571783.
60. Zhang, J.Y.; Wei, G.L.; Ding, D.R.; et al. Probability-Guaranteed Distributed Fusion Estimation with Event-Driven Censored Measurements: A Binary Encoding Scheme. *IEEE Trans. Syst. Man Cybern. Syst.* **2026**, *56*, 1936–1947. https://doi.org/10.1109/TSMC.2025.3646816.
61. Xie, M.L.; Ding, D.R.; Shen, B.; et al. Learning-Based Platooning Control of Automated Vehicles via Multiple Description Encoding Mechanisms. *IEEE Trans. Veh. Technol.* **2024**, *73*, 7693–7707. https://doi.org/10.1109/TVT.2024.3356516.
62. Li, J.X.; Hu, J.; Liu, H.J.; et al. Encoding-Decoding-Based Distributed Filtering for Time-Varying Saturated Systems with Constrained Bit Rate. *IEEE Trans. Circuits Syst. II Express Briefs* **2022**, *69*, 4904–4908. https://doi.org/10.1109/TCSII.2022.3182123.
63. Yang, C.Y.; Liang, J.L. Observer-Based Bounded H_∞ Control for Shift-Varying Linear Repetitive Processes with Constrained Bit Rates over a Finite Horizon. *IEEE Trans. Cybern.* **2025**, *55*, 2514–2520. https://doi.org/10.1109/TCYB.2025.3546704.
64. Yao, M.; Wei, G.L.; Ding, D.R. Dynamic Quantized Output-Feedback Control of Impulsive Systems with Round-Robin Protocols and Transmission Delays. *IEEE Trans. Control Netw. Syst.* **2025**, *12*, 114–124. https://doi.org/10.1109/TCNS.2024.3432952.
65. Song, Y.H.; Zhang, J.N.; Han, F.; et al. Scalable Distributed Estimation for Time-Varying System with Generalized Weighted Try-Once-Discard and Round-Robin Protocols. *IEEE Sensors J.* **2025**, *25*, 31653–31663. https://doi.org/10.1109/JSEN.2025.3582166.
66. Wu, Y.M.; Qian, W.; Shen, B. Improved WTOD Protocol-Based H_∞ Fuzzy PID Control for Networked Nonlinear Systems by an Adaptive Momentum Estimation Algorithm. *IEEE Internet Things J.* **2026**, *13*, 5897–5908. https://doi.org/10.1109/JIOT.2025.3634399.
67. Li, Y.Y.; Liang, J.L. Distributed Tobit Kalman Filtering for Random Parameter 2-D System: Dealing with Amplify-and-Forward Relay and Stochastic Communication Protocol. *Inf. Sci.* **2025**, *718*, 122355. https://doi.org/10.1016/j.ins.2025.122355.
68. Hu, J.; Li, J.X.; Yan, H.C.; et al. Optimized Distributed Filtering for Saturated Systems with Amplify-and-Forward Relays over Sensor Networks: A Dynamic Event-Triggered Approach. *IEEE Trans. Neural Netw. Learn. Syst.* **2024**, *35*, 17742–17753. https://doi.org/10.1109/TNNLS.2023.3308192.
69. Ni, Y.Y.; Wang, Z.D.; Fan, Y.J.; et al. A Switching Memory-Based Event-Trigger Scheme for Synchronization of Lur'e Systems with Actuator Saturation: A Hybrid Lyapunov Method. *IEEE Trans. Neural Netw. Learn. Syst.* **2024**, *35*, 13963–13974. https://doi.org/10.1109/TNNLS.2023.3273917.
70. Liu, Y.F.; Shen, B.; Liu, H.J.; et al. Dynamic Event-Triggered H_∞ State Estimation for Discrete-Time Complex-Valued Memristive Neural Networks with Mixed Time Delays. *Neural Netw.* **2025**, *190*, 107631. https://doi.org/10.1016/j.neunet.2025.107631.
71. Li, Y.; Li, J.J.; Wei, G.L. An Optimal Energy Switching-Based Eavesdropping Attacks for Anti-User Detection in Networked Multi-Sensor Fusion Systems. *Digit. Signal Process.* **2025**, *164*, 105285. https://doi.org/10.1016/j.dsp.2025.105285.
72. Li, X.R.; Zhang, P.; Dong, H.L. Model Reference Observer Based Stealthy Covert Attack on Cyber-Physical Systems. *J. Franklin Inst.* **2026**, *363*, 108271. https://doi.org/10.1016/j.jfranklin.2025.108271.
73. Hu, J.; Xu, B.; Caballero-Águila, R.; et al. Distributed State Estimation for Nonlinear Dynamical Networks with Stochastic Topological Structures Subject to Random Deception Attacks and Bit-Rate Constraints. *IEEE Trans. Syst. Man Cybern. Syst.* **2025**, *55*, 3976–3988. https://doi.org/10.1109/TSMC.2025.3547926.
74. Li, X.R.; Zhang, P.; Dong, H.L. A Robust Covert Attack Strategy for a Class of Uncertain Cyber-Physical Systems. *IEEE Trans. Autom. Control* **2024**, *69*, 1983–1990. https://doi.org/10.1109/TAC.2023.3319071.

75. Wang, Z.G.; Shen, X.J.; Liu, H.Q.; et al. Dual Set-Membership Filter with Minimizing Nonlinear Transformation of Ellipsoid. *IEEE Trans. Autom. Control* **2022**, *67*, 2405–2418. https://doi.org/10.1109/TAC.2021.3081078.
76. Yang, H.; Yan, H.C.; Li, Z.C.; et al. Set-Membership Estimation for Nonlinear Systems Based on Zonotope Analysis. *Automatica* **2025**, *177*, 112278. https://doi.org/10.1016/j.automatica.2025.112278.
77. Wang, Z.G.; Shen, X.J.; Zhu, Y.M.; et al. A Tighter Set-Membership Filter for Some Nonlinear Dynamic Systems. *IEEE Access* **2018**, *6*, 25351–25362. https://doi.org/10.1109/ACCESS.2018.2830350.
78. Wang, Z.G.; Shen, X.J.; Zhu, Y.M. Ellipsoidal Fusion Estimation for Multisensor Dynamic Systems with Bounded Noises. *IEEE Trans. Autom. Control* **2019**, *64*, 4725–4732. https://doi.org/10.1109/TAC.2019.2902722.
79. Ren, W.J.; Guo, S.H.; Ahn, C.K. Guaranteed Set-Membership Estimation for Local Nonlinear Uncertain Fuzzy Systems Subject to Partially Decouplable Unknown Inputs. *IEEE Trans. Fuzzy Syst.* **2023**, *31*, 4336–4349. https://doi.org/10.1109/TFUZZ.2023.3283061.
80. Zhu, K.Q.; Wang, Z.D.; Chen, Y.; et al. Neural-Network-Based Set-Membership Fault Estimation for 2-D Systems under Encoding-Decoding Mechanism. *IEEE Trans. Neural Netw. Learn. Syst.* **2023**, *34*, 786–798. https://doi.org/10.1109/TNNLS.2021.3102127.
81. Zhu, K.Q.; Wang, Z.D.; Wei, G.L.; et al. Adaptive Set-Membership State Estimation for Nonlinear Systems under Bit Rate Allocation Mechanism: A Neural-Network-Based Approach. *IEEE Trans. Neural Netw. Learn. Syst.* **2023**, *34*, 8337–8348. https://doi.org/10.1109/TNNLS.2022.3149540.
82. Kurzhanski, A.; Vályi, I. *Ellipsoidal Calculus for Estimation and Control*; Birkhäuser: Boston, MA, USA, 1997. https://doi.org/10.1007/978-1-4612-0277-6.
83. Scholte, E.; Campbell, M.E. A Nonlinear Set-Membership Filter for On-Line Applications. *Int. J. Robust Nonlinear Control* **2003**, *13*, 1337–1358. https://doi.org/10.1002/rnc.856.
84. Moore, R.E. *Interval Analysis*; Prentice-Hall: Englewood Cliffs, NJ, USA, 1966.
85. Chai, W.; Sun, X.F.; Qiao, J.F. Set Membership State Estimation with Improved Zonotopic Description of Feasible Solution Set. *Int. J. Robust Nonlinear Control* **2013**, *23*, 1642–1654. https://doi.org/10.1002/rnc.2842.
86. Kühn, W. Rigorously Computed Orbits of Dynamical Systems Without the Wrapping Effect. *Computing* **1998**, *61*, 47–67. https://doi.org/10.1007/BF02684450.
87. Yang, X.J.; Scott, J.K. A Comparison of Zonotope Order Reduction Techniques. *Automatica* **2018**, *95*, 378–384. https://doi.org/10.1016/j.automatica.2018.06.006.
88. Zhao, Z.Y.; Wang, Z.D.; Liang, J.L. Zonotopic Set-Membership Fusion Estimation for Multi-Sensor Systems under FlexRay Protocol. *IEEE Internet Things J.* **2026**, in press. https://doi.org/10.1109/JIOT.2026.3677531.
89. Tang, W.T.; Wang, Z.H.; Zhang, Q.H.; et al. Set-Membership Estimation for Linear Time-Varying Descriptor Systems. *Automatica* **2020**, *115*, 108867. https://doi.org/10.1016/j.automatica.2020.108867.
90. Zhao, Z.Y.; Wang, Z.D.; Zou, L. Sequential Fusion Estimation for Multirate Complex Networks with Uniform Quantization: A Zonotopic Set-Membership Approach. *IEEE Trans. Neural Netw. Learn. Syst.* **2024**, *35*, 5764–5777. https://doi.org/10.1109/TNNLS.2022.3209135.
91. Fei, Z.Y.; Yang, L.; Sun, X.M.; et al. Zonotopic Set-Membership State Estimation for Switched Systems with Restricted Switching. *IEEE Trans. Autom. Control* **2022**, *67*, 6127–6134. https://doi.org/10.1109/TAC.2021.3131545.
92. Wang, Y.; Wang, Z.H.; Puig, V.; et al. Zonotopic Set-Membership State Estimation for Discrete-Time Descriptor LPV Systems. *IEEE Trans. Autom. Control* **2019**, *64*, 2092–2099. https://doi.org/10.1109/TAC.2018.2863659.
93. Zhao, Z.Y.; Wang, Z.D.; Zou, L.; et al. Event-Triggered Set-Membership State Estimation for Complex Networks: A Zonotopes-Based Method. *IEEE Trans. Netw. Sci. Eng.* **2022**, *9*, 1175–1186. https://doi.org/10.1109/TNSE.2021.3137320.
94. Zhao, Z.Y.; Wang, Z.D.; Zou, L.; et al. Zonotopic Non-Fragile Set-Membership Fusion Estimation for Nonlinear Systems under Sensor Resolution Effects: Boundedness and Monotonicity. *Inf. Fusion* **2024**, *105*, 102232. https://doi.org/10.1016/j.inffus.2024.102232.
95. Song, H.Y.; Shi, P.; Lim, C.C.; et al. Set-Membership Estimation for Complex Networks Subject to Linear and Nonlinear Bounded Attacks. *IEEE Trans. Neural Netw. Learn. Syst.* **2020**, *31*, 163–173. https://doi.org/10.1109/TNNLS.2019.2900045.
96. Wan, J.; Sharma, S.; Sutton, R. Guaranteed State Estimation for Nonlinear Discrete-Time Systems via Indirectly Implemented Polytopic Set Computation. *IEEE Trans. Autom. Control* **2018**, *63*, 4317–4322. https://doi.org/10.1109/TAC.2018.2816262.
97. Tang, W.T.; Zhang, Q.H.; Wang, Z.H.; et al. Set-Membership Estimation Based on Ellipsoid Bundles for Discrete-Time LPV Descriptor Systems. *Automatica* **2022**, *145*, 110580. https://doi.org/10.1016/j.automatica.2022.110580.
98. Fei, Z.Y.; Ma, Y.K.; Zhao, X.D.; et al. Event-Based Sensor Fault Interval Estimation and PI Controller Design via Ellipsoid Bundles. *IEEE Trans. Ind. Electron.* **2024**, *71*, 13253–13262. https://doi.org/10.1109/TIE.2023.3344812.
99. Zhou, M.; Zhang, Y.Y.; Wang, J.; et al. Robust Fault Detection Method Based on Interval Neural Networks Optimized by Ellipsoid Bundles. *Automatica* **2025**, *176*, 112233. https://doi.org/10.1016/j.automatica.2025.112233.
100. Rego, B.S.; Raffo, G.V.; Scott, J.K.; et al. Guaranteed Methods Based on Constrained Zonotopes for Set-Valued State Estimation of Nonlinear Discrete-Time Systems. *Automatica* **2020**, *111*, 108614. https://doi.org/10.1016/j.automatica.2019

.108614.

101. Scott, J.K.; Raimondo, D.M.; Marseglia, G.R.; et al. Constrained Zonotopes: A New Tool for Set-Based Estimation and Fault Detection. *Automatica* **2016**, *69*, 126–136. https://doi.org/10.1016/j.automatica.2016.02.036.
102. Rego, B.S.; Raimondo, D.M.; Raffo, G.V. Set-Based State Estimation of Nonlinear Systems Using Constrained Zonotopes and Interval Arithmetic. In Proceedings of the 2018 European Control Conference, Limassol, Cyprus, 12–15 June 2018; pp. 1584–1589.
103. Raghuraman, V.; Koeln, J.P. Set Operations and Order Reductions for Constrained Zonotopes. *Automatica* **2022**, *139*, 110204. https://doi.org/10.1016/j.automatica.2022.110204.
104. Rego, F.; Silvestre, D. A Novel and Efficient Order Reduction for Both Constrained Convex Generators and Constrained Zonotopes. *IEEE Trans. Autom. Control* **2025**, *70*, 4016–4023. https://doi.org/10.1109/TAC.2024.3525388.
105. Kochdumper, N.; Althoff, M. Constrained Polynomial Zonotopes. *Acta Inform.* **2023**, *60*, 279–316. https://doi.org/10.1007/s00236-023-00437-5.
106. Kousik, S.; Dai, A.; Gao, G.X. Ellipsotopes: Uniting Ellipsoids and Zonotopes for Reachability Analysis and Fault Detection. *IEEE Trans. Autom. Control* **2023**, *68*, 3440–3452. https://doi.org/10.1109/TAC.2022.3191750.
107. Rego, B.S.; Raimondo, D.M.; Raffo, G.V. Line Zonotopes: A Tool for State Estimation and Fault Diagnosis of Unbounded and Descriptor Systems. *Automatica* **2025**, *179*, 112380. https://doi.org/10.1016/j.automatica.2025.112380.
108. Ge, X.H.; Han, Q.L.; Wang, Z.D. A Dynamic Event-Triggered Transmission Scheme for Distributed Set-Membership Estimation over Wireless Sensor Networks. *IEEE Trans. Cybern.* **2019**, *49*, 171–183. https://doi.org/10.1109/TCYB.2017.2769722.
109. Shen, Y.X.; Wang, Z.D.; Dong, H.L.; et al. Joint State and Unknown Input Estimation for a Class of Artificial Neural Networks with Sensor Resolution: An Encoding-Decoding Mechanism. *IEEE Trans. Neural Netw. Learn. Syst.* **2025**, *36*, 3671–3681. https://doi.org/10.1109/TNNLS.2023.3348752.
110. Zhu, K.Q.; Wang, Z.D.; Ding, D.R.; et al. Proportional-Integral-Observer-Based Fusion Estimation for Artificial Neural Networks: Implementing a One-Bit Encoding Scheme. *IEEE Trans. Neural Netw. Learn. Syst.* **2025**, *36*, 16253–16263. https://doi.org/10.1109/TNNLS.2025.3556370.
111. Li, Q.; Gao, M.H.; Liu, Y.F.; et al. Zonotopic Set-Membership State Estimation for Linear Repetitive Processes with Multirate Measurements under Encoding-Decoding Mechanisms. *Inf. Fusion* **2026**, *129*, 104023. https://doi.org/10.1016/j.inffus.2025.104023.
112. Yang, H.; Yan, H.C.; Li, Y.; et al. Secure Zonotopic Set-Membership State Estimation for Multirate Complex Networks under Encryption-Decryption Mechanism. *IEEE Trans. Autom. Control* **2024**, *69*, 5109–5124. https://doi.org/10.1109/TAC.2023.3347599.
113. Zhao, Z.Y.; Wang, Z.D.; Zou, L.; et al. Zonotopic Distributed Fusion for Nonlinear Networked Systems with Bit Rate Constraint. *Inf. Fusion* **2023**, *90*, 174–184. https://doi.org/10.1016/j.inffus.2022.09.014.
114. Li, J.T.; Wang, Z.H.; Shen, Y.; et al. Security Synthesis for Cyber-Physical Systems. *IEEE Trans. Syst. Man Cybern. Syst.* **2023**, *53*, 1027–1037. https://doi.org/10.1109/TSMC.2022.3189175.
115. Zhang, Y.L.; Zhu, Y.F.; Fan, Q.Q. A Novel Set-Membership Estimation Approach for Preserving Security in Networked Control Systems under Deception Attacks. *Neurocomputing* **2020**, *400*, 440–449. https://doi.org/10.1016/j.neucom.2019.04.082.
116. Qiu, Q.W.; Yang, F.W.; Zhu, Y. Cyber-Attack Localisation and Tolerant Control for Microgrid Energy Management System Based on Set-Membership Estimation. *Int. J. Syst. Sci.* **2021**, *52*, 1206–1222. https://doi.org/10.1080/00207721.2021.1896051.
117. Hu, C.Z.; Ding, S.B.; Xie, X.P. Event-Based Distributed Set-Membership Estimation for Complex Networks under Deception Attacks. *IEEE Trans. Autom. Sci. Eng.* **2024**, *21*, 3719–3729. https://doi.org/10.1109/TASE.2023.3284448.
118. Zha, L.J.; Miao, J.Z.; Liu, J.L.; et al. Privacy-Preserving Distributed Estimation over Sensor Networks with Multi-strategy Injection Attacks: A Chaotic Encryption Scheme. *IEEE Trans. Syst. Man Cybern. Syst.* **2025**, *55*, 4969–4978. https://doi.org/10.1109/TSMC.2025.3560404.
119. Zhao, Z.Y.; Wang, Z.D.; Zou, L.; et al. Zonotopic Multi-Sensor Fusion Estimation with Mixed Delays under Try-Once-Discard Protocol: A Set-Membership Framework. *Inf. Fusion* **2023**, *91*, 681–693. https://doi.org/10.1016/j.inffus.2022.11.012.
120. Liu, H.J.; Wang, Z.D.; Fei, W.Y.; et al. On State Estimation for Discrete Time-Delayed Memristive Neural Networks under the WTOD Protocol: A Resilient Set-Membership Approach. *IEEE Trans. Syst. Man Cybern. Syst.* **2022**, *52*, 2145–2155. https://doi.org/10.1109/TSMC.2021.3049306.
121. Li, M.Y.; Liang, J.L.; Qiu, J.L. Set-Membership Filtering for 2-D Systems under Uniform Quantization and Weighted Try-Once-Discard Protocol. *IEEE Trans. Circuits Syst. II Express Briefs* **2023**, *70*, 3474–3478. https://doi.org/10.1109/TCSII.2023.3263201.
122. Liu, S.; Wang, Z.D.; Wei, G.L.; et al. Distributed Set-Membership Filtering for Multirate Systems under the Round-Robin Scheduling over Sensor Networks. *IEEE Trans. Cybern.* **2020**, *50*, 1910–1920. https://doi.org/10.1109/TCYB.2018.2885653.
123. Li, M.Y.; Liang, J.L.; Wang, F. Robust Set-Membership Filtering for Two-Dimensional Systems with Sensor Saturation

under the Round-Robin Protocol. *Int. J. Syst. Sci.* **2022**, *53*, 2773–2785. https://doi.org/10.1080/00207721.2022.2049918.
124. Liu, S.; Wang, Z.D.; Wang, L.C.; et al. Recursive Set-Membership State Estimation over a FlexRay Network. *IEEE Trans. Syst. Man Cybern. Syst.* **2022**, *52*, 3591–3601. https://doi.org/10.1109/TSMC.2021.3071390.
125. Shen, Y.X.; Wang, Z.D.; Dong, H.L.; et al. Set-Membership State Estimation for Multirate Nonlinear Complex Networks under FlexRay Protocols: A Neural-Network-Based Approach. *IEEE Trans. Neural Netw. Learn. Syst.* **2025**, *36*, 4922–4933. https://doi.org/10.1109/TNNLS.2024.3377537.
126. Li, M.Y.; Liang, J.L. Set-Membership Estimation for Nonlinear 2-D Systems with Missing Measurements. *IEEE Trans. Circuits Syst. II Express Briefs* **2023**, *70*, 146–150. https://doi.org/10.1109/TCSII.2022.3203824.
127. Li, Y.D.; Cong, Y.R.; Dong, J.X. Existence and Completeness of Bounded Disturbance Observers: A Set-Membership Viewpoint. *IEEE Trans. Autom. Control* **2025**, *70*, 2762–2769. https://doi.org/10.1109/TAC.2024.3496581.
128. Li, Y.D.; Cong, Y.R.; Wang, S.M.; et al. Asymptotic Boundedness of Distributed Set-Membership Filtering. *IEEE Trans. Autom. Control* **2026**, in press. https://doi.org/10.1109/TAC.2026.3694609.
129. Song, Y.H.; Shao, S.K.; Han, F.; et al. Optimized Distributed Filtering over Binary Sensor Network: A Dynamic Event-Triggering Protocol with Token Bucket Specifications. *IEEE Trans. Cybern.* **2026**, in press. https://doi.org/10.1109/TCYB.2026.3668877.
130. Xie, M.L.; Ding, D.R.; Ge, X.H.; et al. Distributed Platooning Control of Automated Vehicles Subject to Replay Attacks Based on Proportional Integral Observers. *IEEE/CAA J. Autom. Sin.* **2024**, *11*, 1954–1966. https://doi.org/10.1109/JAS.2022.105941.
131. Yang, F.; Dong, H.L.; Shen, Y.X.; et al. Protocol-Based Non-Fragile State Estimation for Delayed Recurrent Neural Networks Subject to Replay Attacks. *IEEE/CAA J. Autom. Sin.* **2024**, *11*, 249–251. https://doi.org/10.1109/JAS.2023.123936.
132. Dai, D.Y.; Li, J.H.; Zhang, J.N.; et al. Energy-Harvesting Recursive Filtering for Delayed Systems with Amplify-and-Forward Relays: Cooperative Communication Manner. *J. Franklin Inst.* **2024**, *361*, 107265. https://doi.org/10.1016/j.jfranklin.2024.107265.
133. Xu, C.; Sun, J.; Shen, Y.X.; et al. Fault Estimation for Complex Networks with Uncertain Couplings and Randomly Occurring Faults: A Relay-Aided Strategy. *J. Franklin Inst.* **2025**, *362*, 108157. https://doi.org/10.1016/j.jfranklin.2025.108157.
134. Tan, H.L.; Shen, B.; Li, Q.; et al. Recursive Filtering for Stochastic Systems with Filter-and-Forward Successive Relays. *IEEE/CAA J. Autom. Sin.* **2024**, *11*, 1202–1212. https://doi.org/10.1109/JAS.2023.124110.
135. Yang, C.Y.; Liang, J.L. Probability-Guaranteed Filtering for 2-D Nonlinear Systems over Full-Duplex Relay Network with Energy Harvesting Constraint. *IEEE Trans. Syst. Man Cybern. Syst.* **2025**, *55*, 5812–5826. https://doi.org/10.1109/TSMC.2025.3573985.
136. Yang, J.J.; Ma, L.F.; Chen, Y.G. Recursive Distributed Secure State Estimation for Nonlinear Systems with Amplify-and-Forward Relays and Stochastic Measurement Delays over Sensor Network. *IEEE Trans. Signal Inf. Process. Netw.* **2026**, *12*, 187–198. https://doi.org/10.1109/TSIPN.2026.3658854.
137. Fan, J.R.; Xu, N.W.; Wan, X.B.; et al. Finite-Time Asynchronous State Estimation for Two-Time-Scale Complex Networks with Sojourn Probabilities and Event-Based AF Relay Protocols. *Neurocomputing* **2026**, *659*, 131807. https://doi.org/10.1016/j.neucom.2025.131807.
138. Zhang, Y.; Ma, L.F.; Gao, C. Consensus Control of Multiagent Systems under DoS Attacks: A Dynamic-Key-Based Secure Scheme. *IEEE Trans. Cybern.* **2026**, in press. https://doi.org/10.1109/TCYB.2026.3651535.
139. Hu, J.; Li, J.X.; Liu, G.P.; et al. Optimized Distributed Filtering for Time-Varying Saturated Stochastic Systems with Energy Harvesting Sensors over Sensor Networks. *IEEE Trans. Signal Inf. Process. Netw.* **2023**, *9*, 412–426. https://doi.org/10.1109/TSIPN.2023.3288301.
140. Han, F.; Wang, Z.D.; Dong, H.L.; et al. Distributed H_∞-Consensus Estimation for Random Parameter Systems over Binary Sensor Networks: A Local Performance Analysis Method. *IEEE Trans. Netw. Sci. Eng.* **2023**, *10*, 2334–2346. https://doi.org/10.1109/TNSE.2023.3246427.
141. Tong, L.Y.; Liang, J.L. Fault Detectability of Asynchronous Delayed Boolean Control Networks with Sampled-Data Control. *IEEE Trans. Netw. Sci. Eng.* **2024**, *11*, 724–735. https://doi.org/10.1109/TNSE.2023.3317867.
142. Ma, L.F.; Yi, X.J.; Gao, C. Distributed Innovation-Constrained State Estimation over Sensor Networks: A State-Dependent Coefficient Parameterization Approach. *IEEE Trans. Autom. Control* **2026**, in press. https://doi.org/10.1109/TAC.2026.3680120.
143. Zhao, Z.Y.; Wang, Z.D.; Liang, J.L.; et al. Zonotopic Set-Membership Fusion Estimation for Complex Networks: A Buffer-Aided Strategy. *IEEE Trans. Cybern.* **2026**, *56*, 1465–1478. https://doi.org/10.1109/TCYB.2025.3626066.
144. Xia, N.; Yang, F.W.; Han, Q.L. Distributed Networked Set-Membership Filtering with Ellipsoidal State Estimations. *Inf. Sci.* **2018**, *432*, 52–62. https://doi.org/10.1016/j.ins.2017.12.010.
145. Hu, C.Z.; Xie, X.P.; Ding, S.B.; et al. Distributed Set-Membership Fusion Estimation for Complex Networks with Communication Constraints. *IEEE Trans. Autom. Sci. Eng.* **2025**, *22*, 3877–3886. https://doi.org/10.1109/TASE.2024.3401740.
146. Hu, S.Q.; Liu, Z.Y.; Li, M.Y.; et al. CADM+: Confusion-Based Learning Framework with Drift Detection and Adaptation for Real-Time Safety Assessment. *IEEE Trans. Neural Netw. Learn. Syst.* **2025**, *36*, 5126–5139. https://doi.org/10.1109/TNNLS.2024.3369315.

147. Liu, Z.Y.; He, X. Contrastive Preference-Guided Active Learning Approach Based on Ranking Correlation for Real-Time Safety Assessment. *IEEE Trans. Autom. Sci. Eng.* **2025**, *22*, 17370–17381. https://doi.org/10.1109/TASE.2024.3401470.
148. Liu, M.; He, X.Z. Data-Driven Robust State Estimation Based on EK-SVSF. *Neurocomputing* **2026**, *675*, 132869. https://doi.org/10.1016/j.neucom.2026.132869.
149. Liu, Z.Y.; He, X.; Huang, B.; et al. Incremental Learning-Enabled Fault Diagnosis of Dynamic Systems: A Comprehensive Review. *IEEE Trans. Cybern.* **2025**, *55*, 5633–5649. https://doi.org/10.1109/TCYB.2025.3586643.
150. Li, W.; Han, P.Y.; Liu, Z.Y.; et al. Online Minority Cluster-Informed Semi-Supervised Random Vector Functional Link Network for Multi-Mode Intermittent Fault Diagnosis. *IEEE Trans. Ind. Cyber-Phys. Syst.* **2024**, *2*, 404–411. https://doi.org/10.1109/TICPS.2024.3434788.
151. Guo, Y.Q.; He, X. Active Fault Diagnosis for Stochastic Systems under Accuracy-Limited Sensors. *IEEE Trans. Instrum. Meas.* **2024**, *73*, 3521809. https://doi.org/10.1109/TIM.2024.3398099.
152. Fan, S.T.; Hu, J.; Chen, C.; et al. Distributed Fusion Filtering for Multi-Rate Nonlinear Systems with Random Sensor Failures under Event-Triggering Round-Robin-Like Scheme. *Syst. Control Lett.* **2024**, *190*, 105845. https://doi.org/10.1016/j.sysconle.2024.105845.