Citation information: DOI: 10.1109/TAC.2024.3521281, IEEE Transactions on Automatic Control

Unscented Kalman Filtering Over Full-Duplex Relay Networks Under Binary Encoding Schemes

Licheng Wang, Zidong Wang, Shuai Liu, and Daogang Peng

***Abstract*—In this paper, a modified unscented Kalman filter design algorithm is proposed for discrete-time stochastic nonlinear systems over full-duplex relay networks with binary encoding schemes. In order to enhance the transmission reliability, a full-duplex relay is deployed between sensors and the filter, and a self-interference cancellation scheme is introduced to eliminate the interference caused by the relay itself. To accommodate the digital communication manner, a binary encoding scheme is adopted, and a sequence of random variables obeying Bernoulli distribution is introduced to characterize statistical behaviors of the random bit flips. The objective of the addressed problem is to design an unscented Kalman filter over full-duplex relay networks with binary encoding schemes that reflects the impacts of the decoding error, the bit flips, and the full-duplex relay on the filtering performance. A sufficient condition is developed using the matrix inverse lemma to guarantee the exponential mean-square boundedness of the filtering error. Finally, a simulation study is carried out to demonstrate the effectiveness of the developed binary-encoding-based unscented Kalman filter over a full duplex network.**

***Index Terms*—Unscented Kalman filtering, full-duplex relay networks, binary encoding schemes, bit flips, exponential mean-square boundedness.**

I. Introduction

Considerable increase in research on the filtering problem has been witnessed in the past few decades from both the control systems and the signal processing communities [5], [13], [40]–[44]. Various filtering techniques have been proposed and applied to a variety of areas including target tracking, missile guidance and control systems, and fault detection [30], [31], [33], [38], [47]. Notably, the Kalman filtering algorithms have been recognized as an optimal filtering strategy for linear systems under the assumption of Gaussian noises in the sense of least mean square. However, for nonlinear systems, the traditional Kalman filtering algorithm is no longer applicable, which may lead to severe deterioration of filtering performance. As a result, alternative filtering schemes have been put forward for nonlinear systems with Gaussian noises, such as the extended Kalman filter (EKF) method, unscented Kalman filter (UKF) algorithm, and particle filter strategy [2], [9], [14]–[17], [19], [22].

Compared to the EKF algorithm, the UKF algorithm has proven to be an extremely powerful method for stochastic *nonlinear* systems. The UKF algorithm has obvious advantages including 1) effectively avoiding the decrease of filtering performance caused by the linearization error, 2) approximating the probability density function (rather than approximating the nonlinear function itself), 3) suiting for nondifferentiable nonlinearities, and 4) circumventing the calculation of the Jacobian matrix. As a result, the UKF algorithm has attracted ever-growing research attention, and various modified UKF algorithms have been proposed to cope with imperfect signal transmissions [12], [20]. For instance, in [25], the Round-Robin protocol has been incorporated with the UKF algorithm to decrease the communication traffic of the resource-constrained network, where the period scheduling characteristic of the Round-Robin protocol has been reflected. In [26], the UKF algorithm has been applied to the neural networks, where the remote estimator can only receive partial components of the measurement output.

In the remote estimation problem, the measurement signals usually need to be transmitted over a long-distance transmission channel [28], [39]. However, because the sensor's communication capacity is limited and the path loss is nonnegligible, the remote estimator may fail to receive the signal sent by the sensor. In this case, relays are typically deployed between the sensor and the estimator, which are used to amplify and forward the measurement signal. Various relays are commonly used, including amplify-and-forward relays, decode-and-forward relays, and so on [1], [11], [18], [23], [32], which have been pervasively put into practice in various networked systems. For example, in [35], the recursive filtering problem has been discussed for stochastic uncertain systems under the amplify-and-forward relays.

On the other hand, the mobile communication system is usually divided into simplex communication, full-duplex communication, and half-duplex communication [8], [45]. In recent years, full-duplex relays have attracted some research attention, where the relays can receive and send signals at the same time. Consequently, it is of vital importance to appropriately deal with the self-inference signal sent by the relay itself. For example, in [34], a self-inference cancellation technique has been adopted to eliminate the impact of the self-inference caused by the full-duplex relays.

With the popularity of network technology, the digital communication era has arrived with evident advantages in strong anti-interference capability and high reliability compared to the analog pathway [3], [6], [27], [46]. For digital communication equipment, only a finite number of bits can be processed at each execution point, and therefore, the signal needs to be truncated to meet the bit requirement/constraint. After truncation, the signal is encoded into binary codewords to follow the digital communication manner, which is usually referred to as the binary encoding scheme. This encoding technique has been recognized as the most effective and has attracted much research attention [36], [37].

Due to the complicated and noisy communication circumstance, the communication quality cannot be guaranteed during the codeword transmission. As such, bit flips often occur in a random fashion, which can be viewed as one of the main reasons for data distortion that deserves further investigation. Recently, the binary encoding scheme with random bit flips has gained some primary research attention in the filtering problem [21], [48]. For example, in [24], the binary encoding scheme has been expanded to address the moving-horizon estimation problem for linear networks, while in [7], it has been applied to the consensus control problem for multi-agent systems.

Summarized from the above discussions, this paper focuses on

This work was supported in part the National Natural Science Foundation of China under Grants 62473247, 62473261 and 62373241, the Natural Science Foundation of Shanghai of China under Grants 24ZR1425900 and 24ZR1453800, the Royal Society of the UK, and the Alexander von Humboldt Foundation of Germany. *(Corresponding author: Daogang Peng.)*

L. Wang and D. Peng are with the College of Automation Engineering, Shanghai University of Electric Power, Shanghai 200090, China. (Email: wanglicheng1217@163.com)

Z. Wang is with the Department of Computer Science, Brunel University London, Uxbridge, Middlesex, UB8 3PH, United Kingdom. (Email: Zidong.Wang@brunel.ac.uk)

S. Liu is with the College of Science, University of Shanghai for Science and Technology, Shanghai 200093, China.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication.
Citation information: DOI: 10.1109/TAC.2024.3521281, IEEE Transactions on Automatic Control

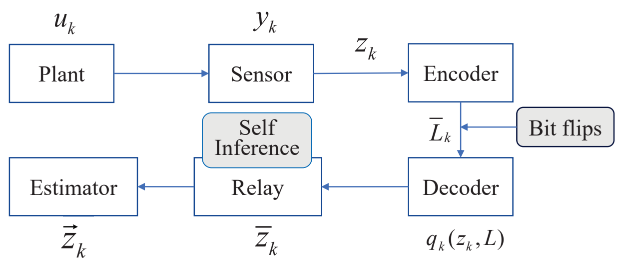

Fig. 1: Block diagram for the remote state estimation problem

the unscented Kalman filtering problem for a class of discrete-time stochastic nonlinear systems over a full-duplex network with the binary encoding scheme subject to random bit flips. The main challenges stem from the following two aspects: 1) establishing a unified measurement model for stochastic nonlinear systems over full-duplex relays with the binary encoding scheme is essentially difficult; and 2) designing an unscented Kalman filter to reflect the impacts of full-duplex replay and the binary encoding scheme on filtering performance is nontrivial. To overcome these two challenges, the main contributions of this paper can be highlighted as follows.

- A rather comprehensive system model is considered, which covers general nonlinearities, Gaussian noises, full-duplex relays, binary encoding schemes, and random bit flips.
- A new unscented Kalman filter algorithm is proposed to account for the impacts of full-duplex relay and binary encoding errors on the filtering error.
- A sufficient condition is established using the matrix inverse lemma to guarantee the exponential mean-square boundedness (EMSB)of the filtering error.

II. Problem Formulation

A. System Model

In this paper, the following stochastic nonlinear system is considered:

$$\begin{cases} u_{k+1} = A_k u_k + f(u_k) + w_k \\ y_k = h(u_k) + v_k \end{cases} \tag{1}$$

where $u_k \in \mathbb{R}^n$ and $y_k \in \mathbb{R}^m$ denote, respectively, the system state to be estimated and the measurement output. $w_k \in \mathbb{R}^n$ and $v_k \in \mathbb{R}^m$ are unrelated zero-mean Gaussian white noise sequences with variances $R_{1,k} = \mathbb{E}\{w_k w_k^T\}$ and $R_{2,k} = \mathbb{E}\{v_k v_k^T\}$ where $R_{1,k}$ and $R_{2,k}$ are known positive-definite matrices. $f(\cdot) : \mathbb{R}^n \to \mathbb{R}^n$ and $h(\cdot) : \mathbb{R}^n \to \mathbb{R}^m$ are nonlinear functions with $f(0) = 0$ and $h(0) = 0$. A_k is a known time-varying matrix.

It should be noted that the focus of this paper is the remote state estimation issue for a stochastic nonlinear system over a full-duplex relay network equipped with a binary encoding scheme, as shown in Fig. 1. Specifically, the measurement signal is first transmitted to the relay side via a digital communication channel with a certain transmission power, and the binary encoding scheme is employed to encode the transmission signal into binary codewords. However, due to the unreliability of the digital network and undesired channel noises, probabilistic bit flips are taken into consideration in the binary encoding process. At the relay side, the received binary codewords are decoded, amplified, and then forwarded to the filter side. Based on the above discussions, the following mathematical descriptions are provided.

The measurement signal is first transmitted to the relay side with certain transmission power and the transmitted signal is then characterized by the following form:

$$z_k = \sqrt{l_k^s t_k^{sr}} y_k + v_k^s \tag{2}$$

where $z_k \in \mathbb{R}^m$ is the transmitted signal, l_k^s is the transmission power, t_k^{sr} denotes the stochastic channel coefficient for the sensor-to-relay network with $\mathbb{E}\{t_k^{sr}\} = \bar{t}_k^{sr}$ and $\mathbb{E}\{(t_k^{sr} - \bar{t}_k^{sr})^2\} = \sigma_k^{sr}$ where $\bar{t}_k^{sr}$ and σ_k^{sr} are known positive scalars. $v_k^s \in \mathbb{R}^m$ stands for the transmission noise satisfying the Gaussian distribution $\mathbb{E}\{v_k^s\} = 0$ and $\mathbb{E}\{v_k^s (v_k^s)^T\} = R_{3,k}$ with $R_{3,k}$ being a known positive-definite matrix.

B. Binary Encoding Scheme

Suppose that a scalar signal g_k falls into a given interval $\mathcal{G} \triangleq [-\bar{g}, \bar{g}]$. Here, $\mathcal{G}$ is uniformly grouped into $2^L - 1$ small intervals denoted by $[x_{1,i}, x_{2,i}]$ where $x_{1,i}$ can be represented as $x_{1,i} = -\bar{g} + \frac{2\bar{g}}{2^L-1}(i-1)$ $(i = 1, 2, \ldots, 2^L - 1)$ and the length of each interval is expressed as $\pi \triangleq \frac{2\bar{g}}{2^L-1}$.

Because of the limited communication bandwidth, only finite bits can be transmitted to the communication network. This means that the original signal g_k needs to be truncated to meet the bandwidth constraint. Without loss of generality, we assume that L bits are permitted for transmission at each time instant. Different from the traditional fixed truncation technique, in this paper, a stochastic truncation function $\mathcal{R} : \ g_k \to q_k(g_k, L)$ is utilized to map g_k to a truncated signal $q_k(g_k, L)$ obeying the following law:

$$\begin{cases} \text{Prob}\{q_k(g_k, L) = x_{1,i}\} = 1 - \xi_k \\ \text{Prob}\{q_k(g_k, L) = x_{2,i}\} = \xi_k \end{cases} \tag{3}$$

where $\xi_k = \frac{g_k - x_{1,i}}{\pi} \in [0, 1)$.

Defining the truncation error as $\delta_k(g_k, L) \triangleq g_k - q_k(g_k, L)$ and considering $g_k = x_{1,i} + \xi_k \pi$, we can easily obtain from (3) that

$$\begin{cases} \text{Prob}\{\delta_k(g_k, L) = \xi_k \pi\} = 1 - \xi_k \\ \text{Prob}\{\delta_k(g_k, L) = (\xi_k - 1)\pi\} = \xi_k. \end{cases} \tag{4}$$

Then, it follows from (4) that the mean of the truncation error $\delta_k(g_k, L)$ is 0 and its variance is bounded by $\frac{\pi^2}{4}$, that is, $\mathbb{E}\{\delta_k(g_k, L)\} = 0$ and $\mathbb{E}\{\delta_k^2(g_k, L)\} \le \frac{\pi^2}{4}$.

In what follows, denote $q_k(g_k, L)$ as a linear combination of the first L terms of the series $\{2^{i-1}\pi\}$, that is, $q_k(g_k, L) = -\bar{g} + \sum_{i=1}^{L} l_{i,g_k} 2^{i-1}\pi$. Moreover, introduce the notation $\mathcal{L}_{g_k} \triangleq \{l_{1,g_k}, l_{2,g_k}, \ldots, l_{L,g_k}\}$ as the codeword sequence with $l_{i,g_k} \in \{0, 1\}$ $(i = 1, 2, \ldots, L)$.

During the transmission of the codeword sequence $\mathcal{L}_{g_k}$ via a memoryless binary symmetric channel, assume that the bit flip occurs in a random manner due to the noisy channel environment. To this end, a Bernoulli distributed random sequence $\zeta_{i,k}$ $(i = 1, 2, \ldots, L)$ is introduced which obeys the following distribution:

$$\text{Prob}\{\zeta_{i,k} = 1\} = \bar{\zeta}, \ \text{Prob}\{\zeta_{i,k} = 0\} = 1 - \bar{\zeta} \tag{5}$$

where $\bar{\zeta} \in [0, 1]$ is a known scalar. $\zeta_{i,k} = 1$ means that the codeword $l_{i,k}$ flips and $\zeta_{i,k} = 1$ indicates that no flip occurs for the ith codeword. Denote the actually received codeword sequence of the relay as

$$\bar{\mathcal{L}}_{g_k} \triangleq \{\bar{l}_{1,g_k}, \bar{l}_{2,g_k}, \ldots, \bar{l}_{L,g_k}\} \tag{6}$$

with $\bar{l}_{i,g_k} = (1 - \zeta_{i,k}) l_{i,g_k} + \zeta_{i,k}(1 - l_{i,g_k})$, based on which the decoded signal of g_k can be denoted as

$$\bar{q}(\bar{\mathcal{L}}_{g_k}, L) \triangleq -\bar{g} + \sum_{i=1}^{L} \bar{l}_{i,g_k} 2^{i-1}\pi. \tag{7}$$

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication.
Citation information: DOI: 10.1109/TAC.2024.3521281, IEEE Transactions on Automatic Control

Specifically, if there is no flip occurring, one has $\bar{q}_k(\bar{\mathcal{L}}_{g_k}, L) = g_k$.

Based on the results in [24], it is not difficult to obtain that the mean and the variance of the decoding signal $\bar{q}_k(g_k, L)$ are, respectively,

$$\mathbb{E}\{\bar{q}_k(\bar{\mathcal{L}}_{g_k}, L)\} = (1 - 2\bar{\zeta})q_k(g_k, L) \tag{8}$$

and

$$\mathrm{Var}\{\bar{q}_k(\bar{\mathcal{L}}_{g_k}, L)\} = \bar{\zeta}(1 - \bar{\zeta})\frac{4\bar{g}^2(2^{2L} - 1)}{3(2^L - 1)^2}. \tag{9}$$

Here, the expectation has been taken with respect to the random variables $\zeta_{i,k}$. It should be pointed out that, due to the bit flips, there exists a distortion between $q_k(g_k, L)$ and $\bar{q}_k(\bar{\mathcal{L}}_{g_k}, L)$. To this end, we define a new signal $\hat{q}_k(\bar{\mathcal{L}}_{g_k}, L) \triangleq \frac{1}{1-2\bar{\zeta}}\bar{q}_k(\bar{\mathcal{L}}_{g_k}, L)$ instead of using $\bar{q}_k(\bar{\mathcal{L}}_{g_k}, L)$ to keep the unbiasedness of the distortion.

By now, we have explained the main transmission principles of the binary encoding scheme for scalar signals. It should be noted that this scheme is also suitable for vector signals in a componentwise manner, i.e. $q_k(g_k, L) = \mathrm{vec}\{q_k(g_{1,k}, L), q_k(g_{2,k}, L), \dots, q_k(g_{m,k}, L)\}$ where $g_{i,k}$ is the ith component of the vector g_k. Therefore, for a vector $b_k \in \mathbb{R}^m$, $q_k(b_k, L) \in \mathbb{R}^m$, $\bar{q}_k(\bar{\mathcal{L}}_{b_k}, L) \in \mathbb{R}^m$ and $\hat{q}_k(\bar{\mathcal{L}}_{b_k}, L) \in \mathbb{R}^m$.

Lemma 1: Define the decoding error as $d_k \triangleq q_k(z_k, L) - \hat{q}_k(\bar{\mathcal{L}}_{z_k}, L)$. d_k satisfies $\mathbb{E}\{d_k\} = 0$ and

$$\mathrm{Var}\{d_k\} = \frac{1}{(1 - 2\bar{\zeta})^2}\mathrm{Var}\{\bar{q}_k(\bar{\mathcal{L}}_{z_k}, L)\}. \tag{10}$$

Proof: It follows readily from $d_k \triangleq q_k(z_k, L) - \hat{q}_k(\bar{\mathcal{L}}_{z_k}, L)$ and $\mathbb{E}\{\bar{q}_k(\bar{\mathcal{L}}_{z_k}, L)\} = (1 - 2\bar{\zeta})q_k(z_k, L)$ as well as $\hat{q}_k(\bar{\mathcal{L}}_{z_k}, L) \triangleq \frac{1}{1-2\bar{\zeta}}\bar{q}_k(\bar{\mathcal{L}}_{z_k}, L)$ that

$$\begin{aligned}
\mathbb{E}\{d_k\} &= \mathbb{E}\{q_k(z_k, L) - \hat{q}_k(\bar{\mathcal{L}}_{z_k}, L)\} \\
&= \mathbb{E}\{q_k(z_k, L) - \frac{1}{1 - 2\bar{\zeta}}\bar{q}_k(\bar{\mathcal{L}}_{z_k}, L)\} \\
&= \mathbb{E}\{q_k(z_k, L)\} - \frac{1}{1 - 2\bar{\zeta}}\mathbb{E}\{\bar{q}_k(\bar{\mathcal{L}}_{z_k}, L)\} \\
&= 0.
\end{aligned} \tag{11}$$

Then, one has

$$\begin{aligned}
&\mathrm{Var}\{d_k\} \\
=&\mathbb{E}\{(q_k(z_k, L) - \hat{q}_k(\bar{\mathcal{L}}_{z_k}, L))(q_k(z_k, L) - \hat{q}_k(\bar{\mathcal{L}}_{z_k}, L))^T\} \\
=&\mathbb{E}\{q_k(z_k, L)q_k^T(z_k, L)\} - \mathbb{E}\{q_k(z_k, L)\hat{q}_k^T(\bar{\mathcal{L}}_{z_k}, L)\} \\
&- \mathbb{E}\{\hat{q}_k(\bar{\mathcal{L}}_{z_k}, L)q_k^T(z_k, L)\} + \mathbb{E}\{\hat{q}_k(\bar{\mathcal{L}}_{z_k}, L)\hat{q}_k^T(\bar{\mathcal{L}}_{z_k}, L)\} \\
=&\mathbb{E}\{q_k(z_k, L)q_k^T(z_k, L)\} \\
&- \frac{1}{1 - 2\bar{\zeta}}\mathbb{E}\{q_k(z_k, L)\bar{q}_k^T(\bar{\mathcal{L}}_{z_k}, L)\} \\
&- \frac{1}{1 - 2\bar{\zeta}}\mathbb{E}\{\bar{q}_k(\bar{\mathcal{L}}_{z_k}, L)q_k^T(z_k, L)\} \\
&+ \frac{1}{(1 - 2\bar{\zeta})^2}\mathbb{E}\{\bar{q}_k(\bar{\mathcal{L}}_{z_k}, L)\bar{q}_k^T(\bar{\mathcal{L}}_{z_k}, L)\}.
\end{aligned} \tag{12}$$

Based on the fact $\mathrm{Var}\{x\} = \mathbb{E}\{x^2\} - (\mathbb{E}\{x\})^2$, one has

$$\begin{aligned}
&\mathrm{Var}\{d_k\} \\
=& - \mathbb{E}\{q_k(z_k, L)q_k^T(z_k, L)\} \\
&+ \frac{1}{(1 - 2\bar{\zeta})^2}\mathbb{E}\{\bar{q}_k(\bar{\mathcal{L}}_{z_k}, L)\bar{q}_k^T(\bar{\mathcal{L}}_{z_k}, L)\} \\
=& - \mathbb{E}\{q_k(z_k, L)q_k^T(z_k, L)\} \\
&+ \frac{1}{(1 - 2\bar{\zeta})^2}\mathrm{Var}\{\bar{q}_k(\bar{\mathcal{L}}_{z_k}, L)\} \\
&+ \frac{1}{(1 - 2\bar{\zeta})^2}\mathbb{E}\{\bar{q}_k(\bar{\mathcal{L}}_{z_k}, L)\}\mathbb{E}\{\bar{q}_k^T(\bar{\mathcal{L}}_{z_k}, L)\} \\
=&\frac{1}{(1 - 2\bar{\zeta})^2}\mathrm{Var}\{\bar{q}_k(\bar{\mathcal{L}}_{z_k}, L)\}.
\end{aligned} \tag{13}$$

This lemma is proofed. ■

C. Full-duplex relay Network

In this paper, the full-duplex relay-assisted communication scheme is employed to enhance the quality of the data transmission from the sensor to the filter. Moreover, taking the binary encoding as well as bit flips into consideration, the diagram of the signal transmission from the sensor to the filter is illustrated in Fig. 1, from which we can see that z_k is the input of the encoder and $\hat{q}_k(z_k, L)$ is the output of the decoder. After obtaining the decoding signal $\hat{q}_k(g_k, L)$, because of the self-interference caused by the full-duplex relay, the signal received by the relay can be described as

$$\bar{z}_k = \hat{q}_k(\bar{\mathcal{L}}_{z_k}, L) + \sqrt{l_{k-1}^r}t_k^{rr}m_k + m_k^c \tag{14}$$

where $m_k \in \mathbb{R}^m$ and $m_k^c \in \mathbb{R}^m$ are the self-interference and the self-interference cancellation, l_k^r is the transmission power of the full-duplex relay and t_k^{rr} is the stochastic coefficient of the relay-to-relay channel satisfying $\mathbb{E}\{t_k^{rr}\} = \bar{t}_k^{rr}$ and $\mathbb{E}\{(t_k^{rr} - \bar{t}_k^{rr})^2\} = \sigma_k^{rr}$ with $\bar{t}_k^{rr}$ and σ_k^{rr} being known parameters.

Inspired by [10], [34], m_k satisfies the following condition:

$$m_k = \begin{cases} 0, & k = 0 \\ \beta_{k-1}\bar{z}_{k-1}, & k > 0 \end{cases} \tag{15}$$

with β_k being a known amplification factor. To remit the negative effect of the self-interference, m_k^c is introduced with the following form:

$$m_k^c = \begin{cases} 0, & k = 0 \\ -\sqrt{l_{k-1}^r}\bar{t}_k^{rr}m_k, & k > 0. \end{cases} \tag{16}$$

Remark 1: Due to the influence of the self-inference, the actual signal received by the relay, which is denoted as $\bar{z}_k$, not only contains the decoded signal $\hat{q}_k(\bar{\mathcal{L}}_{z_k}, L)$, but also involves the signal m_k sent by the relay itself at the last time step $k-1$ (i.e., the self inference term $m_k \triangleq \beta_{k-1}\bar{z}_{k-1}$). Since the self-inference signal m_k is one time-step delayed, the transmission power of the full-duplex relay is accordingly set as the one at the time step $k-1$, namely, l_{k-1}^r.

Next, the signal $\bar{z}_k$ is amplified and forwarded to the remote estimator, and the signal actually received by the remote estimator can then be described as follows:

$$\vec{z}_k = \beta_k\sqrt{l_{k-1}^r}t_k^{rf}\bar{z}_k + v_k^f \tag{17}$$

where $\vec{z}_k \in \mathbb{R}^m$ is the filter input and t_k^{rf} is the stochastic coefficient of the relay-to-filter channel, which satisfies $\mathbb{E}\{t_k^{rf}\} = \bar{t}_k^{rf}$ and $\mathbb{E}\{(t_k^{rf} - \bar{t}_k^{rf})^2\} = \sigma_k^{rf}$ with $\bar{t}_k^{rf}$ and σ_k^{rf} being given scalars. $v_k^f \in \mathbb{R}^m$ is a white noise sequence which is Gaussian and satisfies $\mathbb{E}\{v_k^f\} = 0$ and $\mathbb{E}\{v_k^f(v_k^f)^T\} = R_{4,k}$ with $R_{4,k}$ being a known positive-definite matrix.

It is assumed that all random variables u_0, w_k, v_k, v_k^s, v_k^f, t_k^{sr}, t_k^{rr}, t_k^{rf} and $\zeta_{i,k}$ $(i = 1, 2, \dots, 2^L - 1)$ are unrelated with each other.

It is not difficult to conclude from the definitions of d_k and $\delta_k(z_k, L)$ that $\hat{q}_k(\bar{\mathcal{L}}_{z_k}, L) = z_k - \delta_k(z_k, L) - d_k$. For the sake of the sequel expression convenience, we use δ_k to replace $\delta_k(z_k, L)$. Then, according to (14), one has

$$\begin{aligned}
\vec{z}_k =&b_k h(u_k) + \beta_k l_{k-1}^r t_k^{rf}(t_k^{rr} - \bar{t}_k^{rr})m_k \\
&- \beta_k\sqrt{l_{k-1}^r}t_k^{rf}\delta_k - \beta_k\sqrt{l_{k-1}^r}t_k^{rf}d_k + \bar{\omega}_k.
\end{aligned} \tag{18}$$

where $b_k \triangleq \beta_k\sqrt{l_{k-1}^r l_k^s}t_k^{rf}t_k^{sr}$ and $\bar{\omega}_k \triangleq \beta_k\sqrt{l_{k-1}^r l_k^s}t_k^{rf}t_k^{sr}v_k + \beta_k\sqrt{l_{k-1}^r}t_k^{rf}v_k^s + v_k^f$.

Remark 2: Compared with the existing remote state estimation issue, the main novelties of the considered problem lie in that

Citation information: DOI: 10.1109/TAC.2024.3521281, IEEE Transactions on Automatic Control

1) the full-duplex relay is used to send and forward the signal measured by the sensor for the long-distance transmission and 2) the binary encoding scheme is employed to comply with the digital network in the sensor-to-relay channel. To be more specific, the signal transmission mainly divides into the following steps. First, the raw measurement signal y_k is converted to the signal z_k according to (2) by endowing certain transmission power. Then, z_k is encoded by using the binary encoding scheme so as to comply with the digital channel and a stochastic truncation scheme is proposed in (3)–(4). Subsequently, a sequence of Bernoulli distributed random variables is introduced to cope with bit flits caused by the complicated and noisy channel in (5)–(7). After then, the full-duplex relay receives the decoding signal $\hat{q}_k(z_k, L)$ and the self-inference signal. As such, a self-inference cancellation scheme (15)–(16) is introduced to eliminate the effect of the self-inference of the relay. Finally, the filter receives the signal sent by the relay, i.e., $\vec{z}_k$ in (17).

III. Unscented Kalman Filter Design

In this section, we are going to propose a modified unscented Kalman filter algorithm for the stochastic nonlinear systems over the full-duplex relay network with the binary encoding scheme subject to random bit flips.

Before proceeding, we give the following lemma.

Lemma 2: By defining $M_k \triangleq \mathbb{E}\{m_k m_k^T\}$, one derives

$$\begin{aligned} M_{k+1} =& \beta_k^2 l_{k-1}^r \sigma_k^{rr} M_k + \frac{\beta_k^2}{(1-2\bar{\zeta})^2}\mathrm{Var}\{\bar{q}_k(\bar{\mathcal{L}}_{z_k}, L)\} \\ &+ \beta_k^2 q_k(z_k, L) q_k^T(z_k, L). \end{aligned} \tag{19}$$

Proof: It follows readily from (14)-(15) that

$$\begin{aligned} M_{k+1} =& \beta_k^2 \mathbb{E}\{\bar{z}_k \bar{z}_k^T\} \\ =& \beta_k^2 \mathbb{E}\{(\hat{q}_k(\bar{\mathcal{L}}_{z_k}, L) + \sqrt{l_{k-1}^r} t_k^{rr} m_k - m_k^c) \\ &\times (\hat{q}_k(\bar{\mathcal{L}}_{z_k}, L) + \sqrt{l_{k-1}^r} t_k^{rr} m_k - m_k^c)^T\} \\ =& \beta_k^2 \mathbb{E}\{(\hat{q}_k(\bar{\mathcal{L}}_{z_k}, L) + \sqrt{l_{k-1}^r}(t_k^{rr} - \bar{t}_k^{rr}) m_k) \\ &\times (\hat{q}_k(\bar{\mathcal{L}}_{z_k}, L) + \sqrt{l_{k-1}^r}(t_k^{rr} - \bar{t}_k^{rr}) m_k)^T\} \\ =& \beta_k^2 \mathbb{E}\{\hat{q}_k(\bar{\mathcal{L}}_{z_k}, L)\hat{q}_k^T(\bar{\mathcal{L}}_{z_k}, L)\} + \beta_k^2 l_{k-1}^r \sigma_k^{rr} M_k \\ =& \frac{\beta_k^2}{(1-2\bar{\zeta})^2}\mathbb{E}\{\bar{q}_k(\bar{\mathcal{L}}_{z_k}, L)\bar{q}_k^T(\bar{\mathcal{L}}_{z_k}, L)\} \\ &+ \beta_k^2 l_{k-1}^r \sigma_k^{rr} M_k. \end{aligned} \tag{20}$$

According to the fact $\mathrm{Var}\{x\} = \mathbb{E}\{x^2\} - (\mathbb{E}\{x\})^2$, one has

$$\begin{aligned} &\frac{\beta_k^2}{(1-2\bar{\zeta})^2}\mathbb{E}\{\bar{q}_k(\bar{\mathcal{L}}_{z_k}, L)\bar{q}_k^T(z_k, L)\} \\ =& \frac{\beta_k^2}{(1-2\bar{\zeta})^2}(\mathrm{Var}\{\bar{q}_k(\bar{\mathcal{L}}_{z_k}, L)\} \\ &+ \mathbb{E}\{\bar{q}_k(\bar{\mathcal{L}}_{z_k}, L)\}\mathbb{E}\{\bar{q}_k^T(\bar{\mathcal{L}}_{z_k}, L)\}) \\ =& \frac{\beta_k^2}{(1-2\bar{\zeta})^2}\mathrm{Var}\{\bar{q}_k(\bar{\mathcal{L}}_{z_k}, L)\} + \beta_k^2 q_k(z_k, L) q_k^T(z_k, L). \end{aligned} \tag{21}$$

Therefore, the proof is complete. ■

Denote by $\hat{u}_{k+1|k}$ and $\hat{u}_{k+1}$ the one-step prediction and the estimation for the state u_{k+1}, respectively. Then, define the initial values $\mathbb{E}\{u_0\} = \bar{u}_0$ and $\hat{P}_0 = \mathbb{E}\{(u_0 - \hat{u}_0)(u_0 - \hat{u}_0)^T\}$.

Based on the obtained signal $\vec{z}_k$, next, we shall provide a modified algorithm to design the unscented Kalman filter for the stochastic nonlinear system (1) over the full-duplex relay network with the binary encoding scheme. The following four steps of the algorithm are summarized.

Step 1. At each time instant k $(k \geq 0)$, select $2n+1$ sigma points $\varrho_{i,k}$ $(i = 0, 1, 2, \ldots, 2n)$ based on the known values $\hat{u}_k$ and $\hat{P}_k$ with the following rule:

$$\varrho_{i,k} = \begin{cases} \hat{u}_k, & i = 0 \\ \hat{u}_k + \varpi\phi_{i,k}, & i = 1, 2, \ldots, n \\ \hat{u}_k - \varpi\phi_{i-n,k}, & i = n+1, n+2, \ldots, 2n \end{cases} \tag{22}$$

where ϖ is a positive scaling parameter and $\phi_{i,k} = (\sqrt{n\hat{P}_k})_i$ stands for the ith column the square root of $n\hat{P}_k$ by the Cholesky decomposition.

Step 2. Predict the one-step estimation and its error variance for the state as follows:

$$\begin{cases} \varrho_{i,k+1|k} = A_k \varrho_{i,k} + f(\varrho_{i,k}), \quad i = 0, 1, \ldots, 2n \\ \hat{u}_{k+1|k} = \sum_{i=0}^{2n} \nu_i \varrho_{i,k+1|k} \\ \hat{P}_{k+1|k} = \sum_{i=0}^{2n} \nu_i (\varrho_{i,k+1|k} - \hat{u}_{k+1|k})(\varrho_{i,k+1|k} - \hat{u}_{k+1|k})^T \\ \qquad + R_{1,k}. \end{cases} \tag{23}$$

Then, it follows from (23) and (14) that the prediction measurement and its error covariance are obtained as follows:

$$\begin{cases} \hat{z}_{i,k+1|k} = \bar{b}_{k+1} h(\varrho_{i,k+1|k}), \quad i = 0, 1, \ldots, 2n \\ \check{z}_{k+1|k} = \sum_{i=0}^{2n} \nu_i \hat{z}_{i,k+1|k} \\ \hat{P}_{k+1}^{zz} = \sum_{i=0}^{2n} \nu_i (\hat{z}_{i,k+1|k} - \check{z}_{k+1|k})(\hat{z}_{i,k+1|k} - \check{z}_{k+1|k})^T \\ \qquad + (\beta_{k+1} l_k^r)^2 \bar{\sigma}_{k+1}^{rf} \sigma_{k+1}^{rr} M_{k+1} \\ \qquad + \beta_{k+1}^2 l_k^r \bar{\sigma}_{k+1}^{rf} R_{3,k+1} + \frac{1}{4}\beta_{k+1}^2 l_k^r \bar{\sigma}_{k+1}^{rf} \pi^2 I \\ \qquad + \beta_{k+1}^2 l_k^r l_{k+1}^s \bar{\sigma}_{k+1}^{rf} \bar{\sigma}_{k+1}^{sr} R_{2,k+1} \\ \qquad + \beta_{k+1}^2 l_k^r \bar{\sigma}_{k+1}^{rf} \mathrm{Var}\{d_{k+1}\} + R_{4,k+1} \\ \hat{P}_{k+1}^{uz} = \sum_{i=0}^{2n} \nu_i (\varrho_{i,k+1|k} - \hat{u}_{k+1|k})(\varrho_{i,k+1|k} - \hat{u}_{k+1|k})^T \end{cases} \tag{24}$$

where $\bar{b}_k \triangleq \beta_k \sqrt{l_{k-1}^r l_k^s} \bar{t}_k^{rf} \bar{t}_k^{sr}$, $\bar{\sigma}_k^{rf} \triangleq (\bar{t}_k^{rf})^2 + \sigma_k^{rf}$, $\bar{\sigma}_k^{sr} \triangleq (\bar{t}_k^{sr})^2 + \sigma_k^{sr}$, $\nu_0 \triangleq 1 - \frac{1}{\varpi^2}$ and $\nu_i \triangleq \frac{1}{2n\varpi^2}$ $(i = 1, 2, \ldots, 2n)$.

Step 3. Based on the obtained $\vec{z}_{k+1}$ and the traditional Kalman filter structure, we have the following update formula:

$$\begin{cases} \check{K}_{k+1} = \hat{P}_{k+1}^{uz}(\hat{P}_{k+1}^{zz})^{-1} \\ \hat{u}_{k+1} = \hat{u}_{k+1|k} + \check{K}(\vec{z}_{k+1} - \check{z}_{k+1|k}) \\ \hat{P}_{k+1} = \hat{P}_{k+1|k} - \check{K}_{k+1}(\hat{P}_{k+1}^{uz})^T. \end{cases} \tag{25}$$

Step 4. Repeat the above three steps at next time instant.

IV. Boundedness Analysis

By now, we have developed a new unscented Kalman filtering algorithm for the stochastic nonlinear systems over the full-duplex relay network with the binary encoding scheme. Next, we shall pay our attention on the boundedness analysis of the filtering error.

Denote by $\tilde{u}_{k+1|k} \triangleq u_{k+1} - \hat{u}_{k+1|k}$, $\tilde{u}_{k+1} \triangleq u_{k+1} - \hat{u}_{k+1}$ and $\tilde{z}_{k+1} \triangleq \vec{z}_{k+1} - \check{z}_{k+1|k}$ the one-step prediction error, the filtering error and the measurement prediction error, respectively. Then, by means

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication.
Citation information: DOI: 10.1109/TAC.2024.3521281, IEEE Transactions on Automatic Control

of the linearization technique, the following error dynamics can be derived

$$\begin{cases} \tilde{u}_{k+1|k} = (A_k + \Theta_k C_k)\tilde{u}_k + w_k \\ \tilde{z}_{k|k-1} = \bar{b}_k \Upsilon_k H_k \tilde{u}_{k|k-1} + (b_k - \bar{b}_k)h(u_k) \\ \quad + \beta_k l^r_{k-1} t^{rf}_k (t^{rr}_k - \bar{t}^{rr}_k) m_k \\ \quad - \beta_k \sqrt{l^r_{k-1}} t^{rf}_k \delta_k - \beta_k \sqrt{l^r_{k-1}} t^{rf}_k d_k + \bar{\omega}_k \end{cases} \tag{26}$$

where $C_k \triangleq \frac{\partial f(u)}{\partial u}\big|_{u=\hat{u}_k}$ and $H_k \triangleq \frac{\partial h(u)}{\partial u}\big|_{u=\hat{u}_{k|k-1}}$ are two Jacobian matrices. $\Theta_k \triangleq \mathrm{diag}\{\theta_{1,k}, \theta_{2,k}, \ldots, \theta_{n,k}\}$ and $\Upsilon_k \triangleq \mathrm{diag}\{\gamma_{1,k}, \gamma_{2,k}, \ldots, \gamma_{m,k}\}$ are used to characterized the linearization errors.

Assumption 1: The nonlinear function $h(\cdot): \mathbb{R}^n \to \mathbb{R}^m$ satisfies the condition $\|h(x)\| \le c_1\|x\| + c_2$, where c_1 and c_2 are known positive scalars.

It is not difficult to see from (25) that

$$\tilde{u}_{k+1} = \tilde{u}_{k+1|k} - \check{K}_{k+1}\tilde{z}_{k+1|k}. \tag{27}$$

Combining (26) and (27) yields

$$\begin{aligned} \tilde{u}_{k+1} = & (I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})\tilde{u}_{k+1|k} \\ & - (b_{k+1} - \bar{b}_{k+1})\check{K}_{k+1}h(u_{k+1}) \\ & - \beta_{k+1} l^r_k t^{rf}_{k+1}(t^{rr}_{k+1} - \bar{t}^{rr}_{k+1})\check{K}_{k+1}m_{k+1} \\ & + \beta_{k+1}\sqrt{l^r_k} t^{rf}_{k+1}\check{K}_{k+1}\delta_{k+1} - \check{K}_{k+1}\bar{\omega}_{k+1} \\ & + \beta_{k+1}\sqrt{l^r_k} t^{rf}_{k+1}\check{K}_{k+1}d_{k+1} \end{aligned} \tag{28}$$

and further gives

$$\begin{aligned} \tilde{u}_{k+1} = & (I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})(A_k + \Theta_k C_k)\tilde{u}_k \\ & + (I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})w_k \\ & - (b_{k+1} - \bar{b}_{k+1})\check{K}_{k+1}h(u_{k+1}) \\ & - \beta_{k+1} l^r_k t^{rf}_{k+1}(t^{rr}_{k+1} - \bar{t}^{rr}_{k+1})\check{K}_{k+1}m_{k+1} \\ & + \beta_{k+1}\sqrt{l^r_k} t^{rf}_{k+1}\check{K}_{k+1}\delta_{k+1} \\ & + \beta_{k+1}\sqrt{l^r_k} t^{rf}_{k+1}\check{K}_{k+1}d_{k+1} \\ & - \check{K}_{k+1}\bar{\omega}_{k+1}. \end{aligned} \tag{29}$$

Then, let the covariance of $\tilde{u}_{k+1}$ be denoted as P_{k+1}, which can be derived from (29) as follows:

$$\begin{aligned} P_{k+1} = & (I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})(A_k + \Theta_k C_k)P_k \\ & \times (A_k + \Theta_k C_k)^T (I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})^T \\ & + (I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})R_{1,k} \\ & \times (I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})^T \\ & + \tilde{b}_{k+1}\check{K}_{k+1}\mathbb{E}\{h(u_{k+1})h^T(u_{k+1})\}\check{K}^T_{k+1} \\ & + \beta^2_{k+1}(l^r_k)^2\bar{\sigma}^{rf}_{k+1}\sigma^{rr}_{k+1}\check{K}_{k+1}M_{k+1}\check{K}^T_{k+1} \\ & + \beta^2_{k+1} l^r_k \bar{\sigma}^{rf}_{k+1}\check{K}_{k+1}\mathbb{E}\{\delta^2_{k+1}\}\check{K}^T_{k+1} \\ & + \beta^2_{k+1} l^r_k \bar{\sigma}^{rf}_{k+1}\check{K}_{k+1}\mathrm{Var}\{d_{k+1}\}\check{K}^T_{k+1} \\ & + \check{K}_{k+1}\bar{\Omega}_{k+1}\check{K}^T_{k+1} \end{aligned} \tag{30}$$

where $\tilde{b}_{k+1} \triangleq \beta^2_{k+1} l^r_k l^s_{k+1}\bar{\sigma}^{rf}_{k+1}\bar{\sigma}^{sr}_{k+1}$, $\bar{\Omega}_{k+1} \triangleq \beta^2_{k+1} l^r_k l^s_{k+1}\bar{\sigma}^{rf}_{k+1}\bar{\sigma}^{sr}_{k+1}R_{1,k+1} + \beta^2_{k+1} l^r_k \bar{\sigma}^{rf}_{k+1}R_{3,k+1} + R_{4,k+1}$.

It is inferred from Assumption 1 that there exists a positive scalar ϵ such that

$$\begin{aligned} & \mathbb{E}\{h(u_{k+1})h^T(u_{k+1})\} \\ \le & \mathbb{E}\{\|h(u_{k+1})\|^2 I\} \\ \le & \mathbb{E}\{(c_1\|u_{k+1}\| + c_2)\}I \\ \le & 2[c_1^2\mathrm{tr}\{u_{k+1}u^T_{k+1}\} + c_2^2]I \\ \le & 2[c_1^2\mathrm{tr}\{(1+\epsilon)\hat{u}_{k+1|k}\hat{u}^T_{k+1|k} \\ & + (1+\epsilon^{-1})\tilde{u}_{k+1|k}\tilde{u}^T_{k+1|k}\} + c_2^2]I \\ = & 2[c_1^2\mathrm{tr}\{(1+\epsilon)\hat{u}_{k+1|k}\hat{u}^T_{k+1|k} \\ & + (1+\epsilon^{-1})((A_k + \Theta_k C_k)\hat{P}_k(A_k + \Theta_k C_k)^T \\ & + R_{1,k})\} + c_2^2]I \\ \triangleq & \kappa_k I. \end{aligned} \tag{31}$$

Due to the existence of the $\mathbb{E}\{h(u_k)h^T(u_k)\}$ and $\mathbb{E}\{\delta^2_k\}$, it is impossible to obtain the precise error covariance P_{k+1}. Therefore, to facilitate the subsequent analysis, an upper bound for the error covariance is derived, which is defined as follows:

$$\begin{aligned} \Sigma_{k+1} = & (I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})(A_k + \Theta_k C_k)\Sigma_k \\ & \times (A_k + \Theta_k C_k)^T (I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})^T \\ & + (I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})R_{1,k} \\ & \times (I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})^T \\ & + \beta^2_{k+1}(l^r_k)^2\bar{\sigma}^{rf}_{k+1}\sigma^{rr}_{k+1}\check{K}_{k+1}M_{k+1}\check{K}^T_{k+1} \\ & + \frac{1}{4}\pi^2\beta^2_{k+1} l^r_k \bar{\sigma}^{rf}_{k+1}\check{K}_{k+1}\check{K}^T_{k+1} \\ & + \beta^2_{k+1} l^r_k \bar{\sigma}^{rf}_{k+1}\check{K}_{k+1}\mathrm{Var}\{d_{k+1}\}\check{K}^T_{k+1} \\ & + \check{K}_{k+1}\bar{\Omega}_{k+1}\check{K}^T_{k+1} + \tilde{b}_{k+1}\kappa_k\check{K}_{k+1}\check{K}^T_{k+1}. \end{aligned} \tag{32}$$

From (30)-(31), we can draw a conclusion that $P_{k+1} \le \Sigma_{k+1}$. Denoting $\tilde{P}_{k+1} \triangleq \hat{P}_{k+1} - \Sigma_{k+1}$, one derives from (29) that

$$\begin{aligned} \hat{P}_{k+1} = & (I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})(A_k + \Theta_k C_k)\hat{P}_k \\ & \times (A_k + \Theta_k C_k)^T (I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})^T + Y_{k+1}. \end{aligned} \tag{33}$$

where

$$\begin{aligned} Y_{k+1} = & \tilde{P}_{k+1} - (I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})(A_k + \Theta_k C_k)\tilde{P}_k \\ & \times (A_k + \Theta_k C_k)^T (I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})^T \\ & + (I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})R_{1,k} \\ & \times (I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})^T \\ & + \beta^2_{k+1}(l^r_k)^2\bar{\sigma}^{rf}_{k+1}\sigma^{rr}_{k+1}\check{K}_{k+1}M_{k+1}\check{K}^T_{k+1} \\ & + \frac{1}{4}\pi^2\beta^2_{k+1} l^r_k \bar{\sigma}^{rf}_{k+1}\check{K}_{k+1}\check{K}^T_{k+1} \\ & + \beta^2_{k+1} l^r_k \bar{\sigma}^{rf}_{k+1}\check{K}_{k+1}\mathrm{Var}\{d_{k+1}\}\check{K}^T_{k+1} \\ & + \check{K}_{k+1}\bar{\Omega}_{k+1}\check{K}^T_{k+1} + \tilde{b}_{k+1}\kappa_k\check{K}_{k+1}\check{K}^T_{k+1}. \end{aligned}$$

To proceed further, some preliminary knowledge is introduced to ensure the EMSB of the filtering error $\tilde{u}_k$.

Lemma 3: [29]. For the stochastic process $\tilde{u}_k$, if there exist $\bar{p} > 0$, $\underline{p} > 0$, $\eta_0 > 0$ and $0 < \eta_1 < 1$ such that, for $\forall k > 0$,

$$\underline{p}\|\tilde{u}_k\|^2 \le V_k(\tilde{u}_k) \le \bar{p}\|\tilde{u}_k\|^2 \tag{34}$$

and

$$\mathbb{E}\{V_k(\tilde{u}_k)|\tilde{u}_{k-1}\} \le (1-\eta_1)V_{k-1}(\tilde{u}_{k-1}) + \eta_0, \tag{35}$$

then, the stochastic process $\tilde{u}_k$ is said to achieve the EMSB, i.e.

$$\mathbb{E}\{\|\tilde{u}_k\|^2\} \le \frac{\bar{p}}{\underline{p}}\mathbb{E}\{\|\tilde{u}_0\|^2\}(1-\eta_1)^k + \frac{\eta_0}{\underline{p}}\sum_{i=1}^{k}(1-\eta_1)^i. \tag{36}$$

Citation information: DOI: 10.1109/TAC.2024.3521281, IEEE Transactions on Automatic Control

We are now in a position to derive a sufficient condition to ensure the EMSB of the filtering error and, to achieve this goal, the following assumptions are introduced.

Assumption 2: There exist positive scalars $\bar{a}$, $\bar{c}$, $\bar{h}$, $\bar{\theta}$, $\bar{\gamma}$, $\underline{y}$, $\underline{p}_1$, $\bar{p}_1$, $\underline{r}_4$, $\bar{r}_1$, $\check{u}$ and $\check{\omega}$ such that the following conditions

$$\begin{aligned}&\|A_k\| \le \bar{a},\ \|C_k\| \le \bar{c},\ \|H_k\| \le \bar{h},\ \Theta_k \le \bar{\theta} I\\&\Upsilon_k \le \bar{\gamma} I,\ Y_k \ge \underline{y} I, \underline{p}_1 I \le \hat{P}_{k+1|k} \le \bar{p}_1 I\\&\underline{r}_4 I \le R_{4,k+1},\ \|M_k\| \le \acute{a},\ R_{1,k+1} \le \bar{r}_1 I\\&\hat{u}_{k+1|k}\hat{u}^T_{k+1|k} \le \check{u} I,\ \bar{\Omega}_k \le \check{\omega} I\end{aligned} \tag{37}$$

hold. In addition, we fix $\beta_k = \beta$, $\bar{b}_k = \bar{b}$, $\tilde{b}_k = \tilde{b}$, $l^r_k = l^r$, $\bar{\sigma}^{rf}_k = \bar{\sigma}^{rf}$ and $\sigma^{rr}_k = \sigma^{rr}$ for any k.

Theorem 1: Under Assumption 2, for the nonlinear stochastic system (1) over the full-duplex relay network with the binary encoding scheme, the filtering error $\tilde{u}_k$ is exponentially mean-square bounded.

Proof: Noting the boundedness of $\hat{P}_{k+1|k}$ and the fact $\hat{P}_0 > 0$, there must exist two scalars $\bar{p} > 0$ and $\underline{p} > 0$ such that

$$\underline{p} I \le \hat{P}_k \le \bar{p} I, \tag{38}$$

which satisfies the condition (34) of Lemma 3.

Next, we rewrite (29) as the following form:

$$\tilde{u}_{k+1} = (I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})(A_k + \Theta_k C_k)\tilde{u}_k + \tilde{y}_{k+1} \tag{39}$$

where

$$\begin{aligned}\tilde{y}_{k+1} \triangleq &- \beta_{k+1} l^r_k t^{rf}_{k+1}(t^{rr}_{k+1} - \bar{t}^{rr}_{k+1})\check{K}_{k+1} m_{k+1}\\&+ (I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})w_k\\&- (b_{k+1} - \bar{b}_{k+1})\check{K}_{k+1} h(u_{k+1})\\&+ \beta_{k+1}\sqrt{l^r_k} t^{rf}_{k+1}\check{K}_{k+1}\delta_{k+1}\\&+ \beta_{k+1}\sqrt{l^r_k} t^{rf}_{k+1}\check{K}_{k+1} d_{k+1} - \check{K}_{k+1}\bar{\omega}_{k+1}.\end{aligned} \tag{40}$$

Based on (23)–(24) and the conclusion obtained from [4], we have

$$\hat{P}^{uz}_{k+1} = \hat{P}_{k+1|k}\bar{b}_{k+1}H^T_{k+1}\Upsilon^T_{k+1}. \tag{41}$$

Then, it is concluded from (24), (25) and Assumption 2 that

$$\begin{aligned}\|\check{K}_{k+1}\| =&\|\hat{P}^{uz}_{k+1}(\hat{P}^{zz}_{k+1})^{-1}\|\\\le&\|\hat{P}_{k+1|k}\bar{b}_{k+1}H^T_{k+1}\Upsilon^T_{k+1}R^{-1}_{4,k+1}\|\\\le&\frac{\bar{p}_1\bar{b}\bar{h}\bar{\gamma}}{\underline{r}_4} \triangleq \check{a}.\end{aligned} \tag{42}$$

Considering the independence among the noises, it is easily known from (40) that

$$\begin{aligned}&\mathbb{E}\{\tilde{y}^T_{k+1}\tilde{y}_{k+1}\}\\=&\mathbb{E}\{w^T_k(I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})^T\\&\times (I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})w_k\}\\&+ \tilde{b}_{k+1}\mathbb{E}\{h^T(u_{k+1})\check{K}^T_{k+1}\check{K}_{k+1}h(u_{k+1})\}\\&+ \beta^2_{k+1}(l^r_k)^2\bar{\sigma}^{rf}_{k+1}\sigma^{rr}_{k+1}\mathbb{E}\{m^T_{k+1}\check{K}^T_{k+1}\check{K}_{k+1}m_{k+1}\}\\&+ \beta^2_{k+1}l^r_k\bar{\sigma}^{rf}_{k+1}\mathbb{E}\{\delta^T_{k+1}\check{K}^T_{k+1}\check{K}_{k+1}\delta_{k+1}\}\\&+ \beta^2_{k+1}l^r_k\bar{\sigma}^{rf}_{k+1}\mathbb{E}\{d^T_{k+1}\check{K}^T_{k+1}\check{K}_{k+1}d_{k+1}\}\\&+ \mathbb{E}\{\bar{\omega}^T_{k+1}\check{K}^T_{k+1}\check{K}_{k+1}\bar{\omega}_{k+1}\}.\end{aligned} \tag{43}$$

Taking into account (19) and (31), we arrive at

$$\begin{aligned}\kappa_k =&2[c^2_1\mathrm{tr}\{(1+\epsilon)\hat{u}_{k+1|k}\hat{u}^T_{k+1|k}\\&+ (1+\epsilon^{-1})((A_k + \Theta_k C_k)\hat{P}_k(A_k + \Theta_k C_k)^T\\&+ R_{1,k})\} + c^2_2]\\\le&2[c^2_1\mathrm{tr}\{(1+\epsilon)\check{u} + (1+\epsilon^{-1})((\bar{a}+\bar{\theta}\bar{c})^2\bar{p} + \bar{r}_1) + c^2_2]\\\triangleq&\bar{\kappa}\end{aligned} \tag{44}$$

and

$$\|M_{k+1}\| \le \acute{a}. \tag{45}$$

According to Assumption 2, (44) and (45), one immediately has

$$\begin{aligned}&\mathbb{E}\{\tilde{y}^T_{k+1}\tilde{y}_{k+1}\}\\\le&(1+\bar{b}\check{a}\bar{\gamma}\bar{h})^2 n\bar{r}_1 + \tilde{b}\bar{\kappa}\check{a}^2 m\\&+ \beta^2(l^r)^2\bar{\sigma}^{rf}\sigma^{rr}\acute{a}^2 m + \frac{1}{4}\beta^2 l^r\bar{\sigma}^{rf}\check{a}^2\pi^2\\&+ \beta^2 l^r\bar{\sigma}^{rf}\check{a}^2\mathrm{Var}\{d_k\} + \check{a}^2\check{\omega} \triangleq \grave{a}.\end{aligned} \tag{46}$$

It is easy to see from (25) and the fact $\hat{P}^{zz}_{k+1} > 0$ that

$$\begin{aligned}\hat{P}_{k+1} =&\hat{P}_{k+1|k} - \check{K}_{k+1}(\hat{P}^{uz}_{k+1})^T\\=&\hat{P}_{k+1|k} - \hat{P}^{uz}_{k+1}(\hat{P}^{zz}_{k+1})^{-1}(\hat{P}^{uz}_{k+1})^T\\\le&\hat{P}_{k+1|k}.\end{aligned} \tag{47}$$

Constructing $V_k(\tilde{u}_k) \triangleq \tilde{u}^T_k\hat{P}^{-1}_k\tilde{u}_k$, it follows from (39) that

$$\begin{aligned}&\mathbb{E}\{V_{k+1}(\tilde{u}_{k+1})\} - V_k(\tilde{u}_k)\\=&\mathbb{E}\{[(I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})\\&\times (A_k + \Theta_k C_k)\tilde{u}_k + \tilde{y}_{k+1}]^T\hat{P}^{-1}_{k+1}\\&\times [(I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})\\&\times (A_k + \Theta_k C_k)\tilde{u}_k + \tilde{y}_{k+1}]\} - \tilde{u}^T_k\hat{P}^{-1}_k\tilde{u}_k\\=&\tilde{u}^T_k[(A_k + \Theta_k C_k)^T(I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})^T\\&\times \hat{P}^{-1}_{k+1}(I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})\\&\times (A_k + \Theta_k C_k) - \hat{P}^{-1}_k]\tilde{u}_k + \mathbb{E}\{\tilde{y}^T_{k+1}\hat{P}^{-1}_{k+1}\tilde{y}_{k+1}\}.\end{aligned} \tag{48}$$

With the help of the noted matrix inverse lemma, one has

$$\begin{aligned}&\hat{P}^{-1}_k - [(I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})(A_k + \Theta_k C_k)]^T\\&\times \hat{P}^{-1}_{k+1}(I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})(A_k + \Theta_k C_k)\\=&\{\hat{P}_k + \hat{P}_k[(I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})(A_k + \Theta_k C_k)]^T\\&\times Y^{-1}_{k+1}[(I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})(A_k + \Theta_k C_k)]\hat{P}_k\}^{-1}\\=&\{I + [(I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})(A_k + \Theta_k C_k)]^T Y^{-1}_{k+1}\\&\times [(I - \bar{b}_{k+1}\check{K}_{k+1}\Upsilon_{k+1}H_{k+1})(A_k + \Theta_k C_k)]\hat{P}_k\}^{-1}\hat{P}^{-1}_k\\\ge&\left[1 + \frac{(1+\bar{b}\check{a}\bar{\gamma}\bar{h})^2(\bar{a}+\bar{\theta}\bar{c})^2\bar{p}}{\underline{y}}\right]^{-1}\hat{P}^{-1}_k.\end{aligned} \tag{49}$$

Letting $\varepsilon \triangleq \left[1 + \frac{(1+\bar{b}\check{a}\bar{\gamma}\bar{h})^2(\bar{a}+\bar{\theta}\bar{c})^2\bar{p}}{\underline{y}}\right]^{-1}$ and $\vartheta \triangleq \frac{\grave{a}}{\underline{p}}$, we can derive from (48) that

$$\mathbb{E}\{V_{k+1}(\tilde{u}_{k+1})\} - V_k(\tilde{u}_k) \le -\varepsilon V_k(\tilde{u}_k) + \vartheta, \tag{50}$$

which verifies the condition (35) of Lemma 3. To this end, we can conclude from Lemma 3 that the filtering error $\tilde{u}_k$ has the expected EMSB, which completes the proof of this theorem. ■

Remark 3: In the unscented Kalman filter design algorithm (22)–(25), there are four primary factors that increase the filter design complexity, that is, the relay, the full-duplex communication, the binary encoding and the random bit flips. Besides, all these factors are reflected in the sufficient condition (i.e. Theorem 1) that ensures the EMSB of the filtering error.

Remark 4: In this paper, the first attempt has been made to address the remote state estimation problem for the stochastic nonlinear systems over a full-duplex network with binary encoding scheme subject to random bit flips. The main novelties include 1) the considered model is comprehensive which involves the nonlinearities, the stochastic noises, the full-duplex relay, the binary encoding and the random bit flips; and 2) the proposed unscented Kalman filter

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication.
Citation information: DOI: 10.1109/TAC.2024.3521281, IEEE Transactions on Automatic Control

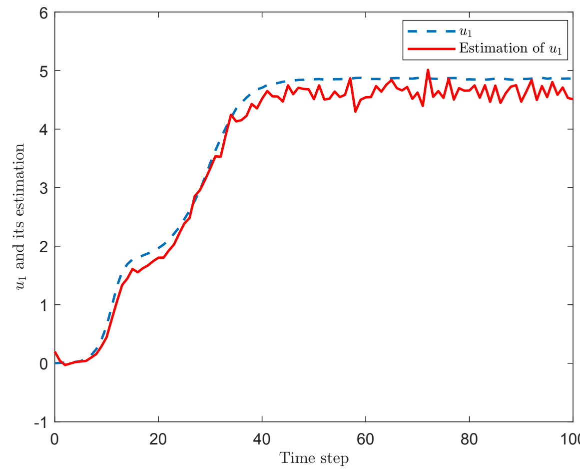

Fig. 2: State $u_{1,k}$ and its estimates $\hat{u}_{1,k}$.

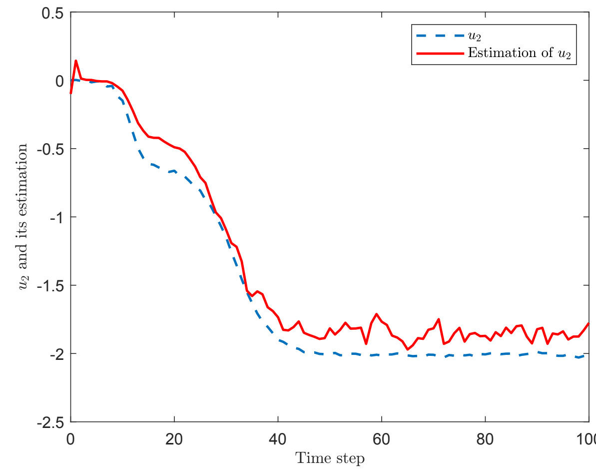

Fig. 3: State $u_{2,k}$ and its estimates $\hat{u}_{2,k}$.

algorithm is complicated, which accounts for the impact from the full-duplex relay and the binary encoding scheme.

V. An Illustrative Example

This section presents a numerical simulation to showcase the validity of the proposed UKF algorithm over the full-duplex relay network with the binary encoding scheme. For the considered system (1), the following parameter are given:

$$A_k = \begin{bmatrix} 0.3 & 0.2 & 0.7 \\ -0.6 & 0.2 & 0.1 \\ 0 & 0 & 0.7 \end{bmatrix}, \; f(u_k) = \begin{bmatrix} 1.4\tanh(u_1(k)) \\ -\tanh(u_2(k)) \\ 1.1\tanh(0.5u_3(k)) \end{bmatrix}$$

and $h(u_k) = \begin{bmatrix} 0.5u_1(k) + 0.4\sin(u_2(k)) \\ 1.3u_2(k) - 0.6\sin(u_3(k)) \end{bmatrix}$. The covariances of the noises w_k, v_k, v_k^s and v_k^f are selected as $R_1 = R_2 = R_3 = R_4 = 4 \times 10^{-4}$. The initial values are $u(0) = \begin{bmatrix} 0 & 0 & 0 \end{bmatrix}^T$, $\hat{u}(0) = \begin{bmatrix} 0.2 & -0.1 & 0.6 \end{bmatrix}^T$ and $m_0 = \begin{bmatrix} 0 & 0 \end{bmatrix}^T$.

For the binary encoding scheme with bit flips, set $\bar{g} = 6$, $L = 8$ and $\bar{\zeta} = 0.01$. For the UKF, the weighted coefficient is $\varpi = \sqrt{2}$ and the initial covariance is $\hat{P}_0 = 0.1I$. For the full-duplex relay network, the related parameters are set as $l_k^s = l_k^r = 2$, $\bar{t}_k^{sr} = 0.5$, $\bar{t}_k^{rr} = 0.95$, $\beta_k = 1, \bar{t}_k^{rf} = 0.95$, $\sigma^{sr} = \sigma^{rr} = \sigma^{rf} = 0.0001$. The stochastic channel coefficients t_k^{sr}, t_k^{rr} and t_k^{rf} are assumed to obey the normal distribution. Figs. 2–4 present the simulation results, depicting the trajectories of the actual state and its estimate for each component of the state, thereby confirming the effectiveness of the proposed UKF algorithm.

VI. Conclusions

The unscented Kalman filter design issue for a class of discrete-time stochastic nonlinear systems over a full-duplex relay with the binary encoding scheme has been addressed in this paper. To describe the phenomenon of bit flips resulting from the complicated and noisy communication environment, a sequence of Bernoulli distributed random variables has been introduced. A full-duplex relay has been employed between the sensor and the filter to improve the reliability of the signal transmission. The proposed UKF algorithm has accounted for the impacts of the full-duplex relay and the binary encoding scheme on the filtering performance. A sufficient condition has been established using the matrix inverse lemma to ensure the EMSB of the filtering error. Finally, the effectiveness of the proposed filter design algorithm has been confirmed through a numerical simulation.

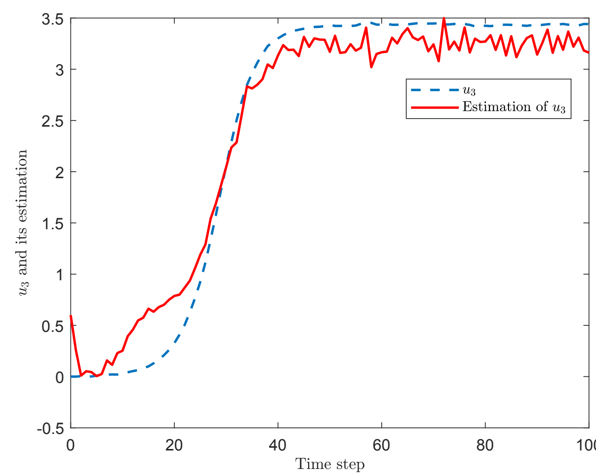

Fig. 4: State $u_{3,k}$ and its estimates $\hat{u}_{3,k}$.

References

[1] B. Ali, J. Mirza, J. Zhang, G. Zheng, S. Saleem and K. K. Wong, Full-duplex amplify-and-forward relay selection in cooperative cognitive radio networks, *IEEE Transactions on Vehicular Technology*, vol. 68, no. 6, pp. 6142–6146, 2019.

[2] M. S. Arulampalam, S. Maskell, N. Gordon, T. Clapp, A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking, *IEEE Transactions on Signal Processing*, vol. 50, no. 2, pp. 174–188, Feb. 2002.

[3] A. Bernstein, K. Steiglitz and J. Hopcroft, Encoding of analog signals for binary symmetric channels, *IEEE Transactions on Information Theory*, vol. 12, no. 4, pp. 425–430, Oct. 1966.

[4] M. Boutayeb and D. Aubry, A strong tracking extended Kalman observer for nonlinear discrete-time systems, *IEEE Transactions on Automatic Control*, vol. 8, no. 44, pp. 1550–1556, 1999.

[5] R. Caballero-Aguila, A. Hermoso-Carazo and J. Linares-Perez, Fusion estimation using measured outputs with random parameter matrices subject to random delays and packet dropouts, *Signal Processing*, vol. 127, pp. 12–23, Oct. 2016.

[6] R. Carli, F. Bullo and S. Zampieri, Quantized average consensus via dynamic coding/decoding schemes, *International Journal of Robust and Nolinear Control*, vol. 20, no. 2, pp. 156–175, 2010.

[7] W. Chen, Z. Wang, D. Ding and H. Dong, Consensusability of discrete-time multi-agent systems under binary encoding with bit errors, *Automatica*, vol.133, art. no. 109867, 2021.

[8] D. Ciuonzo, A. Aubry, and V. Carotenuto, Rician MIMO channel- and jamming-aware decision fusion, *IEEE Transactions on Signal Processing*, vol. 65, no. 15, pp. 3866–3880, 2017.

[9] D. Crisan and A. Doucet, A survey of convergence results on particle filtering methods for practitioners, *IEEE Transactions on Signal Processing*, vol. 50, no. 3, pp. 736–746, Mar. 2002.

[10] H. Cui, M. Ma, L. Song and B. Jiao, Relay selection for two-way full duplex relay networks with amplify-and-forward protocol, *IEEE Transactions on Wireless Communications*, nol. 13, no. 7, pp. 3768–3777, Jul. 2014.

[11] D. Dai, J. Li, Y. Song and F. Yang, Event-based recursive filtering for nonlinear bias-corrupted systems with amplify-and-forward relays, *Systems Science & Control Engineering*, vol. 12, no. 1, art. no. 2332419, 2024.

[12] Y. Guo and B. Huang, State estimation incorporating infrequent, delayed and integral measurements, *Automatica*, vol. 58, pp. 32–38, Aug. 2015.

[13] M. Hernandez-Gonzalez, M. Basin and O. Stepanov, Discrete-time state estimation for stochastic polynomial systems over polynomial observations, *International Journal of General Systems*, vol. 47, no. 5, pp. 512–528, 2018.

[14] F. Jin, L. Ma, C. Zhao and Q. Liu, State estimation in networked control systems with a real-time transport protocol, *Systems Science & Control Engineering*, vol. 12, no. 1, art. no. 2347885, 2024.

[15] S. Julier, J. Uhlmann and H. F. Durrant-Whyte, A new method for the nonlinear transformation of means and covariances in filters and estimators, *IEEE Transactions on Automatic Control*, vol. 45, no. 3, pp. 477–482, Mar. 2000.

[16] S. Julier and J. Uhlmann, Unscented filtering and nonlinear estimation, *Proceeding of the IEEE*, vol. 92, no. 3, pp. 401–422, Mar. 2004.

[17] S. Kluge, K. Reif and M. Brokate, Stochastic stability of the extended Kalman filter with intermittent observations, *IEEE Transactions on Automatic Control*, vol. 55, no. 2, pp. 514–518, 2010.

[18] I. Krikidis, H. A. Suraweera, P. J. Smith and C. Yuen, Full-duplex relay selection for amplify-and-forward cooperative networks, *IEEE Transactions on Wireless Communications*, vol. 11, no. 12, pp. 4381–4393, 2012.

[19] L. Li and Y. Xia, Stochastic stability of the unscented Kalman filter with intermittent observations, *Automatica*, vol. 48, no. 5, pp. 978–981, May 2012.

[20] L. Li and Y. Xia, Unscented Kalman filter over unreliable communication networks with Markovian packet dropouts, *IEEE Transactions on Automatic Control*, vol. 58, no. 12, pp. 3224–3230, Dec. 2013.

[21] T. Li, M. Fu, L. Xie and J.-F. Zhang, Distributed consensus with limited communication data rate, *IEEE Transactions on Automatic Control*, vol. 56, no. 2, pp. 279–292, 2011.

[22] X. Li and D. Ye, Dynamic event-triggered distributed filtering design for interval type-2 fuzzy systems over sensor networks under deception attacks, *International Journal of Systems Science*, vol. 54, no. 15, pp. 2875–2890, 2023.

[23] A. S. Leong and D. E. Quevedo, Kalman filtering with relays over wireless fading channels, *IEEE Transansactions on Automatic Control*, vol. 61, no. 6, pp. 1643–1648, Jan. 2016.

[24] Q. Liu, and Z. Wang, Moving-horizon estimation for linear dynamic networks with binary encoding schemes, *IEEE Transactions on Automatic Control*, Vol. 66, No. 4, pp. 1763–1770, Apr. 2021.

[25] S. Liu, Z. Wang, Y. Chen and G. Wei, Protocol-based unscented Kalman filtering in the presence of stochastic uncertainties, *IEEE Transactions on Automatic Control*, vol. 65, no. 3, pp. 1303–1309, Mar. 2020.

[26] Y. Liu, Z. Wang and D. Zhou, UKF-based remote state estimation for discrete artificial neural networks with communication bandwidth constraints, *Neural Networks*, vol. 108, pp. 393–398, Dec. 2018.

[27] Z. Lu and G. Guo, Control and communication scheduling co-design for networked control systems: a survey, *International Journal of Systems Science*, vol. 54, no. 1, pp. 189–203, 2023.

[28] X. Luo, H. Wu, Z. Wang, J. Wang, and D. Meng, A novel approach to large-scale dynamically weighted directed network representation, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 44, no. 12, pp. 9756-9773, Dec. 2022.

[29] K. Reif, S. Gunther, E. Yaz and R. Unbehauen, Stochastic stability of the discrete-time extended Kalman filter, *IEEE Transactions on Automatic Control*, vol. 44, no. 4, pp. 714–728, 1999.

[30] Y. S. Shmaliy, F. Lehmann, S. Zhao and C. K. Ahn, Comparing robustness of the Kalman, H_∞, and UFIR filters, *IEEE Transactions on Signal Processing*, vol. 66, no. 13, pp. 3447–3458, 2018.

[31] K. Reif, F. Sonnemann and R. Unbehauen, An EKF-based nonlinear observer with a prescribed degree of stability, *Automatica*, vol. 34, no. 9, pp. 1119–1123, 1998.

[32] K. Singh, M. Ku, J. Lin and T. Ratnarajah, Toward optimal power control and transfer for energy harvesting amplify-and-forward relay networks, *IEEE Transactions on Wireless Communications*, vol. 17, no. 8, pp. 4971–4986, 2018.

[33] B. Sinopoli, L. Schenato, M. Franceschetti, K. Poolla, et al., Kalman filtering with intermittent observations, *IEEE Transactions on Automatic Control*, vol. 49, no. 9, pp. 1453–1464, Sept. 2004.

[34] H. Tan, B. Shen, Q. Li and W. Qian, Recursive filtering for nonlinear systems with self-interference over full-duplex relay networks, *IEEE/CAA Journal of Automatica Sinica*, vol. 9, no. 11, pp. 2037–2040, Nov. 2022.

[35] H. Tan, B. Shen, K. Peng and H. Liu, Robust recursive filtering for uncertain stochastic systems with amplify-and-forward relays, *International Journal of Systems Science*, vol. 51, no. 7, pp. 1188-1199, May 2020.

[36] L. Wang, Z. Wang, D. Zhao and G. Wei, Event-based state estimation under constrained bit rate: An encoding-decoding approach, *Automatica*, vol. 143, art. no. 110421, Sept. 2022.

[37] L. Wang, Z. Wang, B. Shen and G. Wei, Recursive filtering with measurement fading: A multiple description coding scheme, *IEEE Transactions on Automatic Control*, vol. 66, no. 11, pp. 5144–5159, Nov. 2021.

[38] W. Wang, L. Ma, Q. Rui and C. Gao, A survey on privacy-preserving control and filtering of networked control systems, *International Journal of Systems Science*, vol. 55, no. 11, pp. 2269–2288, 2024.

[39] Y.-A. Wang, B. Shen, L. Zou and Q.-L. Han, A survey on recent advances in distributed filtering over sensor networks subject to communication constraints, *International Journal of Network Dynamics and Intelligence*, vol. 2, no. 2, art. no. 100007, Jun. 2023.

[40] Y. Xu, W. Lv, W. Lin, R. Lu, and D. E. Quevedo, On extended state estimation for nonlinear uncertain systems with round-robin protocol, *Automatica*, vol. 138, Article 110154, 2022.

[41] X. Yi and T. Xu, Distributed event-triggered estimation for dynamic average consensus: A perturbation-injected privacy-preservation scheme, *Information Fusion*, vol. 108, art. no. 102396, Aug. 2024.

[42] X. Yi, Z. Wang, S. Liu and Q. Tang, Acceleration model considering multi-stress coupling effect and reliability modeling method based on nonlinear Wiener process, *Quality and Reliability Engineering International*, vol. 40, no. 6, pp. 3055-3078, May. 2024.

[43] X. Yi, C. Xu, X. Fang and S. Liu, A new reliability analysis method for software-intensive systems with degradation accumulation effect based on goal oriented methodology, *Quality and Reliability Engineering International*, vol. 40, no. 1, pp. 236-260, May. 2023.

[44] Y. Yuan, H. Zhang, Y. Wu, T. Zhu and H. Ding, Bayesian learning-based model-predictive vibration control for thin-walled workpiece machining processes, *IEEE/ASME transactions on mechatronics*, vol. 22, no. 1, pp. 509-520, 2016.

[45] S. Zhang, X. Chai, K. P. Long, A. V. Vasilakos and L. Hanzo, Full duplex techniques for 5G networks: Self-interference cancellation, protocol design, and relay selection, *IEEE Communications Magazine*, vol. 53, no. 5, pp. 128–137, May 2015.

[46] Z. Zhao, Z. Wang and L. Zou, Sequential fusion estimation for multi-rate complex networks with uniform quantization: a zonotopic set-membership approach, *IEEE Transactions on Neural Networks and Learning Systems*, vol. 35, no. 4, pp. 5764–5777, Apr. 2024.

[47] M. Zhong, X. Zhu, T. Xue and L. Zhang, An overview of recent advances in model-based event-triggered fault detection and estimation, *International Journal of Systems Science*, vol. 54, no. 4, pp. 929–943, 2023.

[48] L. Zou, Z. Wang, H. Dong, X. Yi and Q.-L. Han, Recursive filtering under probabilistic encoding-decoding schemes: handling randomly occurring measurement outliers, *IEEE Transactions on Cybernetics*, vol. 54, no. 6, pp. 3378–3391, Jun. 2024.