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Survey/Review Study

An Overview of Filtering for Sampled-Data Systems under Communication Constraints

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Abstract: The sampled-data systems have been extensively applied to practical engineering because the digital signal shows great advantages in data transmission, storage and exchange. As a result, the analysis and synthesis problems of sampled-data systems have attracted ever-growing research interest due mainly to their significant application potential. On the other hand, the filtering or state estimation (which intends to reconstruct real system states from noisy measurements) is viewed as one of the most fundamental research topics in the control community. Until now, a lot of research efforts have been devoted to the filtering problem of sampled-data systems. The objective of the survey is to exhibit a systematic review with respect to filtering and control methods for sampled-data systems under communication constraints. First, some effective filtering algorithms are given. Then, the recent advances are shown in the filtering and control of sampled-data systems subject to network-induced phenomena based on the sampling methods. Finally, some future research topics are given on state estimation of sampled-data systems.

Keywords: sampled-data system; communication constraints; periodic sampling; aperiodic sampling; filtering

1. Introduction

In the past few decades, the networked control system has shown great application potential in many fields, including the Internet of Things, chemical production and so on [1−5]. Different from the traditional point-to-point connection, the critical components in networked control systems, such as sensors, state estimators, controllers and actuators, usually transmit signals through shared wireless communication networks. The networked control system is capable of remote operation and control, which further shows great advantages of low costs and easy installation. Therefore, the networked control system has gradually become a research hotspot in the control community [6−12]. However, due mainly to the undesired constraints in wireless communication (e.g. the data processing capacity of wireless devices and the limited network bandwidth), there would inevitably exist some network-induced phenomena, such as the packet loss [13, 14], quantization [15, 16] and data saturation [17, 18]. As such, the traditional control and filtering methods may be no longer applicable in networked control systems under communication constraints. Therefore, many efforts have been devoted to the analysis and synthesis of networked control systems with communication constraints.

In networked control systems, filtering has been regarded as one of the most fundamental issues. In the existing literature, many filtering methods have been developed with various performance indexes [19−26]. Typically, for linear systems subject to Gaussian distributed white noises, the classical Kalman filtering has been viewed as the most effective filtering method since it achieves the globally optimal state estimation in the sense of the minimum filtering error covariance [19]. When there exist nonlinearities and uncertainties in the stochastic systems, it is always difficult to acquire the accurate filtering error covariance, which renders the traditional Kalman filtering invalid. In this case, the robust recursive filtering has been chosen as an alternative method in which an upper bound is guaranteed for the filtering error covariance [24]. In the case that the dynamic system is disturbed by the energy-bounded noises, the H_∞ filtering method has been proposed such that the attenuation level of estimation errors against the exogenous noises is guaranteed to be within a prespecified disturbance attenuation level [22]. Moreover, in the case that the noises can be limited into an ellipsoid, the set-membership filtering method has been developed such that the filtering errors are also constrained in an ellipsoid [25, 26].

In practice, it is a common case that the concerned plant is described as a continuous-time system, whereas the data is transmitted in a discrete-time digital form. This gives rise to the so-called sampled-data systems [27−29]. Since the sampled-data system can describe essential characteristics of practical engineering more accurately than the continuous/discrete-time system, it has received ever-growing research attention [30, 31]. To transfer continuous-time analog signals into discrete-time digital signals, sampling is an essential technique that determines whether the discrete-time signal matches the original continuous-time signal. In traditional sampled-data systems, the sampling period has been usually assumed to be a constant for the sake of simplicity. Unfortunately, due mainly to the undesired external interference (such as the shake and clock error), it is technically difficult to adopt uniform sampling. To cater for real requirements, many other sampling models have been proposed for sampled-data systems. Those available models include, but are not limited to, the bounded deterministic but uncertain sampling model [32, 33], the stochastic sampling model [34, 35], the multi-rate sampling model [22, 36], and the event-triggering sampling model [37, 38].

It should be mentioned that, the existing filtering methods have been mainly applied to continuous/discrete-time systems, and found to be inefficient in dealing with the sampled-data system. This brings great challenges to traditional filtering methods. Nowadays, many effective methods have been proposed to transform the sampled-data systems into common continuous/discrete-time systems. Typically, the discretization method directly converts the sampled-data system into the discrete-time system by utilizing the matrix exponential technique [10]. In the input-output method, the sampling period is viewed as the time delay and the sampled-data system is further equivalently denoted by the time-delay continuous-time system [39]. For multi-rate sampled-data systems, the lifting technique is the most popular method that transforms the multi-rate sampled-data systems into single-rate systems [40]. By utilizing these heuristic methods, many significant research results have been obtained on the filtering of sampled-data systems under communication constraints.

In this paper, we aim to provide a systematic review of the existing results on filtering problems for sampled-data systems with communication constraints. The remainder of this paper is outlined as follows. In Section 2, the traditional filtering method is presented. In Section 3, research results are discussed on filtering and control of sampled-data systems. Section 4 provides the conclusion and the future research topics.

2. Filtering of Networked Control Systems

Filtering is a method that reconstructs real system states from noisy measurements. Nowadays, many efforts have been devoted to developing high-accuracy and easy-to-implemented filtering schemes. The typical research results are listed as follows.

2.1. Kalman Filtering and Its Variants

In the traditional Kalman filtering proposed in [19], the globally optimal state estimate has been obtained in the minimum mean square error variance sense. Such a filtering method is able to be online implemented because the minimum filtering error covariance is derived by recursively solving the Ricatti difference equation. In this case, the Kalman filtering has gained much research attention [41−52]. Typically, the boundedness stability has been analyzed in [51] for Kalman filtering with intermittent measurements. Moreover, the probability that the filtering error covariance is bounded has been investigated in [52] over a packet-dropping network. In [41−43], constrained Kalman filters have been designed for state-constrained systems with equality/inequality constraints. In [53], a distributed Gossip Kalman filtering method has been proposed for systems over sensor networks. In [54−56], the Kalman-consistency filtering has been proposed by combining the traditional Kalman filtering method with the consistency algorithm.

When there exist nonlinearities or uncertain parameters, the classical Kalman filtering is usually inappropriate since it is usually technically impossible to obtain accurate filtering error covariances. Thus, many variants have been developed to broaden the application scope of the Kalman filtering, such as the extended Kalman filter [57−60], unscented Kalman filter [61−64], cubature Kalman filter [23, 65−67] and the robust recursive filter (RRF) [24, 68−73]. Among them, the RRF has received particular research attention due mainly to its robustness. In the RRF, an upper bound is guaranteed on the actual filtering error covariance and further minimized by designing the filter gain properly. In [71−73], the RRF has been designed for stochastic nonlinear systems. In [24, 70], the RRF has been proposed for a class of uncertain systems where the uncertainties have been described by a class of norm-bounded uncertain matrices. In [68, 69], the RRF design problem has been considered for two-dimensional systems.

2.2. H_∞ Filtering

When the considered systems are subject to deterministic but energy-bounded noises, the H_∞ filtering method has been proposed such that the prescribed attenuation level of estimation errors against the exogenous noises can be reached [74−79]. In [74, 76, 77], the event-based H_∞ filtering problem has been investigated where the existence condition of the filter has been presented by a class of linear matrix inequalities. In [80, 81], the H_∞ filters have been constructed for the sampled-data systems based on the aperiodic sampling period. In [82−84], the H_∞ filtering problem has been discussed for a class of multi-rate sampled-data systems where the lifting technique has been employed to accommodate the multi-rate sampling. In [63, 85], the distributed H_∞ filtering problem has been considered for the networked control systems with network-induced phenomena.

2.3. Set-Membership Filtering

The aforementioned Kalman filtering and the H_∞ filtering both belong to the so-called point estimation where the state estimate is derived exactly. Contrarily, the set-membership filtering is a kind of interval-based state estimation method, and only obtains a reliable geometric domain to contain the state estimate. Nowadays, many set-membership filtering methods have been proposed by utilizing various of geometric domains [25, 86−96]. Typically, in [89, 90], the set-membership filters have been constructed for discrete-time systems where the intervals have been adopted to contain the state estimate. In [87, 88, 91, 92], the set-membership filtering methods have been developed such that the state estimates have been included into a class of ellipsoids. In [86, 94, 96], a new type of set-membership filtering method, named the zonotopic set-membership filtering method, has been proposed where the zonotopes and zonotope-based operations have been embedded in the set-membership filtering algorithms.

3. Filtering and Control for Sampled-data Systems

In reality, many networked control systems (NCSs) can be typically represented as continuous models. With the development of microelectronics and digital technologies, the method (of sampling continuous analog signals and converting them into discrete digital signals) has been widely used in industrial control, network communication, voice transmission, image processing and other fields. In this case, a special kind of NCSs, called the sampled-data system, has begun to attract ever-growing research attention. In what follows, we will make a brief overview of the latest results on filtering and control problems for sampled-data systems.

3.1. Periodic Sampling

In the traditional sampling method, the sampling period is usually assumed to be a constant for the sake of simplicity. Based on the periodic sampling method, a sampler is usually used to periodically sample the measurement information that is employed as the input of the filter and controller.

Consider the following continuous-time system:

$$\begin{cases}\dot{x}(t) = Ax(t) + Bw(t),\\ y(t) = Cx(t) + Dv(t)\end{cases} \tag{1}$$

where $x(t)$ and $y(t)$ are, respectively, the state and measurement outputs, $w(t)$ and $v(t)$ stand for the disturbance noises, and A, B, C and D are known matrices with appropriate dimensions. Before being transmitted to the filter, the measurement $y(t)$ is periodically sampled by a sampler. Thus, the following sampled-data system is further obtained.

$$\begin{cases}\dot{x}(t) = Ax(t) + Bw(t),\\ y(t_k) = Cx(t_k) + Dv(t_k)\end{cases} \tag{2}$$

Define the constant sampling period by

$$T = t_{k+1} - t_k \tag{3}$$

where t_k is the k-th sampling time instant.

In recent years, the analysis and synthesis problems of sampled-data systems with periodic sampling have received extensive research attention [97−105]. For example, in [97], the lifting technique, which converts a continuous signal into a discrete signal sequence according to the sampling time instants, has been adopted to convert the continuous-time system into an equivalent discrete-time system. Based on the sampled discrete-time signal, an H_∞ sampled-data controller has been further designed. In [98], the exponential stability has been studied for periodically sampled-data systems in the case of control input loss. Sufficient conditions for exponential stability have been obtained. Moreover, the effects have been analyzed quantitatively from the sampling period, exponential parameters, nominal packet loss rate and actual packet loss rate on the system stability. In [99], the linear quadratic control problem of periodic systems has been transformed into a sampled-data output feedback control problem, where an optimal periodic controller has been designed when the system suffers from incomplete information or measurement delays. In [100], the sampled-data output feedback control problem has been considered for a class of nonlinear systems by discretizing the high gain continuous observer. Moreover, it has been shown that, when the sampling period is sufficiently small, the performance of the continuous state feedback controller can be realized by a sampled-data controller with a sampled-data observer. In [101], by obtaining the explicit analytical solution to the nonlinear differential equation, the considered nonlinear continuous system has been discretized by periodic sampling. The discrete controller has been designed by using such a discrete model. Then, sufficient conditions have been obtained to stabilize the sampled-data systems.

3.2. Aperiodic Sampling

In practice, it is usually difficult to achieve periodic sampling owing to the unavoidable interference, such as the vibration of machines and the jitter of the pointer. In this case, the sampling period is essentially aperiodic or even random. When the sampling period has uncertainty and randomness, it will affect the performance of the concerned dynamic system and bring essential difficulties in designing of filters and controllers. Therefore, it is of practical significance to study sampled-data systems with aperiodic sampling methods (e.g. uncertain sampling [21, 27, 28, 32, 33, 106−111], stochastic sampling [30, 34, 35, 112−117], multi-rate sampling [31, 40, 118−123] and so on).

1) *Uncertain Sampling*

For the uncertain but deterministic sampling method, it is usually assumed that the sampling period is a bounded unknown variable. More specifically, the unknown sampling period $T_k = t_{k+1} - t_k$ satisfies the following constraints

$$T_k \in (\underline{T}, \bar{T}) \tag{4}$$

where $0 \leqslant \underline{T} \leqslant \bar{T}$ are the bounds determined by the sampling error of the sampler.

Nowadays, a rich body of research results have been obtained on the sampled-data systems with uncertain sampling. For example, the synchronization and state estimation problems have been investigated in [27] for a class of singularly perturbed complex networks with uncertain sampling. By utilizing the Lyapunov functional and the Kronecker product method, sufficient conditions for the exponential synchronization have been obtained for the considered complex networks. In addition, estimator gains (that guarantee the exponential stability of the estimation error system) have been further designed by adopting the matrix inequality technique. In [106], the sampled-data control input has been transformed by employing the input-output method. By constructing a time-dependent Lyapunov functional, the stability of the system has been guaranteed when the sampling period is greater than the given upper bound. In [107], the fault estimation problem has been studied for non-uniform sampled-data systems. By utilizing the input-output method, an augmented observer has been constructed to realize continuous fault estimation based on non-uniform discrete-time sampled-data measurements, which has established the foundation for fault estimation problems of non-uniform sampled-data systems. In [32], the discretization method has been used to convert the uncertain sampling period into the uncertain system parameters. Multiple norm-bounded uncertain matrices have been further employed in [28] to better describe the uncertainty caused by the sampling period.

2) *Stochastic Sampling*

In many cases such as the sampling of seismic data, the sampling usually occurs with a certain probability due to the influence of noises, giving rise to random characteristics. Therefore, the sampling period should be described as a random variable following a specific probability distribution.

In [112], the optimal control problem has been studied for sampled-data systems by characterizing the sampling period as a random variable obeying the Erlang distribution. More specifically, the sampling period T_k is modelled as

$$T_k = T + \varsigma_k \tag{5}$$

where T stands for the nominal sampling period. ς_k is the stochastic sampling error obeying the following probability density function:

$$f(s, \mathcal{K}, \mu) = \frac{\mu^{\mathcal{K}} s^{\mathcal{K}-1} e^{-\mu s}}{(\mathcal{K}-1)!}, \; s > 0 \tag{6}$$

where $\mathcal{K} \in N$ is the shape parameter and $\mu > 0$ is the rate parameter.

In [113], a Bernoulli distributed random variable has been utilized to describe the sampling period. Through converting the sampling period into time delays, a robust H_∞ controller has been designed for the sampled-data system with parameter uncertainties. It has been also pointed out that, the sampling period can also be assumed to switch randomly among multiple modes. Concretely, it is assumed that the sampling period T_k satisfies

$$\Pr\{T_k = T_1\} = \beta, \; \Pr\{T_k = T_2\} = 1 - \beta \tag{7}$$

where $0 < T_1 < T_2$ are known values, and $0 < \beta < 1$ is a given constant.

Based on this method, a sampled-data synchronization controller has been designed to guarantee the exponential mean square stability of the dynamic network in [35]. Furthermore, in [114], a sampled-data controller with random switching sampling periods has been designed in the case of data loss and adaptive time-varying delays. In [39], the random sampling method has been used to sample the measurement output and a distributed H_∞ filter has been constructed based on the sampled measurement output. In [115], the state estimation problem has been considered for neural networks with time-varying delays. By designing a sampled-data controller with random switching modes, the globally mean-square exponential stability of the estimation error system has been guaranteed for neural networks with random sampling. It is worth mentioning that, although the stochastic sampling has been considered in the existing literature, it has been always assumed that the sampling period switches randomly between two or more modes with a certain probability, which is highly conservative. In [116], random variables following an arbitrary probability distribution have been employed to model sampling errors in order to obtain a relatively perfect mathematical model. Based on this model, a sampled-data controller has been designed to ensure the stochastic stability of sampled-data systems.

3) *Multi-Rate Sampling*

In practice, it is usually difficult to ensure that each sensor has the same sampling period, and this gives rise to the multi-rate sampled-data systems. The multi-rate sampled-data system is usually denoted as follows:

$$\begin{cases} x(t_{k+1}) = Ax(t_k) + Bw(t_k), \\ y_i(t_k^i) = C_i x(t_k^i) + D_i v(t_k^i),\ i = 1,2,\cdots,N \end{cases} \tag{8}$$

where $h = t_{k+1} - t_k$ is the sampling period of the plant, and $h_i = t_{k+1}^i - t_k^i$ is the sampling period of the ith sensor node. Moreover, the sampling period h_i satisfies $h_i = l_i h$ where l_i is a positive integer.

Due mainly to its great application potential, many important results have been obtained in filtering and control of multi-rate sampled-data systems. For example, in [118], the optimal sampled-data controllers have been designed for linear time-invariant systems with different A/D and D/A conversion rates. In [124], the consistency problem has been studied for sampled-data systems with multiple A/D and D/A conversion rates, and the H_2 optimal controller has been designed by utilizing the lifting technique. In [119], the H_2 and H_∞ filtering problems have been studied where the output sampling rate is slower than the state updating rate. It has been shown that the multi-rate sampling will cause nonconvexity, which makes it very difficult to solve the linear matrix inequalities (LMIs). Furthermore, a reduction algorithm has been proposed to solve LMIs with nonconvex constraints caused by the multi-rate sampling. In [40], the Kalman filter has been designed for multi-rate sampled-data systems where the measured transmission rate, estimated update rate and state update rate are all different from each other. In [31], the lifting technique has been adopted to transform the multi-rate sampled continuous-time system into a discrete-time system. Moreover, the state estimation and fault detection problems have been studied for the multi-rate sampled-data system. In [120, 125, 126], the fault estimation problem has been further studied for multi-rate sampled-data systems where the multi-rate systems have been transformed into signal-rate systems. In [29, 127−130], the system identification and parameter estimation problems have been studied for continuous-time systems by using the multi-rate periodic sampling method. At the same time, the controllability and observability of the original system have been analyzed. In [22, 36, 131], the fusion state estimation problem has been studied for linear multi-rate systems over sensor networks. In [132], the state estimation problem has been studied for nonlinear multi-rate systems with packet loss. In [133], the set-membership filtering problem has been considered for multi-rate systems, and a zonotope that includes the real system states has been obtained recursively.

4) *Event-Triggering Sampling*

Notably, the periodic sampling, the stochastic sampling and the multi-rate sampling methods can be classified as the time-based sampling methods. Although simple to implement in practical engineering, the time-based sampling methods also transmit redundant information, which takes up a lot of communication resources, especially when communication bandwidth and energy are limited. An event-triggered mechanism based sampling method is able to reduce the energy consumption and communication burden in signal transmission.

In [134], the event-triggering sampling method has been developed and further studied to solve the event-triggered PID control problem. In the event-triggered mechanism (with an irregular execution mode), the current data will not be transmitted until the triggering conditions are met, thus eliminating redundant information and reducing transmission times to save transmission energy and communication resources. So far, much research attention has been devoted to designing different types of event-triggering mechanisms such as the static event-triggering mechanisms [37, 38, 135−137], self-triggering mechanisms [138−142], and adaptive-triggering mechanisms [143−145]. It is worth mentioning that, a kind of dynamic event-triggering mechanism has been designed in [146] by introducing an internal dynamic variable related to the system state or measurement. This mechanism can further reduce the transmission times and ensure the system performance. Due mainly to its outstanding advantages, the dynamic event-triggering mechanism has attracted extensive attention [147−150]. Specifically, the control problem has been considered in [151−153] where the event-triggering mechanism has been utilized to regulate signal transmissions. In [154−156], the filtering problem has been studied where the data communication between sensors and filters has been executed by the event-triggering mechanism. In [157−159], the fusion estimation problem has been discussed for multi-sensor systems under the event-triggering mechanism. In [26, 160, 161], the event-based set-membership filtering problem has been investigated for NCSs where the error induced by the event-triggering mechanism has been transformed into the uncertainty bounded by ellipsoids.

Up to now, we have analyzed the related research results on the control and filtering problems of sampled-data systems. In the next section, we will present some future research topics.

4. Future Work for Sampled-Data Systems

4.1. More Complex Sampled-Data Systems

Although many efforts have been devoted to the filtering problem for sampled-data systems, there are still many problems to be solved. First, the stochastic sampling model is still very conservative, which should be expanded to cater for real requirements. Then, the multi-objective filtering for sampled-data systems with stochastic sampling is still a very challenging problem. Moreover, in multi-rate systems, the lifting technique is the most common method that transforms linear multi-rate systems into single-rate systems. When there exist uncertainties and nonlinearities in the systems, this method is no longer applicable, and thus new methods need to be developed. Finally, it is always the case that different sampling methods may be adopted simultaneously in sampled-data systems. In order to describe the sampled-data systems more accurately, various sampling methods should the considered at the same time, whereas the sampled-data system with mixed sampling methods has not drawn enough attention due probably to the underlying complexity and difficulty.

4.2. More Complex Network-Induced Phenomena

Although network-induced phenomena have been considered in sampled-data systems, there still exist some challenging problems that should be considered seriously. Typically, in wireless networks, the transmission distance of the signal sources (such as the sensor) is usually limited. In this case, signals broadcasted by signal sources may not be successfully transmitted to the destination (the filter and controller). In order to assure the efficient signal transmission, the relay network has been proposed where a relay (locating between the source and the destination) has been adopted to assist signal transmissions. Due mainly to its great advantages in the long-distance wireless communication, the relay network has attracted a lot of research interest from communication communities [162−164]. Accordingly, many effective relay techniques have been proposed to cater for real engineering applications such as the half-duplex relay, the virtual full-duplex relay and the full-duplex relay. Despite the fact that relay techniques have shown their potential in improving the performance of wireless networks, they will inevitably complicate the process of signal transmissions, and even cause signal distortion. Therefore, new filtering methods should be developed for sampled-data systems to accommodate the relay networks. Undoubtedly, the development of the new method will be a critical and challenging problem.

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