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On Distributed Observers for Linear Time-invariant Systems Under Intermittent Information Constraints

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Abstract: We study the problem of estimating the state of a linear time-invariant plant in a distributed fashion over networks allowing only intermittent transmission of information. By attaching to each node an observer that employs information received from its neighbors in an intermittent fashion, we propose a distributed state observer that guarantees global asymptotic stability of the zero estimation error set. We also characterize the proposed observer’s robustness to measurement and communication noise in terms of ISS. The design of parameters is formulated as matrix inequalities. The properties of the proposed observer are shown analytically and validated numerically.

Keywords: Distributed estimation, Intermittent communication, Hybrid systems

1. INTRODUCTION

State estimation in multi-agent systems over generic connected networks has seen increased attention recently. A typical challenge in this setting comes in the form of each agent being unable to generate an estimate alone, therefore, communication to other systems is needed. One methodology to solve this problem is to design an appropriate information fusion protocol which uses the local information available to an agent so as to guarantee convergence of the local state estimates to the state of the plant of interest. For example, the estimation of the trajectories of a moving target can be solved by using distributed sensor networks, see, e.g., Wang and Ren (2015) and Kamal et al. (2013). In Li and Sanfelice (2016), robust decentralized estimation with performance guarantees is explored under the assumption that information is available continuously. The distributed Kalman filtering is employed for achieving spatially-distributed estimation tasks in Cortes (2009). In Hong et al. (2008), switching inter-agent topologies are used to design distributed observers for a leader-follower problem in multi-agent systems.

In this paper, we consider the problem of designing a distributed estimation algorithm to estimate the state of the linear time-invariant plant

\[ \dot{x} = Ax \]

when measurement of its output is only available intermittently, i.e., at isolated (potentially nonperiodic) time instances. For the case of a single estimator, Ferrante et al. (2013) proposes a hybrid observer guaranteeing global exponential stability of the zero estimation error set. In the context of multi-agent systems, Cheng and Xie (2014) proposes a distributed observer with undirected fixed communication topology and switching communication topology for periodic sampling time/communication events. In contrast to the latter work, in this paper, we consider the case where the agents may only receive information from their neighbors intermittently, say, to reduce the cost of communication and computation. In our setting, agents are only allowed to take measurements and communicate at isolated (potentially nonperiodic) events, where the time elapsed between two consecutive events are governed by a random variable. Our contributions include the following:

1. We establish a hybrid model for a distributed state observer under intermittent information transmission that is well-posed;
2. We propose sufficient conditions to guarantee uniform global asymptotic stability of the zero estimation error set. Moreover, robustness of the stability property of the proposed observer with respect to communication and measurement noise is characterized in terms of input-to-state stability (ISS).

The remainder of this paper is organized as follows. In Section 2, some preliminaries on the hybrid systems framework used and graph theory are briefly discussed. The main results are presented in Section 3. In Section 4, the scenario of asynchronous event times is studied. Numerical and analytical examples illustrating the results are discussed throughout the paper.

2. PRELIMINARIES

2.1 Notation

Given a matrix \( A \), the set \( \text{eig}(A) \) contains all eigenvalues of \( A \) and \( |A| := \max\{|\lambda|^2 : \lambda \in \text{eig}(A^T A)\} \). Given two vectors \( u, v \in \mathbb{R}^n \), \(|u| := \sqrt{u^T u} \) and notation \([u^T v^T]^T\) is equivalent to \((u, v)\). Given a function \( m : \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}_{\geq 0} \), \( |m|_{\infty} := \sup_{t\geq 0}|m(t)| \). \( \mathbb{Z}_{\geq 1} \) denotes the set of positive integers, i.e., \( \mathbb{Z}_{\geq 1} := \{1, 2, 3, \ldots\} \). \( \mathbb{N} \) denotes the set of natural numbers including zero, i.e., \( \mathbb{N} := \{0, 1, 2, 3, \ldots\} \). Given a symmetric matrix \( P \), \( \text{eig}(P) := \max\{\lambda : \lambda \in \text{eig}(P)\} \) and \( \text{deg}(P) := \min\{\lambda : \lambda \in \text{eig}(P)\} \). Given matrices \( A, B \) with proper dimensions, we define the operator
3. INTERMITTENT STATE OBSERVERS WITH SYNCHRONOUS COMMUNICATION EVENTS

3.1 Configuration and basic properties

Consider \( N \) agents that are connected via a directed graph and where each agent runs a local observer of the state \( x \) of (1). Each local observer uses its own measurement and information received from its neighbors. In particular, the local observer at the \( i \)-th agent has a local estimate \( \hat{x}_i \) and it has a measurement of the state \( x_i \), which is given by

\[
y_i = H_i x_i \in \mathbb{R}^p
\]

as well as information from all its connected neighbors. However, the availability of such measurements is at isolated time instances \( \{ t_{s} \}_{s=1}^{\infty} \), where \( s \) is the communication event index. More precisely, the \( i \)-th agent receives \( y_i(t_s) = H_i x(t_s), y_k(t_s) = H_k x(t_s) \), and \( \hat{x}_k(t_s) \) at each communication event, where \( k \in N(i) \). Furthermore, it is assumed that a random variable \( \Omega_k \in [T_1, T_2] \) determines the time elapsed between such communication events, i.e.,

\[
t_{s+1} - t_s = \Omega_s
\]

where \( s \in \{1, 2, 3, \ldots \} \) and \( T_2 \geq T_1 > 0 \). The scalar values \( T_1 \) and \( T_2 \) define the lower and upper bounds, respectively, of the time allowed to elapse between consecutive communication events. Due to the impulsive nature of such communication mechanism, the communication events are triggered when the timer \( \tau \) reaches zero, which is then reset to a point in \([T_1, T_2]\), from where it decreases with ordinary time. Namely, the timer \( \tau \) evolves according to

\[
\dot{\tau} = -1 \quad \tau \in [0, T_2], \quad (5a)
\]

\[
\tau^+ = [T_1, T_2] \quad \tau = 0. \quad (5b)
\]

This hybrid system generates any possible sequence of time instances \( \{ t_s \}_{s=1}^{\infty} \), at which events occur and satisfy (4) with \( \Omega_k \) given by any probability distribution function that assigns \( \Omega_k \in [T_1, T_2] \).

The proposed distributed observer is as follows. The \( i \)-th agent runs the following local observer:

\[
\hat{x}_i = A \hat{x}_i + \eta_i
\]

where \( \eta_i \), referred as the information fusion state, is a variable that stores the information obtained at each communication event. Due to the intermittent nature of availability of information, \( \eta_i \) is updated impulsively when new information arrives. The generic dynamics of \( \eta_i \) can be captured by

\[
\begin{align*}
\dot{\eta}_i &= f_{\eta_i}(\hat{x}_i, \eta_i) & \tau \in [0, T_2] \quad (7) \\
\eta_i^+ &= \sum_{k \in \mathcal{V}} g_{ik} \eta_k & \tau = 0 \quad (8)
\end{align*}
\]

for each \( i \in \mathcal{V} \), where the map \( f_{\eta_i} : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}^n \) defines the continuous evolution of the information fusion state and the map \( g_{ik} : \mathbb{R}^n \times \mathbb{R}^n \times \mathbb{R}^p \to \mathbb{R}^n \) defines the impulsive update law when new information is collected from the \( k \)-th neighbor.

The resulting hybrid closed-loop system is given by the interconnection between the plant in (1), all local observers in form (6) and the dynamics of the information fusion state in (7)-(8). We denote the close-loop hybrid system by \( \mathcal{H} = (C, f, D, G) \), which has state \( z = (x, \xi_1, \ldots, \xi_N, \tau) \in X := \mathbb{R}^n \times S^N \times [0, T_2] \), where \( S := \mathbb{R}^n \times \mathbb{R}^n \) and \( \xi_i = (\hat{x}_i, \eta_i) \) for each \( i \in \mathcal{V} \). Its continuous dynamics are given by

\[
\dot{z} = f(z) = (Ax, f_1(\xi_1), \ldots, f_N(\xi_N), -1) \quad z \in C \quad (9)
\]
where $C := X$ and $f_i(\zeta_i) := (A\dot{x}_i + \eta_i, f_o(\dot{x}_i, \eta_i))$ for each $i \in V$. Since the communication and update events are induced by the timer with dynamics as in (5), the jump event set $D$ for $\mathcal{H}_o$ is defined as $D := \{z \in X : \tau = 0\}$. Then $z^+ \in G(z) := \{x, G_1(z), \ldots, G_N(z), [T_1, T_2]\}$ $z \in D$, (10) where $G_i(z) := (\dot{x}_i, \sum_{k \in V} y_{ik} G_{ik}(\dot{x}_i, \dot{x}_k, y_{ik}))$ for all $i \in V$.

With the construction above, the data of the hybrid closed-loop system $\mathcal{H}_o$ satisfies the following property.

**Lemma 3.1.** Suppose that, for each $i \in V$, the flow map $f_{oi} : \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}^n$ is continuous; and for each $(k, i) \in L$, the map $G_{ik}^o : \mathbb{R}^{2n} \times \mathbb{R}^{p_i} \times \mathbb{R}^{p_k} \rightarrow \mathbb{R}^n$ is continuous. Then, the hybrid system $\mathcal{H}_o$ satisfies the hybrid basic conditions.

**Remark 3.2.** Note that satisfying the hybrid basic conditions implies that the hybrid system $\mathcal{H}_o$ is well-posed and, with asymptotic stability of a compact set, leads to robustness to small enough perturbations; see Goebel et al. (2012) for more information.

### 3.2 Sample-and-hold estimation protocol

In this section, we consider the estimation for $\eta$ defining a specific hybrid information fusion strategy: $f_{oi}(\dot{x}_i, \eta_i) = 0$ (11) for all $(\dot{x}_i, \eta_i) \in \mathbb{R}^n \times \mathbb{R}^n$ and, for all $(\dot{x}_i, \dot{x}_k, y_{ik}, y_{ik}) \in \mathbb{R}^n \times \mathbb{R}^n \times \mathbb{R}^{p_i} \times \mathbb{R}^{p_k}$,

$$G_{ik}(\dot{x}_i, \dot{x}_k, y_{ik}) = \frac{1}{d_{ik}} K_n y_{ik} + K_k y_{ik}^T + \gamma(\dot{x}_i - \dot{x}_k)$$

(12)

where, for each $i, k \in V$, $y_{ik}^T = H_i \dot{x}_i - y_i$, $K_n \in \mathbb{R}^{p_i} \times \mathbb{R}^{p_k}$, and $\gamma \in \mathbb{R}$ are the gain matrices for the $i$-th agent. Note that due to the specific update law in (8) and the definition of $g_{ik}$, the second term in (12) uses the output error of each $k$-th agent that is a neighborhood of the $i$-th agent, and the third term in (12) uses the difference between the estimates $\dot{x}_i$ and $\dot{x}_k$. These are the quantities that are transmitted at communication events.

**Remark 3.3.** The hybrid information fusion strategy proposed in (11)-(12) falls into the category of zero-order sample-and-hold control; see, e.g., Naghshtabrizi et al. (2008) and Raff et al. (2008). Note that the work in Naghshtabrizi et al. (2008) and Raff et al. (2008) pertain to single-agent systems and that robustness to measurement and communication noise is not studied.

To analyze the hybrid system $\mathcal{H}_o$, for each $i \in V$, denote the local estimation error $e_i = \dot{x}_i - x$. Then, it follows that the continuous dynamics of $e_i$ and $\eta_i$ are given by

$$\dot{e}_i = Ae_i + \eta_i, \quad \eta_i = 0,$$

(13)

(14)

for each $\tau \in [0, T_2]$, and, when $\tau = 0$, the discrete dynamics are

$$e_i^+ = e_i, \quad \eta_i^+ = K_n H_i e_i + \sum_{k \in V} g_{ik} K_{ik} H_k e_k + \gamma \sum_{k \in V} g_{ik} (e_i - e_k).$$

(15)

(16)

By denoting $e = (e_1, e_2, \cdots, e_N)$ and $\eta = (\eta_1, \eta_2, \cdots, \eta_N)$, it follows that

$$\dot{e} = (I_N \otimes A)e + \eta, \quad \eta = 0,$$

(17)

(18)

for each $\tau \in [0, T_2]$, while when $\tau = 0$,

$$e^+ = e, \quad \eta^+ = (K_n H_o \ast (I_N + \mathbb{G}) + \gamma \mathbb{L} \otimes I_n)e,$$

where the matrix $H_o = \text{diag}(H_1, H_2, \ldots, H_N)$ is block diagonal and $K_n \in \mathbb{R}^{n \times p_i}$ is a $N \times N$ block matrix with the $(i, k)$-th entry given by $K_{ik} \in \mathbb{R}^{p_i \times p_k}$ for all $i, k \in V$ with $p = \sum_{i \in V} p_i$. Note that the operation “$\ast$” denotes the Khatri-Rao product, where the matrix $K_n H_o$ is treated as a $N \times N$ block matrix.

Then, in the $(\epsilon, \eta)$ coordinates, the system $\mathcal{H}_o$ can be written as a hybrid system $\mathcal{H} = (C_n, f_o, D_s, G_s)$ with state space $\chi = (\sigma, \tau) \in \chi_o = \mathbb{R}^{2n} \times \mathbb{R}^{2n} \times [0, T_2]$ with $\sigma = (\epsilon, \eta)$, and data given by

$$f_\sigma(\chi) := (A f_\sigma - 1), \quad \forall \chi \in C_s$$

(19)

$$G_\sigma(\chi) := (A g_\sigma[T_1, T_2]), \quad \forall \chi \in D_s$$

(20)

where $C_s := \chi_o$, $D_s := \mathbb{R}^{2n} \times \mathbb{R}^{2n} \times \mathbb{R}^n \times \{0\}$,

$$A_f := \begin{bmatrix} \mathbb{I}_N \otimes A & I_{nN} \\ 0 & 0 \end{bmatrix},$$

(21)

$$A_g := \begin{bmatrix} K_n H_o \ast (I_N + \mathbb{G}) + \gamma \mathbb{L} \otimes I_n & 0 \end{bmatrix}.$$ 

(22)

Note that $\mathcal{H}_o$ is autonomous; in particular, its dynamics are independent of the dynamics of $\mathcal{H}_o$.

**Remark 3.4.** Due to the jumps being triggered by the timer $τ$ with dynamics (5) reaching zero, the hybrid time domain of any maximal solution to $\mathcal{H}_o$ (or to $\mathcal{H}_o$) satisfies the following property. For any given $ϕ \in \mathcal{S}_H_o$ (or $ϕ \in \mathcal{S}_H$), $T_1 \leq t_{j+1} - t_j \leq T_2$ for all $j \geq 1$ and $0 < t_1 \leq T_2$ and

$$\| (j - 1) T_1 \leq t \leq (j + 1) T_2 \| \quad \forall j \geq 1$$

(23)

for all $(t, j) \in \text{dom} \, ϕ$. As the objective of each agent is to estimate the state $x$ of the plant, i.e., for each $i \in V$, make $\hat{x}_i$ converge to $x$ asymptotically, and since $\eta$ approaches zero as $\epsilon$ approaches zero, the set of interest is defined as

$$A = \{0_n \times 0_n \times \{0, T_2\}.$$ 

(24)

The following result provides a sufficient condition for uniform global asymptotic stability of $A$.

**Theorem 3.5.** Let $0 < T_1 \leq T_2$ be given. Suppose there exist matrices $K_n \in \mathbb{R}^{n \times p_i}$ and $P \in \mathbb{R}^{2n \times 2n}$ such that $P = P^T > 0$ and

$$A_y \exp(A_f \sqrt{\nu} P \exp(A_f \sqrt{\nu} A_g - P < 0$$

(25)

for all $\nu \in [T_1, T_2]$. Then, the set $A$ in (24) is UGAS for the hybrid system $\mathcal{H}_o$.

**Remark 3.6.** Note that when condition (25) holds, Theorem 3.5 guarantees that $\epsilon$ and $\eta$ converges to zero asymptotically. Recalling that $e_i = \dot{x}_i - x$, this implies that $\hat{x}_i$ converges to $x$ asymptotically for all $i \in V$. Furthermore, due to the multiplication of the parameters $\nu, P$, and $K_n$ in the first term of (25), it might be difficult to efficiently check (25) numerically. It is worth pointing out that condition (25) is satisfied if, for all $\nu \in [T_1, T_2]$, the eigenvalues of $\exp(A_f \sqrt{\nu} A_g$ are contained in the unit circle.

Note that the pair $(H_i, A)$ is not explicitly assumed to be detectable in this work. In fact, as we will show in the following example, even when $(H_i, A)$ are not detectable for each $i \in V$, we can still guarantee UGAS of $A$ by satisfying (25).

**Example 3.7.** Consider an oscillatory plant as in (1) with $A = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}.$
and \(  \hat{\eta} \) loses the capability of receiving measurements, i.e., asymptotically as guaranteed by Theorem 3.5.

Let the measurements of \( x \), \( \tilde{x} \), and \( \hat{\eta} \) from the simulation, it can be seen that even though the agent has measurement connected, namely, \( \gamma = -0.4 \) while the rest of the parameters are the same as those used for the simulations in Figure 1.

Consider the case of two agents that are all-to-all connected, namely,

\[
G = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}.
\]

Let the measurements of \( x \) at agent 1 be

\[
y_1 = H_1 x, \quad H_1 = [1 \ 0]
\]

and the measurements at agent 2 be

\[
y_2 = H_2 x, \quad H_2 = [0 \ 1].
\]

Let \( T_1 = 0.5 \) and \( T_2 = 1.7 \). By solving inequality (25) in Theorem 3.5, we obtain the following parameters:

\[
K_{11} = \begin{bmatrix} -0.5 & -0.2 \end{bmatrix}^T, \quad K_{12} = \begin{bmatrix} -0.2 & -0.2 \end{bmatrix}^T,
\]

\[
K_{21} = \begin{bmatrix} 0.2 & 0.3 \end{bmatrix}^T, \quad K_{22} = \begin{bmatrix} -0.1 & -0.5 \end{bmatrix}^T,
\]

with \( \gamma = -0.1 \). A simulation with these parameters is shown in Figure 1. The estimates \( \hat{x}_1 \) and \( \hat{x}_2 \) converge to \( x \) asymptotically as guaranteed by Theorem 3.5.

More interestingly, consider the scenario where agent 1 loses the capability of receiving measurements, i.e., \( H_1 = 0 \). A simulation with same initial conditions and gains as those in Figure 1 is shown in Figure 2. As suggested from the simulation, it can be seen that even though the agent has measurement \( y_1 \equiv 0 \), through the consensus-like term (the third term in (12)), the components \( \hat{x}_1 \) and \( \hat{x}_2 \) reach consensus first and then converge to \( x \) asymptotically. This highlights further a benefit of the third term in the dynamics of \( \eta \) in (12). In fact, the third term enforces consensus between the estimates \( \hat{x}_1 \) and \( \hat{x}_2 \). Another benefit of using this term will be seen in the next example.

Next, we establish another sufficient condition to guarantee that the estimation error \( e \) converges to zero asymptotically. Following the idea in Ferrante et al. (2015), by defining the variable \( \theta = \sum_{k \in \mathbb{N}} y_k G_k (x, \tilde{x}_k, y_k) - \eta_t \) and \( \sigma = (\theta_1, \theta_2, \ldots, \theta_N) \), we have that the continuous evolution of \( e \) and \( \theta \) is given by

\[
\dot{e} = A_p e - \theta, \quad \dot{\theta} = K \Delta e - K \theta,
\]

when \( \tau \in [0, T_2] \), where \( A_p = I_N \otimes A + K \) and \( K = K \theta H_p \) \((I_N + G) + \gamma C \otimes I_n \). Moreover, the discrete dynamics of \( e \) and \( \theta \) are given by \( e^+ = e \) and \( \theta^+ = \theta \) when \( \tau = 0 \). Then, the system in coordinates \( e \) and \( \theta \) can be written as a hybrid system \( H_{\theta} = (C_\theta, f_\theta, D_\theta, G_\theta) \) with state \( \chi_\theta = (\sigma_\theta, \tau) \in \chi, \sigma_\theta = (e, \theta) \), and data given by

\[
f_\theta (\chi_\theta) := (A_{p\theta} \sigma_\theta, -1)
\]

for each \( \chi_\theta \in C_\theta := \mathbb{R}^{nN} \times \mathbb{R}^{nN} \times [0, T_2] \), and

\[
G_\theta (\chi_\theta) := (A_{\theta \theta} \sigma_\theta, (T_1, T_2))
\]

when \( \chi_\theta \in D_\theta := \mathbb{R}^{nN} \times \mathbb{R}^{nN} \times \{0\} \), where

\[
A_{\theta \theta} = \begin{bmatrix} A_{\theta 1} & -I_{nN} & -K \\ K & -A_{\theta 2} & -K \end{bmatrix}, \quad A_{\theta 1} = \begin{bmatrix} I_{nN} & 0 \\ 0 & 0 \end{bmatrix}.
\]

Since the state \( e \) denotes the estimation error, the variable \( \theta \) denotes the difference between the current information fusion state (\( \eta_t \)) and the new value of the fusion state (\( \eta_t^{+} \)), we are also interested in guaranteeing asymptotic stability of the set \( A \) defined in (24). In these new coordinates, we establish the following result.

**Theorem 3.8.** Let \( 0 < T_1 \leq T_2 \) be given. Suppose there exist \( \delta > 0 \) and matrices \( K \theta \in \mathbb{R}^{nN \times nP}, P, Q \in \mathbb{R}^{nN \times nN} \) satisfying \( P = P^T > 0 \), \( Q = Q^T > 0 \), and

\[
\begin{bmatrix}
\text{He}(A_{\theta}, P) & -P + \text{exp}(\delta_1)A_{\theta} K^T Q \\
-P + \text{exp}(\delta_1)A_{\theta} K^T Q & -P + \text{exp}(\delta_1)A_{\theta} K^T Q
\end{bmatrix} < 0
\]

for all \( \nu \in [0, T_2] \). Then, the set \( A \) in (24) is UGAS for the hybrid system \( H_{\theta} \).

Note that the condition in (30) needs to be checked over a closed interval \([0, T_2]\), which is a difficult task. The following result relaxes this requirement.

**Proposition 3.9.** Let \( T_2 > 0 \) be given. The inequality in (30) holds for each \( \nu \in [0, T_2] \) if there exist \( \delta > 0 \) and matrices \( P, Q \in \mathbb{R}^{nN \times nN} \) satisfying \( P = P^T > 0 \), \( Q = Q^T > 0 \), and

\[
\begin{bmatrix}
\text{He}(A_{\theta}, P) & -P + A_{\theta} K^T Q \\
-P + A_{\theta} K^T Q & -P + A_{\theta} K^T Q
\end{bmatrix} < 0,
\]

\[
\begin{bmatrix}
\text{He}(A_{\theta}, P) & -P + \text{exp}(\delta_2)A_{\theta} K^T Q \\
-P + \text{exp}(\delta_2)A_{\theta} K^T Q & -P + \text{exp}(\delta_2)A_{\theta} K^T Q
\end{bmatrix} < 0.
\]

**Example 3.10.** Consider the network estimation problem in Example 3.7. Using the same parameters \( K_{11}, K_{12}, K_{21}, K_{22} \) and \( \gamma \) therein, it can be verified that (31) and (32) hold for \( \delta = 10 \) and a maximum value of \( T_2 \approx 0.4 \). As expected, replacing condition (30) by (31) and (32), which is a relaxation of (30), the largest \( T_2 \) allowed becomes smaller.

**Remark 3.11.** Note that the matrices \( E_1 \) and \( E_2 \) involve the multiplication of \( QKA_{\theta} \), which contains cross terms.
3.3 Robustness to measurement noise and channel noise

In this section, we investigate the scenario when the measurements $y_k$ are noisy, i.e., for each $i \in V$, $y_k = y_k + m_i$, where $m_i : \mathbb{R}_+ \to \mathbb{R}^p$ denotes the measurement noise on the information received by agent $i$. Moreover, when agent $i$ receives information (including $\hat{x}_k, y_k$) from agent $k$ ($k \in N(i)$), it is also affected by channel noise, i.e., $\tilde{x}_k = \hat{x}_k + \epsilon_k$ and $\tilde{y}_k = y_k + e_k$, where $c_i = (c_{i1}, c_{i2}, \ldots, c_{iN}) : \mathbb{R}_+ \to \mathbb{R}^{N+1}$ is the channel noise when agent $i$ receives information from its neighbors. Then, according to the design in (11)-(12), the noise is injected through the update law of $\eta_i$, that is,

$$\dot{\eta}_i = 0$$

when $\tau \in [0, T_2]$, and

$$\eta_i^+ = K_i H_i e_i + \sum_{k \in V} g_{ik}(K_i H_k e_k) + e_k - e_k + \zeta_i$$

when $\tau = 0$, where

$$\zeta_i = -K_i m_i + \sum_{k \in V} g_{ik} K_i H_k (c_{k} - c_{i} - m_k) - \gamma \sum_{k \in V} g_{ik} c_{k}.$$  

Then, the closed-loop system in (19) and (20) with added noise can be written in the following compact form:

$$\dot{X} = f_\tau(X) := (A_\tau \sigma, -1) \chi \in C_\tau,$$

$$\chi^+ = G_\tau(X, \zeta) := (A_\tau \sigma + \zeta, [T_i, T_2]) \chi \in D_\tau,$$

where $A_\tau$ and $A_\tau$ are given in (21) and (22), respectively, $\zeta = (0, K_m m + K_e, c)$, $K_m = -K_\tau * (I + G)$, $K_e = [(K_\tau H_\tau - \gamma I) * G - K_\tau * G]$, $m = (m_1, m_2, \ldots, m_N)$, $c = (c_1, c_2, \ldots, c_N)$, and $c_i = (c_{i1}, c_{i2}, \ldots, c_{IN})$. For this perturbed hybrid system, we have the following result.

**Theorem 3.12.** Let $0 < T_1 \leq T_2$ be given. Suppose there exist matrices $K_\tau \in \mathbb{R}^{N \times p}$ and $P \in \mathbb{R}^{2n \times 2n}$ such that $P = P^T > 0$ and condition (25) holds. Then, the set $A$ is ISS with respect to measurement noise and communication noise, i.e., each $\phi \in S_{\mathcal{H}_\tau}$ satisfies, for any $(t, j) \in \partial \phi$, $|\phi(t, j)|_A \leq \max \left\{ \sqrt{\lambda_2} / \mu, \eta_\tau(m) |m|, \gamma_0(j) |e| \right\}$, where

$$\lambda_2 = -\frac{1}{\mu_2} + \epsilon \in (0, 1), \eta_\tau(m) = 2\sqrt{\frac{1 - \lambda_3}{1 - \lambda_2}} |K_m|,$$

$$\gamma_0(j) = 2\sqrt{\frac{1 - \lambda_3}{1 - \lambda_2}} |K_e|, \rho = \frac{1}{\mu_1} w_1 + w_2, \epsilon \in (0, \frac{1}{\mu_2}), \mu \in \min \left\{ \alpha_2, -\beta \right\},$$

$$\alpha_1 = \min_{\mu \in [0, T_2]} \frac{1}{2} \frac{1 - \lambda_3}{1 - \lambda_2} |K_e|, \alpha_2 = \max_{\mu \in [0, T_2]} \frac{1}{2} \frac{1 - \lambda_3}{1 - \lambda_2} |K_e|,$$

$$\varphi_1 = \max_{\mu \in [T_1, T_2]} |\exp(A_\mu \nu \varphi_1) P \exp(A_\mu \nu)|,$$

$$\varphi_2 = \max_{\mu \in [T_1, T_2]} |\exp(A_\mu \nu \varphi_2) P \exp(A_\mu \nu)|,$$

$$\varphi_3 = \max_{\mu \in [T_1, T_2]} |\exp(\beta \delta \varphi_3) \exp(A_\mu \nu \varphi_3) P \exp(A_\mu \nu \varphi_3)|,$$

$$\tau_i = -1 \quad \tau_i \in [0, T_2],$$

$$\tau_i^+ \in [T_1, T_2] \quad \tau_i = 0,$$

for each $i \in V$. Moreover, for each $i \in V$, the resulting flow dynamics of $\eta_i$ is given by (14) when $\tau_i \in [0, T_2]$, and the jump dynamics of $\eta_i$ is given by (16) when $\tau_i = 0$. Let $e_i = \hat{x}_i - x$ and $e = (e_1, \ldots, e_N)$, $\theta = (\theta_1, \ldots, \theta_N)$, $\tau = (\tau_1, \ldots, \tau_N)$, and

$$\theta_i = K_i g_{ik} y_{ik}^\tau + \sum_{k \in V} g_{ik} K_i K_i y_{ik}^\tau + \gamma \sum_{k \in V} g_{ik} (e_i - e_k) \eta_i.$$  

Then, the interconnection between (1), (6), (37), and (38) leads to a hybrid system $\mathcal{H}_{\tau} = (C_\tau, f_\tau, D_\tau, G_\tau)$ with state $x = (\sigma, \tau) \in X_{\tau} := \mathbb{R}^N \times \mathbb{R}^N \times [0, T_2]^N$, $\sigma = (\epsilon, \theta)$ and data given by

$$f_\tau(\chi_{\tau}) := (A_\tau \sigma \theta, -\chi_{\tau}),$$

for each $\chi_{\tau} \in C_\tau$, and

$$G_\tau(\chi_{\tau}) := \{G_\tau(\chi_{\tau}) : \chi_{\tau} \in D_i, i \in V\}$$

when $\chi_{\tau} \in D_{\tau} = \bigcup_{i \in V} D_i$, $D_i = \{\chi_{\tau} \in C_\tau : \tau_i = 0\}$.

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3. Note that the Khatri-Rao product $-$ $-K_\tau * (I + G)$ is such that the $(i, k)$-th entry $K_{ik}$ is multiplied by the $(i, k)$-th scalar entry of the matrix $I + G$ for all $i, k \in V$. 

![Figure 3](image-url)  

**Example 3.13.** To show the effect of communication noise and measurement noise, we revisit Example 3.7. Moreover, we consider the hybrid system $\mathcal{H}_{\tau}$ satisfies the hybrid basic conditions and, under the conditions in Theorem 3.5, the compact set $A$ is UGAS for $\mathcal{H}_{\tau}$, it follows from (Goebel et al., 2012, Lemma 7.20) that the stability of $A$ is robust to general small perturbations.

4. ASYNCHRONOUS EVENT TIMES

In this section, we study the scenario where each agent receives information asynchronously. To model such mechanism, instead of having one timer for all agents, each agent has a timer $\tau_i$ that triggers the events following the dynamics in (5), i.e.,

$$\tau_i = -1 \quad \tau_i \in [0, T_2],$$

$$\tau_i^+ \in [T_1, T_2] \quad \tau_i = 0,$$

for each $i \in V$. Moreover, for each $i \in V$, the resulting flow dynamics of $\eta_i$ is given by (14) when $\tau_i \in [0, T_2]$, and the jump dynamics of $\eta_i$ is given by (16) when $\tau_i = 0$. Let $e_i = \hat{x}_i - x$ and $e = (e_1, \ldots, e_N)$, $\theta = (\theta_1, \ldots, \theta_N)$, $\tau = (\tau_1, \ldots, \tau_N)$, and

$$\theta_i = K_i g_{ik} y_{ik}^\tau + \sum_{k \in V} g_{ik} K_i K_i y_{ik}^\tau + \gamma \sum_{k \in V} g_{ik} (e_i - e_k) \eta_i.$$  

Then, the interconnection between (1), (6), (37), and (38) leads to a hybrid system $\mathcal{H}_{\tau} = (C_\tau, f_\tau, D_\tau, G_\tau)$ with state $x = (\sigma, \tau) \in X_{\tau} := \mathbb{R}^N \times \mathbb{R}^N \times [0, T_2]^N$, $\sigma = (\epsilon, \theta)$ and data given by

$$f_\tau(\chi_{\tau}) := (A_\tau \sigma \theta, -\chi_{\tau}),$$

for each $\chi_{\tau} \in C_\tau$, and

$$G_\tau(\chi_{\tau}) := \{G_\tau(\chi_{\tau}) : \chi_{\tau} \in D_i, i \in V\}$$

when $\chi_{\tau} \in D_{\tau} = \bigcup_{i \in V} D_i$, $D_i = \{\chi_{\tau} \in C_\tau : \tau_i = 0\}$,
Proposition 4.2. Let \( e_i \) for all \( i \in \{1, 2\} \). Initial conditions are \( x(0) = (2, 2), \hat{x}_1(0) = (5, 5), \hat{x}_2(0) = (-1, 0) \), \( \eta_1(0) = (1, 1), \eta_2(0) = (-1, -1) \), \( \tau(0) = 0.2 \).

Consider the network system in Example 4.3. As expected, these conditions are expected to also guarantee UGAS of the convergence of estimation error to zero are presented. Though not explored in detail, these conditions are expected to also guarantee global exponential stability. Furthermore, robustness of the stability under certain conditions with respect to communication and measurement noises are studied in terms of ISS.

Theorem 4.1. Let \( 0 < T_1 \leq T_2 \) be given. Suppose \( N \) agents are connected via a digraph \( G = (V, E, \hat{Q}) \). Moreover, suppose there exist \( \delta > 0 \) and matrices \( K_\delta \in \mathbb{R}^{n \times N}, P_i, Q_i \in \mathbb{R}^{n \times N} \) satisfying \( P_i = P_i^T > 0, Q_i = Q_i^T > 0 \) for all \( i \in V \), and

\[
G_i(\chi_a) = \begin{bmatrix}
\theta_1, \theta_2, \cdots, \theta_i, 0, \theta_{i+1}, \cdots, \theta_N \\
(\tau_1, \tau_2, \cdots, \tau_i, [T_1, T_2], \tau_{i+1}, \cdots, \tau_N)
\end{bmatrix},
\]

where \( A_{\delta P} \) is given in (29). In this case, the set of interest is \( A_a = \{0_n \} \times \{0_n \} \times \{0, T_2 \}^N \).

Proposition 4.2. Let \( T_2 > 0 \) be given. The inequality in (39) holds if there exist \( \delta > 0 \) and matrices \( K_\delta \in \mathbb{R}^{n \times N}, P_i, Q_i \in \mathbb{R}^{n \times N} \) satisfying \( P_i = P_i^T > 0, Q_i = Q_i^T > 0 \) for all \( i \in V \) such that

\[
\begin{align*}
\text{He}(A_\delta, P) - P + A_\delta^T K_\delta^T \tilde{Q}(\nu) &\preceq 0, \\
&\prec -\delta \tilde{Q}(\nu) - \text{He}(K_\delta, \tilde{Q}(\nu)),
\end{align*}
\]

for all \( \nu = (\nu_1, \nu_2, \cdots, \nu_N) \in [0, T_2]^N \), where \( P = \text{diag}(P_1, P_2, \cdots, P_N) \),

\[
\tilde{Q}(\nu) = \text{diag}(\hat{Q}_1(\nu_1), \hat{Q}_2(\nu_2), \cdots, \hat{Q}_N(\nu_N))
\]

and \( \hat{Q}_i(\nu_i) = \exp(\delta \nu_i) Q_i \) for each \( i \in V \). Then, the set \( A_a \) is UGAS for the hybrid system \( H_a \).

Condition (39) needs to be checked over a closed set \( [0, T_2]^N \), which might be a difficult task. The following result relaxes this requirement.

Example 4.3. Consider the network system in Example 3.7. Using the same parameters \( K_{11}, K_{12}, K_{21}, K_{22} \), and \( \gamma \) therein, it can be verified that (40) and (41) hold for \( \delta = 10 \) and a maximum value of \( T_2 \approx 0.3 \). As expected, for the case of asynchronous event times, the maximum value of \( T_2 \) allowed is smaller than the one obtained for synchronous event times (\( T_2 = 1 \)). A simulation 4 is shown in Figure 4 with \( T_1 = 0.1 \) and \( T_2 = 0.3 \).

5. CONCLUSION

In this paper, a distributed state observer under intermittent information communication is proposed. In contrast to classic observers for linear time-invariant systems, a node with enough information from its neighbors can estimate the plant state even without detectability or even taking measurements of the plant output. Sufficient conditions that guarantee UGAS of the convergence of estimation error to zero are presented. Though not explored in detail, these conditions are expected to also guarantee global exponential stability. Furthermore, robustness of the stability under certain conditions with respect to communication and measurement noises are studied in terms of ISS.

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4 Code at https://github.com/HisyrdynSysLab/UsbSyncTimes2nd.