New sampled data observer for class of nonlinear hybrid systems

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***Abstract*—This paper investigates the problem of state estimation for nonlinear hybrid systems with sampled-data outputs and unknown switching modes. The hybrid nature of these systems, combining continuous dynamics with switching behaviors, makes observer design particularly challenging when the active mode is not directly available.**

A hybrid observer structure is proposed, based on an inter-sample output predictor and a bank of mode-dependent observers. Each observer corresponds to a candidate subsystem, and a selection mechanism is used to identify the observer consistent with the measured sampled output. The selected observer provides the state estimate of the system.

Simulation results illustrate the effectiveness of the proposed approach under sampled-data measurements and switching conditions.

***Index Terms*—Hybrid observer, switched systems, Sampled data systems.**

I. Introduction

Hybrid systems, which integrate continuous-time dynamics with discrete events, have emerged as a powerful modeling framework for complex engineering applications such as robotics, process control, and power electronics. Their mixed nature allows the description of systems involving logic-based decisions, switching actions, or sampled-data interactions, but also introduces significant challenges in analysis, control, and state estimation.

In particular, designing observers capable of accurately reconstructing the continuous states and discrete modes remains a central issue, especially for nonlinear systems operating under hybrid or sampled-data conditions. Several observer design methodologies have addressed these issues, including high-gain observers for uniformly observable nonlinear hybrid systems [1], observer design for switched nonlinear systems [7], and continuous-discrete time observers for nonlinear systems with sampled measurements [2]. Additional contributions have characterized multi-output uniformly observable nonlinear structures and proposed associated high-gain observers [4], while other works have bridged continuous-time observer design with sampled-data implementations using inter-sample output predictors [3], [8].

In the context of sampled-data systems, significant advances have also been made for systems with time delays, where continuous-time observers are adapted through inter-sample predictors to preserve exponential convergence under sufficiently small sampling periods [4], [9], [10]. Observer design for nonlinear systems with distributed output delays has also been investigated using delay-based formulations [11]. Adaptive observers for nonlinear sampled-data systems with unknown parameters have been proposed, exploiting predictor-based mechanisms that reset at each sampling instant to ensure exponential convergence and to derive explicit bounds on the maximum admissible sampling period [5]. More recently, hybrid high-gain observer-based output feedback strategies have been developed for nonlinear sampled-data systems using Zero-Order-Hold devices, providing stability guarantees through suitable Lyapunov functionals [6]. Despite this rich body of work, the construction of hybrid observers ensuring robust state estimation for nonlinear sampled-data hybrid systems with unknown active modes remains an open and active research direction.

Building on the observer framework proposed in [1], which addresses uniformly observable nonlinear hybrid systems, the present work extends this approach to the case of sampled-data hybrid systems with multiple outputs and unknown active modes. In contrast with [1], where the active subsystem and its corresponding output are assumed to be known at each instant, we consider a switching system for which the measured output may originate from any subsystem involved in the commutation. To handle this uncertainty, an inter-sample output predictor is incorporated, enabling the reconstruction of the expected output between sampling instants for each candidate mode. A bank of observers, one for each subsystem, is then deployed, and the selection of the active observer relies on the consistency between the measured output and the predictor-based estimates. The selected observer provides the final state estimation, ensuring robust reconstruction of the hybrid system dynamics despite mode uncertainty and sampled-data constraints.

The remainder of this paper is organized as follows. Section II formulates the problem studied in this work and recalls the main assumptions related to the class of nonlinear hybrid sampled-data systems under consideration. Section III presents the design of the hybrid observer for multi-output switching systems, including the construction of the inter-sample output predictor and the selection mechanism among the observer bank. Section IV provides numerical simulations to illustrate the effectiveness of the proposed approach and to highlight the behavior of the observer under different switching scenarios. Finally, Section V concludes the paper and discusses possible directions for future research.

II. PROBLEM FORMULATION

We consider a class of nonlinear continuous-time switched systems that can be interpreted as sampled-data hybrid dynamics. For each mode $q \in \Pi = \{1, 2, \ldots, M\}$, the system is described by

$$(\Sigma_q) : \begin{cases} \dot{x}(t) = f_q(x(t)) + g_q(x(t))\, u(t), \\ y(t) = h_q(x(t)), \end{cases} \qquad t \in [t_k, t_{k+1}), \tag{1}$$

where $x(t) \in \mathbb{R}^n$ denotes the state vector and $y(t) \in \mathbb{R}^p$ the measured output, with $p \geq 1$. The dynamics are written in the standard input-affine form: the nonlinear vector field f_q characterizes the autonomous behaviour of each mode, while the term $g_q(x)u(t)$ represents the contribution of the control input. The output is defined by the mode-dependent nonlinear mapping h_q.

Switching between subsystems is governed by a piecewise constant switching signal $\sigma(t) \in \Pi$, which specifies at each instant the active mode. The time axis is partitioned into intervals $[\tau_i, \tau_{i+1}[$ during which a single subsystem remains active, and mode transitions can only occur at the switching instants τ_i.

Each subsystem is assumed to be uniformly observable, meaning that its internal state can be reconstructed from the measured output independently of the switching instants. Furthermore, for every activation interval, we assume the existence of a diffeomorphism that transforms the dynamics into a coordinate representation more suitable for observer design. Thus, for each mode q and each interval $[\tau_i, \tau_{i+1}[$, the system can be rewritten in coordinates where the output and its Lie derivatives are explicitly represented. More precisely, we introduce the change of variables

$$z_q = \phi_q(x) = \begin{bmatrix} h_q(x) \\ L_{f_q} h_q(x) \\ \vdots \\ L_{f_q}^{n-1} h_q(x) \end{bmatrix}.$$

III. HYBRID OBSERVER DESIGN

In this section, we introduce a hybrid high-gain observer (HHGO) specifically designed for sampled-data nonlinear hybrid systems. The observer aims to estimate both the discrete mode of the system and its continuous state simultaneously. The main objective is to ensure exponential convergence of the estimation error and to analyze the stability of the observer in the context of switching systems, as well as hybrid systems that may exhibit state jumps. A general representation of the proposed structure is depicted in Fig. 1.

The proposed approach consists in constructing M observers, each associated with one of the possible modes of the system. At each sampling instant, these observers generate residuals $r_k^{q,\hat{q}}$ for every $k \in \Pi$ and $q = 1, \ldots, M$. Each residual is then compared to a predefined threshold $Th > 0$. When a residual satisfies $r_k^{q,\hat{q}} \leq Th$, the estimated mode $\hat{q}$ is considered consistent with the true active mode q. The observer corresponding to this mode is then selected to provide the continuous-state estimation. Following this principle, we construct a family of M hybrid observers, each with the structure described in the following formulation. We propose the following hybrid observer with sampled data measurements:

$$\begin{cases} \dot{Z}_{\hat{q},i} = Z_{\hat{q},i+1} - l_{\hat{q},i}{\theta_{\hat{q}}}^{i}(Z_{\hat{q},1} - w_q), \\ i = 1, \ldots, n-1, \qquad \hat{q} \in \Pi = \{1, \ldots, M\} \\ \dot{Z}_{\hat{q},n} = f_{\hat{q}}(Z_{\hat{q}}, u) - l_{\hat{q},n}{\theta_{\hat{q}}}^{n}(Z_{\hat{q},1} - w_q) \quad t \in [t_k, t_{k+1}) \\ \dot{w}_q = Z_{\hat{q},2} - K(w_q - Z\hat{q}_1) \quad t \in [t_k, t_{k+1}) \\ w_q(t_k) = y_q(t_k) \end{cases} \tag{2}$$

where $Z_{\hat{q}}$ represent the state estimation of, ω and $\hat{\omega}$ are the most recently output value and the observer output, v is feedback control.

$e_{q\hat{q}} = Z_{\hat{q}} - X_q$ is the dynamical error system, $e_\omega = \omega_q - x_{q,1}$ is observation error then we obtain

$$\begin{cases} \dot{e}_{q\hat{q},i} = e_{q\hat{q},i+1} - l_{\hat{q},i}\theta_{\hat{q}}{}^i e_{q\hat{q},1} - l_{\hat{q},i}\theta_{\hat{q}}{}^i e_w(t) \\ i = 1,\dots,n-1, \quad q \in \Pi = \{1,\dots,M\}, \quad \hat{q} \in \Pi = \{1,\dots,M\} \\ \dot{e}_{q\hat{q},n} = f_{\hat{q}}(Z_{\hat{q}},u) - f_q(X_q,u)) - \\ l_{\hat{q},n}\theta_{\hat{q}}{}^n e_{q\hat{q},1} - l_{\hat{q},n}\theta_{\hat{q}}{}^n e_w \quad t \in [t_k, t_{k+1}) \\ \dot{e}_w = e_{q\hat{q},2} - K e_{q\hat{q},1} - K e_w \quad t \in [t_k, t_{k+1}) \\ e_w(t_k) = 0 \\ \dot{X}_{q,i} = X_{q,i+1}, \quad i = 1,\dots,n-1 \\ \dot{X}_{n,\hat{q}} = f(X_q,u) \end{cases} \tag{3}$$

by using the classical change of variables $\xi_{q\hat{q},i} = \theta_{\hat{q}}{}^{1-i} e_{q\hat{q},i}$, we obtain:

$$\begin{cases} \dot{\xi}_{q\hat{q},i} = \theta_{\hat{q}}\xi_{q\hat{q},i+1} - \theta_{\hat{q}} l_{\hat{q},i}\xi_{q\hat{q},1} - l_{q\hat{q},i}\theta_{\hat{q}} e_w(t), \\ i = 1,\dots,n-1, \quad q \in \Pi = \{1,\dots,M\}, \quad \hat{q} \in \Pi = \{1,\dots,M\} \\ \dot{\xi}_{q\hat{q},n} = \theta_{\hat{q}}{}^{1-n}\left[f_{\hat{q}}(Z_{\hat{q}},u) - f_q(X_q,u)\right] - \\ \theta_{\hat{q}} l_{\hat{q},n}\xi_{q\hat{q},1} - \theta l_{\hat{q},n} e_w(t) \quad t \in [t_k, t_{k+1}) \\ \dot{e}_w = \theta\xi_{q\hat{q},2} - K\xi_{q\hat{q},1} - K e_w \quad t \in [t_k, t_{k+1}) \\ e_w(t_k) = 0 \\ \dot{X}_{q,i} = X_{q,i+1}, \quad i = 1,\dots,n-1 \\ \dot{X}_{q,n} = f_q(X_q,u) \quad t \in [t_k, t_{k+1}) \end{cases}$$

Theorem 1: Consider the system described by (1). There exists a maximum allowable sampling period $T_h > 0$ ensuring exponential convergence of the observer to the system state for all $t \in [t_k, t_{k+1})$.

Sketch of proof The proof of the above theorem is based on the following Lyapunov function

$$V = \xi_{q\hat{q}} P \xi_{q\hat{q}}^T,$$

and by combining the technique used in the paper [1] and Theorem 1 of paper [2].

IV. Application to the quadruple tank process

We consider the following class of nonlinear sampled data hybrid systems:

$$\begin{cases} \dot{X}_{q_i} = X_{q_{i+1}} \quad i = 1,.,n-1 \quad q \in \Pi = 1,2,..,m \\ \dot{X}_{q_1} = f_q(X_q,u) \\ y_q(t_k) = X_{q_1}(t_k) \end{cases} \tag{4}$$

$$X = [\theta, \dot{\theta}, \tau_p]^T$$

Where u and y are respectively the input and the output of the above systems

The sampling instants t_k are increasing sequences defined as:

$$0 = t_0 \le t_1 \le ... \le t_k \le ..., \lim_{i\to\infty} t_k = \infty$$

$t_{k+1} - t_k \le h$, where $h \ge 0$ is the maximum allowable sampling period.

This section provides an example to demonstrate the effectiveness of the nonlinear high-gain hybrid observer introduced earlier. The example is the same tank process considered in [2], described as follows.

$$(\Sigma_1): \begin{cases} \dot{x}_1 = -c_1\sqrt{x_1} + c_2\sqrt{x_3} + c_3\sqrt{x_4} \\ \dot{x}_2 = -c_4\sqrt{x_2} + c_5\sqrt{x_3} + c_6\sqrt{x_4} \\ \dot{x}_3 = -c_7\sqrt{x_3} + c_8 u_1 \\ \dot{x}_4 = -c_9\sqrt{x_4} + c_{10} u_2 \\ y(t) = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = h_1(x(t)) \end{cases} \tag{5}$$

$$(\Sigma_2): \begin{cases} \dot{x}_1 = -c_1\sqrt{x_1} + c_2\sqrt{x_3} \\ \dot{x}_2 = -c_4\sqrt{x_2} + c_6\sqrt{x_4} \\ \dot{x}_3 = -c_2\sqrt{x_3} + c_8 u_1 \\ \dot{x}_4 = -c_6\sqrt{x_4} + c_{10} u_2 \\ y(t) = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = h_2(x(t)) \end{cases} \tag{6}$$

$$(\Sigma_3): \begin{cases} \dot{x}_1 = -c_1\sqrt{x_1} + c_3\sqrt{x_4} \\ \dot{x}_2 = -c_4\sqrt{x_2} + c_5\sqrt{x_3} \\ \dot{x}_3 = -c_5\sqrt{x_3} + c_8 u_1 \\ \dot{x}_4 = -c_3\sqrt{x_4} + c_{10} u_2 \\ y(t) = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}^T = h_3(x(t)), \end{cases} \tag{7}$$

Based on the proposed hybrid high-gain observer framework, the observer associated with subsystem (Σ_i) is defined as follows.

$$(O_1): \begin{cases} \dot{\hat{x}}_{11} = -c_1\sqrt{\hat{x}_{11}} + c_2\sqrt{\hat{x}_{13}} + c_3\sqrt{\hat{x}_{14}} - 2\theta_1 e_{\omega_1} \\ \dot{\hat{x}}_{12} = -c_4\sqrt{\hat{x}_{12}} + c_5\sqrt{\hat{x}_{13}} + c_6\sqrt{\hat{x}_{14}} - 2\theta_1 e_{\omega_2} \\ \dot{\hat{x}}_{13} = -c_7\sqrt{\hat{x}_{13}} + c_8 u_1 \dfrac{\sqrt{\hat{x}_{13}}}{D}\Big[\\ \quad -c_6\Big(\dfrac{2\theta_1 c_1}{\sqrt{\hat{x}_{11}}} + \theta_1^2\Big)e_{\omega_1} + c_3\Big(\dfrac{2\theta_1 c_4}{\sqrt{\hat{x}_{11}}} + \theta_1^2\Big)e_{\omega_2}\Big] \\ \dot{\hat{x}}_{14} = -c_9\sqrt{\hat{x}_{14}} + c_{10} u_2 + \dfrac{\sqrt{\hat{x}_{14}}}{D}\Big[c_5\Big(\dfrac{2\theta_1 c_1}{\sqrt{\hat{x}_{11}}} + \theta_1^2\Big)e_{\omega_1} \\ \quad -c_2\Big(\dfrac{2\theta_1 c_4}{\sqrt{\hat{x}_{11}}} + \theta_1^2\Big)e_{\omega_2}\Big] \\ \dot{\omega}_{11} = -c_1\sqrt{\hat{x}_{11}} + c_2\sqrt{\hat{x}_{13}} + c_3\sqrt{\hat{x}_{14}} \quad t \in [t_k, t_{k+1}) \\ \dot{\omega}_{12} = -c_4\sqrt{\hat{x}_{12}} + c_5\sqrt{\hat{x}_{13}} + c_6\sqrt{\hat{x}_{14}} \quad t \in [t_k, t_{k+1}) \end{cases} \tag{8}$$

$$(O_2): \begin{cases} \dot{\hat{x}}_{21} = -c_1\sqrt{\hat{x}_{21}} + c_2\sqrt{\hat{x}_{23}} - 2\theta_2 e_{\omega_1} \\ \dot{\hat{x}}_{22} = -c_4\sqrt{\hat{x}_{22}} + c_6\sqrt{\hat{x}_{24}} - 2\theta_2 e_{\omega_2} \\ \dot{\hat{x}}_{23} = -c_2\sqrt{\hat{x}_{23}} + c_8 u_1 - \dfrac{2\sqrt{\hat{x}_{23}}}{c_2}\Big(\dfrac{c_1\theta_2}{\sqrt{\hat{x}_{21}}} + \theta_2^2\Big)e_{\omega_1} \\ \dot{\hat{x}}_{24} = -c_6\sqrt{\hat{x}_{24}} + c_{10} u_2 - \dfrac{2\sqrt{\hat{x}_{24}}}{c_6}\Big(\dfrac{c_4\theta_2}{\sqrt{\hat{x}_{22}}} + \theta_2^2\Big)e_{\omega_2} \\ \dot{\omega}_{21} = -c_1\sqrt{\hat{x}_{21}} + c_2\sqrt{\hat{x}_{23}} \quad t \in [t_k, t_{k+1}) \\ \dot{\omega}_{22} = -c_4\sqrt{\hat{x}_{22}} + c_6\sqrt{\hat{x}_{24}} \quad t \in [t_k, t_{k+1}) \end{cases} \tag{9}$$

$$
(O_3): \begin{cases}
\dot{\hat{x}}_1 = -c_1\sqrt{\hat{x}_1} + c_3\sqrt{\hat{x}_4} - 2\theta_3 e_{\omega_1} \\
\dot{\hat{x}}_2 = -c_4\sqrt{\hat{x}_2} + c_5\sqrt{\hat{x}_3} - 2\theta_3 e_{\omega_2} \\
\dot{\hat{x}}_3 = -c_5\sqrt{\hat{x}_3} + c_8 u_1 - \dfrac{2\sqrt{\hat{x}_3}}{c_5}\left(\dfrac{c_4\theta_3}{\sqrt{\hat{x}_2}} + \theta_3^2\right)e_{\omega_2} \\
\dot{\hat{x}}_4 = -c_3\sqrt{\hat{x}_4} + c_{10} u_2 - \dfrac{2\sqrt{\hat{x}_4}}{c_3}\left(\dfrac{c_1\theta_3}{\sqrt{\hat{x}_1}} + \theta_3^2\right)e_{\omega_1} \\
\dot{\omega}_{31} = -c_1\sqrt{\hat{x}_{31}} + c_3\sqrt{\hat{x}_{34}} \quad t \in [t_k, t_{k+1}) \\
\dot{\omega}_{32} = -c_4\sqrt{\hat{x}_{32}} + c_5\sqrt{\hat{x}_{33}} \quad t \in [t_k, t_{k+1})
\end{cases} \tag{10}
$$

This observer provides an estimate of the system state as well as a predicted output, which is later used in the residual-based selection mechanism to identify the active subsystem.

The effectiveness of the proposed hybrid observer is illustrated through the following numerical simulation results.

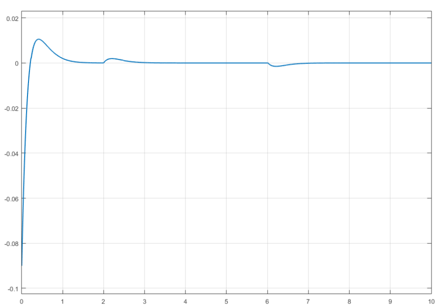

Fig. 1. e_1

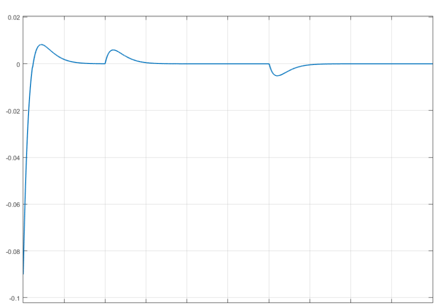

Fig. 2. e_2

A. Simulation Results

The performance of the proposed hybrid high-gain observer is evaluated through numerical simulations carried out on a nonlinear sampled-data switching system composed of three subsystems. The system is subject to unknown switching between modes, and the output is available only at discrete sampling instants. A bank of three hybrid observers, one for each subsystem, is implemented together with the inter-sample output predictor and the residual-based selection mechanism.

Figures 1 and 2 show the observation errors corresponding to the two output components of the system. Since the system

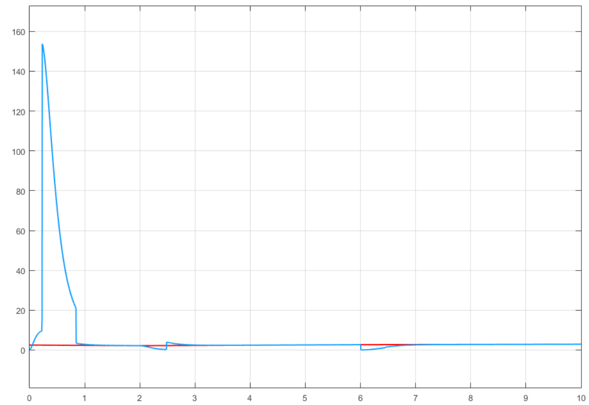

Fig. 3. x_3 and $\hat{x}_3$

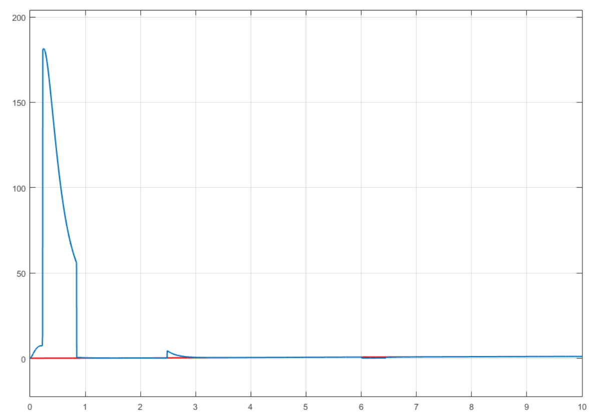

Fig. 4. x_4 and $\hat{x}_4$

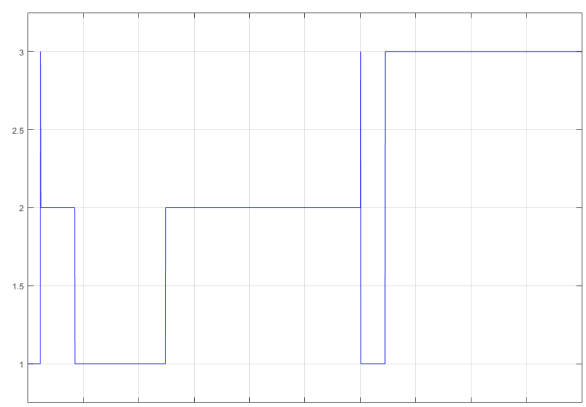

Fig. 5. $\hat{q}$

is multi-output, two observation errors are considered. It can be observed that, after a short transient phase, the observation errors converge toward zero, which indicates that the proposed observer is able to accurately reconstruct the measured outputs despite the sampled-data nature of the system and the presence of switching.

Figures 3 and 4 depict the evolution of the state components x_3 and x_4 together with their corresponding estimates $\hat{x}_3$ and

$\hat{x}_4$. The results show that the estimated states closely track the actual system states after a brief transient period. Small deviations may appear at the switching instants; however, the estimation errors remain bounded and rapidly vanish, confirming the effectiveness of the proposed observer in reconstructing the continuous state.

Figure 5 illustrates the evolution of the estimated discrete mode $\hat{q}$ over time. The values of $\hat{q}$ take values in $\{1, 2, 3\}$ and represent the active observer selected among the available observers. The results confirm that the proposed selection mechanism successfully identifies the active mode and allows the appropriate observer to be selected in order to provide the correct state estimation.

Overall, these simulation results demonstrate that the proposed hybrid observer ensures accurate output estimation, reliable state reconstruction, and correct identification of the active mode in nonlinear sampled-data switching systems.

V. Conclusion

In this paper, a hybrid high-gain observer has been proposed for a class of nonlinear sampled-data switching systems with unknown active modes. The proposed approach relies on a bank of observers combined with an inter-sample output predictor and a residual-based selection mechanism to simultaneously estimate the continuous state and identify the active subsystem. Theoretical analysis ensures the convergence properties of the observer, while simulation results demonstrate its effectiveness in accurately reconstructing the system outputs, estimating the state variables, and identifying the active mode despite switching and sampled-data constraints. Future work will focus on extending the proposed framework to more general classes of hybrid systems and addressing robustness issues in the presence of measurement noise and uncertainties.

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