Stability Analysis of Event-Triggered Networked Control Systems with Time-Varying Sampling

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Abstract. In this paper, the stability analysis of event-triggered networked control systems is investigated. First, a more advanced event-triggered algorithm is introduced. Second, the nonperiodic sampled-data system is modeled as a state delay system. Third, a stability result is derived based on Lyapunov-Krasovskii functional approach. Finally, some simulation results are given to verify the effectiveness of the proposed method.

Keywords: Sampled-data systems · Event-triggering scheme · Linear matrix inequalities

1 Introduction

In recent years, sampled-data systems have attracted the attention of many researchers [1, 2] due to the high-speed development of the digital control systems and networked control systems. Most results about sampled-data systems use a periodic triggered control method [3], periodic sampling method is easy for system modeling and analysis [4], but considering the resource utilization, this way has its limitations. When the system is running smoothly, periodical transmission will result in a waste of resources and bandwidth. At the same time, we should have noticed another fact, with the growing of the systems scale [5, 6], the amount of data transmitted by the network is great, thus, it is necessary to save resources and bandwidth. From the two aspects, the event-triggering mechanism shows its unique advantages [7]. Recently, the research of networked control system based on event-driven mechanism gets an increasing attention, and so far, many research results have been achieved [8–10]. Therefore, it is necessary to analyze and design the networked control system based on the event-driven mechanism.

In the event-triggered mechanism, the transmission of data mainly depends on the predefined trigger algorithm [11]. Therefore, the advantage of an event-triggered mechanism depends on the choice of trigger algorithm and the corresponding parameters settings. At the same time, the stability analysis based on the event-triggered

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mechanism is dependent on the selection of the Lyapunov-Krasovskii equation, an appropriate Lyapunov-Krasovskii equation and the treatment of the corresponding integral term will reduce the conservativeness of the system to a certain extent. A smaller degree of conservatism will make the proposed solution more valuable.

Inspired by literature [12, 13], compared to other aperiodic sampling methods, we take nonperiodic sampled-data system into account and model it as a state delay system, then we proposed a more advanced event-triggered algorithm based on non-periodic sampling, this algorithm has its own unique advantage. Simultaneously, after changing the corresponding parameters, the different set of the element in Θ can reduce the amount of transmitted sampled data. In the selection of the Lyapunov-Krasovskii equation, we choose a discrete Lyapunov-Krasovskii equation to reduce the conservative. At the same time, in the processing of some integral items, we choose the improved Jason inequality [14] and some results in literature [15] to further reduce the conservative.

2 Problem Formulation

Consider a class of linear systems:

$$\dot{x}(t) = Ax(t) + Bu(t) \tag{1}$$

where $x(t) \in R^n$ is the state vector, $u(t) \in R^m$ is the control input, $A \in R^{n\times n}$, $B \in R^{n\times m}$ are known constant matrices with appropriate dimensions.

Similar to [13], this paper considers an event-triggered mechanism, the last released instant $r_k, k = 1, 2, \ldots$ the next released instant $r_{k+1} = r_k + \sum_{s=0}^{l_k} \Delta t_s$ $1 \le l_k < \infty$, $l_k \in N$, then we divide the time interval $[r_k, r_{k+1})$ into the following subintervals:

$$[r_k, r_{k+1}) = U_{d=-1}^{l_k-1} I_d^k \tag{2}$$

where $I_d^k = [r_k + \sum_{s=0}^{d} \Delta t_s, r_k + \sum_{s=0}^{d+1} \Delta t_s), d \in [0, l_k - 1]$, and the trigger instants r_k satisfying $0 = r_0 < r_1 < \ldots < r_k < \ldots$ and $0 \le \underline{r} \le r_{k+1} - r_k \le \bar{r}$, for $\forall k \in N$.

The triggered algorithm proposed in this paper is:

$$\varepsilon^2 e^T(r_k + \sum_{s=0}^{d} \Delta t_s)\Omega_1 e(r_k + \sum_{s=0}^{d} \Delta t_s) \le x^T(r_k)\Theta\,\Omega_2\Theta x(r_k)$$

where

$e(r_k + \sum_{s=0}^{d} \Delta t_s) = x(r_k + \sum_{s=0}^{d} \Delta t_s) - x(r_k), \Theta = diag\{\sqrt{\sigma_1}, \sqrt{\sigma_2}, \ldots, \sqrt{\sigma_n}\}$ with $\sigma_i > 0 (i = 1, 2, \ldots, n), \Omega_1 > 0$, and $\Omega_2 > 0$ are two weighting matrices.

Remark 1. Notice that, compared with traditional event-triggered algorithm, this algorithm introduces a diagonal matrix Θ, this matrix contains different weighting factor σ_i which corresponds to each component x_i of the latest transmitted sampled state x, the different set of the element in Θ can reduce the amount of transmitted sampled data, in this way, the communication and computation resources will be saved deeply. Another point, we can see: if taking $\Theta = diag\{\sqrt{\sigma}, \sqrt{\sigma}, \ldots, \sqrt{\sigma}\}$, $\varepsilon = 1$, this event-triggered algorithm turns into a traditional algorithm. Therefor, this event-triggered algorithm is more general than some existing ones.

Similar to [13], define a time-varying delay $\tau(t)$ as:

$$\tau(t) = \begin{cases} t - r_k, t \in [r_k, r_k + \Delta t_0) \\ t - r_k - \sum\limits_{s=0}^{d} \Delta t_s, t \in [r_k + \sum\limits_{s=0}^{d} \Delta t_s, r_k + \sum\limits_{s=0}^{d+1} \Delta t_s) \end{cases}$$

where $d \in [0, l_k - 1]$.

Then we have

$$e(r_k + \sum_{s=0}^{d} \Delta t_s) = e(t - \tau(t)) = e_\tau(t),$$
$$x(r_k) = x(t - \tau(t)) - e(r_k + \sum_{s=0}^{d} \Delta t_s) = x_\tau(t) - e_\tau(t)$$

The event-triggered algorithm can be written as:

$$\varepsilon^2 e_\tau^T(t)\Omega_1 e_\tau(t) \le [x_\tau(t) - e_\tau(t)]^T \Theta\, \Omega_2 \Theta [x_\tau(t) - e_\tau(t)]$$

Considering the event-triggered mechanism, we can design the controller as follow:

$$u(t) = Kx(r_k), t \in [r_k, r_{k+1}) \tag{3}$$

where $u(t) \in R^m$ is the control input satisfying $u(t) = u(r_k)$.

$$x(r_k) = x_\tau(t) - e_\tau(t) \tag{4}$$

Substituting (3) into (1) yields.

$$\dot{x}(t) = Ax(t) + BKx(r_k) \tag{5}$$

Then substituting (4) into (5) yields, the original model can be converted into:

$$\dot{x}(t) = Ax(t) + A_1(x_\tau(t) - e_\tau(t)), t \in [r_k, r_{k+1}) \tag{6}$$

where $A_1 = BK$.

Lemma 1 [14]. For a given matrix $R \in S_+^n$, any differentiable function x in $[a, b] \to R^n$, the inequality holds:

$$\int_a^b \dot{x}^T(u)R\dot{x}(u)du \geq \frac{1}{b-a}\Omega^T diag(R, 3R)\Omega$$

where

$$\Omega = \begin{bmatrix} x(b) - x(a) \\ x(b) + x(a) - \frac{2}{b-a}\int_a^b x(u)du \end{bmatrix}$$

3 Stability Analysis

Theorem 1. For given positive $\underline{r}$ and $\bar{r}$, $1 \times n$ matrix K, if there exist symmetric matrix $P > 0$, $Q > 0$, $\Omega > 0, Q_1 > 0, Q_2 \in R^{n\times n} M_1, M_2 \in R^{n\times n}$ and N_{1j}, N_{2j}, $N_{3j} \in R^{n\times n}(j = 1, 2, 3, 4)$, the following inequalities hold.

$$\begin{bmatrix} \Pi_{11} & * & * & * & * & * \\ \Pi_{21} & \Pi_{22} & * & * & * & * \\ \Pi_{31} & \Pi_{32} & \Pi_{33} & * & * & * \\ \Pi_{41} & \Pi_{42} & \Pi_{43} & \Pi_{44} & * & * \\ rN_{11}^T & rN_{12}^T & rN_{13}^T & rN_{14}^T & -rQ & * \\ 3rN_{21}^T & 3rN_{22}^T & 3rN_{23}^T & 3rN_{24}^T & 0 & -3rQ \end{bmatrix} < 0$$

$$\begin{bmatrix} X_{11} & * & * & * & * \\ X_{21} & X_{22} & * & * & * \\ X_{31} & X_{32} & X_{33} & * & * \\ X_{41} & X_{42} & X_{43} & X_{44} & * \\ rAQ & rA_1Q & -rA_1Q & 0 & -rQ \end{bmatrix} < 0$$

where

$$\begin{aligned}
\Pi_{11} &= A^TP + PA - N_{11} - N_{11}^T - N_{31} - N_{31}^T - 3N_{21} - 3N_{21}^T - 2M_1 \\
\Pi_{21} &= A_1^TP - N_{12} + N_{11}^T - N_{32} + N_{31}^T - 3N_{22} - 3N_{21}^T - M_2 + M_1 + rA_1^TN_{31}^T \\
\Pi_{22} &= N_{12} + N_{12}^T + N_{32} + N_{32}^T - 3N_{22} - 3N_{22}^T + 2M_2 + rN_{32}A_1 + rA_1^TN_{32}^T \\
&\quad - rQ_2 + \Theta\,\Omega\,\Theta \\
\Pi_{31} &= A_1^TP - N_{13} - N_{11}^T - N_{33} - N_{31}^T - 3N_{23} + 3N_{21}^T + M_2 - M_1 - rA_1^TN_{31}^T \\
\Pi_{32} &= N_{13} - N_{12}^T + N_{33} - N_{32}^T - 3N_{23} + 3N_{22}^T - 2M_2 + rN_{33}A_1 - rA_1^TN_{32}^T \\
&\quad + rQ_2 - \Theta\,\Omega\,\Theta \\
\Pi_{33} &= -N_{13} - N_{13}^T - N_{33} - N_{33}^T + 3N_{23} + 3N_{23}^T + 2M_2 - rN_{33}A_1 - rA_1^TN_{33}^T \\
&\quad - rQ_2 - \varepsilon^2\Omega + \Theta\,\Omega\,\Theta
\end{aligned}$$

$$\Pi_{41} = -N_{14} - N_{34} - 3N_{24} + 6N_{21}^T + rA^TN_{31}^T$$
$$\Pi_{42} = N_{14} + N_{34} - 3N_{24} + 6N_{22}^T + rN_{34}A_1 + rA^TN_{32}^T$$
$$\Pi_{43} = -N_{14} - N_{34} + 3N_{24} + 6N_{23}^T - rN_{34}A_1 + rA^TN_{33}^T$$
$$\Pi_{44} = 6N_{24} + 6N_{24}^T + rN_{34}A + rA^TN_{34}^T - rQ_1$$

$$\begin{aligned}
X_{11} &= A^TP + PA - N_{11} - N_{11}^T - N_{31} - N_{31}^T - 3N_{21} - 3N_{21}^T - 2M_1 + rA^TM_1 \\
&\quad + 2rM_1A + rA^TM_1 + rQ_1 \\
X_{21} &= A_1^TP - N_{12} + N_{11}^T - N_{32} + N_{31}^T - 3N_{22} - 3N_{21}^T - M_2 + M_1 + rA_1^TM_1 \\
&\quad + rM_2A + rA_1^TM_1 - rM_1A \\
X_{22} &= N_{12} + N_{12}^T + N_{32} + N_{32}^T - 3N_{22} - 3N_{22}^T + 2M_2 - rA_1^TM_1 + rM_2A_1 \\
&\quad - rM_1A_1 + rA_1^TM_2 + rQ_2 \\
X_{31} &= A_1^TP - N_{13} - N_{11}^T - N_{33} - N_{31}^T - 3N_{23} + 3N_{21}^T + M_2 - M_1 - rA_1^TM_1 \\
&\quad - rM_2A - rA_1^TM_1 + rM_1A \\
X_{32} &= N_{13} - N_{12}^T + N_{33} - N_{32}^T - 3N_{23} + 3N_{22}^T - 2M_2 + rA_1^TM_1 - rM_2A_1 \\
&\quad + rM_1A_1 - rA_1^TM_2 - rQ_2 \\
X_{33} &= -N_{13} - N_{13}^T - N_{33} - N_{33}^T + 3N_{23} + 3N_{23}^T + 2M_2 - rA_1^TM_1 + rM_2A_1 \\
&\quad - rM_1A_1 + rA_1^TM_2 + rQ_2 \\
X_{41} &= -N_{14} - N_{34} - 3N_{24} + 6N_{21}^T \\
X_{42} &= N_{14} + N_{34} - 3N_{24} + 6N_{22}^T \\
X_{43} &= -N_{14} - N_{34} + 3N_{24} + 6N_{23}^T
\end{aligned}$$

Then the system (6) is asymptotically stable.

Proof. Similar to [12], select a Lyapunov-like functional:

$$V(x(t), t) = V_1(x(t)) + V_2(x(t), t) + V_3(x(t), t)$$

where

$$V_1(x(t)) = x^T(t)Px(t)$$
$$V_2(x(t), t) = 2(r_{k+1} - t)(x^T(t)M_1 + x^T(r_k)M_2)(x(t) - x(r_k)) + (r_{k+1} - t)\int_{r_k}^{t} \dot{x}(s)Q\dot{x}(s)ds$$
$$V_3(x(t), t) = (r_{k+1} - t)\int_{r_k}^{t} x^T(s)Q_1x(s)ds + (r_{k+1} - t)(t - r_k)x^T(r_k)Q_2x(r_k)$$

Then define $\xi(t) = \begin{bmatrix} x^T(t) & x_\tau^T(t) & e_\tau^T(t) & v^T(t) \end{bmatrix}^T$
where $v(t) = \frac{1}{t-r_k}\int_{r_k}^{t} x(s)ds$.

Taking the derivative of $V(x(t), t)$ along the trajectory of system (6).

$$\dot{V}(x(t),t) = \dot{V}_1(x(t)) + \dot{V}_2(x(t),t) + \dot{V}_3(x(t),t)$$
$$\dot{V}_1(x(t)) = x^T(t)(A^TP + PA)x(t) + 2x^T(t)PA_1x_\tau(t) - 2x^T(t)PA_1e_\tau(t)$$
$$\dot{V}_2(x(t),t) = 2\xi^T(t)Z_1\xi(t) + (r_{k+1} - t)\xi^T(t)(He(Z_2) + Z_3)\xi(t) - \int_{r_k}^{t} \dot{x}^T(s)Q\dot{x}(s)ds$$
$$\dot{V}_3(x(t),t) = (r_{k+1} - t)\xi^T(t)\Gamma_1\xi(t) + (r_{k+1} - t)\xi^T(t)\Gamma_2\xi(t) - (t - r_k)\xi^T(t)\Gamma_2\xi(t) - \int_{r_k}^{t} x^T(s)Q_1x(s)ds$$

where

$$Z_1 = \begin{bmatrix} -M_1 & M_1 & -M_1 & 0 \\ -M_2 & M_2 & -M_2 & 0 \\ M_2 & -M_2 & M_2 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$Z_2 = \begin{bmatrix} A^TM_1 + M_1A & M_1A_1 - A^TM_1 & -M_1A_1 + A^TM_1 & 0 \\ A_1^TM_1 + M_2A & -A_1^TM_1 + M_2A_1 & A_1^TM_1 - M_2A_1 & 0 \\ -A_1^TM_1 - M_2A & A_1^TM_1 - M_2A_1 & -A_1^TM_1 + M_2A_1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$Z_3 = \begin{bmatrix} A^TQA & * & * & * \\ A_1^TQA & A_1^TQA_1 & * & * \\ -A_1^TQA & -A_1^TQA_1 & A_1^TQA_1 & * \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\Gamma_1 = \begin{bmatrix} Q_1 & * & * & * \\ 0 & 0 & * & * \\ 0 & 0 & 0 & * \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad \Gamma_2 = \begin{bmatrix} 0 & * & * & * \\ 0 & Q_2 & * & * \\ 0 & -Q_2 & Q_2 & * \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Integrating both sides of system (5) 0n $[r_k, t)$, we have

$$x(t) - x(r_k) = A\int_{r_k}^{t} x(s)ds + (t - r_k)A_1x(r_k) \tag{7}$$

According to (7), there exists $N_3 \in R^{4n\times n}$ such that

$$\begin{aligned} -2\xi^T(t)N_3(e_1 - e_2 + e_3)\xi(t) + 2(t - r_k)\xi^T(t)N_3Ae_4\xi(t) \\ + 2(t - r_k)\xi^T(t)N_3A_1(e_2 - e_3)\xi(t) = 0 \end{aligned} \tag{8}$$

By Lemma 1, we have

$$-\int_{r_k}^{t} \dot{x}^T(s)Q\dot{x}(s)ds \leq -\frac{1}{t-r_k}\xi^T(t)(e_1-e_2+e_3)^T Q(e_1-e_2+e_3)\xi(t)$$
$$-\frac{3}{t-r_k}\xi^T(t)(e_1+e_2-e_3-2e_4)^T Q(e_1+e_2-e_3-2e_4)\xi(t)$$

In addition, there exist $N_1, N_2 \in R^{4n\times n}$ satisfies the following inequalities.

$$\begin{aligned} -\int_{r_k}^{t} \dot{x}^T(s)Q\dot{x}(s)ds \leq (t-r_k)N_1Q^{-1}N_1^T - N_1(e_1-e_2+e_3) - N_1^T(e_1-e_2+e_3)^T \\ +3(t-r_k)N_2Q^{-1}N_2^T - 3N_2(e_1+e_2-e_3-2e_4) - 3N_2^T(e_1+e_2-e_3-2e_4)^T \end{aligned} \tag{9}$$

where

$e_1 = [I \quad 0 \quad 0 \quad 0], e_2 = [0 \quad I \quad 0 \quad 0], e_3 = [0 \quad 0 \quad I \quad 0], e_4 = [0 \quad 0 \quad 0 \quad I]$
According to Jensen inequality, we have the following inequality.

$$-\int_{r_k}^{t} x^T(s)Q_1x(s)ds \leq -(t-r_k)v^T(t)Q_1v(t) \tag{10}$$

From (8)–(10), by Schur complement lemma, Theorem 1 can be derived for $r \in \{\underline{r}, \bar{r}\}$.

4 Numerical Examples

In this section, a numerical simulation is given to verify the results proposed in the previous section.

Example 1. Consider the system in [12] with the parameter matrices.

$$A = \begin{bmatrix} 0 & 1 \\ 0 & -0.1 \end{bmatrix}, \quad A_1 = \begin{bmatrix} 0 & 0 \\ -0.375 & -1.15 \end{bmatrix}$$

When $\underline{r} = 0$, the admissible upper bound $\bar{r}$ can be calculated by Matlab LMI toolbox according to Theorem 1.

(1) Case 1: Set event-trigger parameters

$$\varepsilon = 1, \Theta = diag\{0.59, 0.47\}$$

The admissible upper bound $\bar{r}$ and some results in [12, 16, 17] are shown in Table 1.

From Table 1, it can be seen clearly that Theorem 1 has a less conservatism than the results in [12, 16, 17].

Table 1. Admissible upper bound $\bar{r}$ under different schemes

Schemes	[12]	[16]	[17]	Theorem 1
$\bar{r}$	1.729	1.69	1.7216	2.44

So as to further verify the effectiveness of the event-triggered algorithm, we make the following experiments.

(2) Case 2: we set different ε to do several simulations.

$$\varepsilon_1 = 10, \varepsilon_2 = 15, \varepsilon_3 = 30$$

The admissible upper bounds corresponding to different ε are shown in Table 2.

From Table 2, we can see clearly that different ε can reduce the conservatism to different degrees.

Table 2. Admissible upper bound $\bar{r}$ with different ε

Different ε	ε_1	ε_2	ε_3
$\bar{r}$	2.51	2.54	2.59

Example 2. Consider the system in [12].

$$A = \begin{bmatrix} 0.05 & 0.6 & 0.1 \\ -3 & -2 & 0.1 \\ 0.1 & 0 & -2 \end{bmatrix}, \quad A_1 = \begin{bmatrix} 0.05 & 0.05 & 0.4 \\ -1 & 1 & 0.05 \\ 0.5 & 0.05 & -0.9 \end{bmatrix}$$

(1) Case 1: Set event-trigger parameters

$$\varepsilon = 15, \quad \Theta = diag\{0.59, 0.47, 0.51\}$$

The admissible upper bound and some results in [14, 17] are shown in Table 3.

For the different simulation model, the Table 3 shows that Theorem 1 has a less conservatism than the results in [14, 17].

Table 3. Admissible upper bound $\bar{r}$ under different schemes

Schemes	[14]	[17]	Theorem 1
$\bar{r}$	2.33	2.00	2.51

(1) Case 2: Now we set $\Theta = diag\{0.59, 0.47, 0.51\}$ and choose different ε to do several simulations.

$$\varepsilon_1 = 20, \varepsilon_2 = 25, \varepsilon_3 = 30$$

The admissible upper bounds $\bar{r}$ corresponding to different ε are shown in Table 4.

From Table 4, we can see clearly that different ε can reduce the conservatism to different degrees.

From Tables 1 and 3, it is seen clearly that Theorem 1 is less conservative than the results in literature [16, 17]. From Tables 2 and 4, we can see clearly that the event-triggering algorithm has a certain effect in reducing conservatism.

Table 4. Admissible upper bound $\bar{r}$ with different ε

Different ε	ε_1	ε_2	ε_3
$\bar{r}$	2.66	2.77	2.84

5 Conclusion

In this paper, based on the sampling-dependent stability for sampled-data systems, a more general event-triggering mechanism is taken into account. In terms of reducing conservatism, we utilize a Lyapunov-like functional including the integral of the state. Simultaneously, we use the improved Jensen inequality for the derivative of the Lyapunov-like functional. At last, a sampling-dependent stability theorem is derived. The validity of this theorem is verified by several simulation experiments.

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