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Research article

Generalized fault estimator-based prescribed performance control for a class of strict-feedback nonlinear systems

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Abstract: This paper addresses fault estimation and prescribed performance control for strict-feedback nonlinear systems subject to unknown time-varying faults. By introducing a novel intermediate variable for fault estimation, an adaptive fault estimator and a fault-tolerant controller are proposed. Utilizing a proof by contradiction, the designed prescribed performance control scheme resolves the complex coupling between fault estimation and adaptive control. Furthermore, all closed-loop signals are proven bounded, with both tracking and state errors converging to predesigned compact sets. Finally, numerical simulation on a single-link robot system validates the effectiveness of the proposed algorithm.

Keywords: generalized fault estimator; prescribed performance control; nonlinear system; intermediate variable; fault-tolerant control
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1. Introduction

In many complex engineering systems, such as aerospace, surface ships, etc., their automation components inevitably suffer from faults of varying degrees, such as actuator faults or process faults. If faults cannot be detected and eliminated in a timely manner, it may cause abnormal operation of the control system, system paralysis, and even catastrophic accidents [1–3]. Since many engineering systems can be simulated by corresponding nonlinear structures [4–6], it is of great significance to study the fault-tolerant control of nonlinear systems.

How to achieve accurate tracking and global stability of the system in the case of time-varying faults is a key problem.To this end, Fault Detection and Isolation (FDI) techniques [7–9] provide the foundational methods for identifying and diagnosing system anomalies to ensure safe, reliable, and efficient operation. However, in practical engineering, unexpected factors, such as operator actions and environmental changes, make the fault detection and isolation task in these systems challenging. Moreover, it is quite difficult to obtain the exact shape and size of faults only by the FDI scheme [10–12]. In order to reproduce the dynamic process of faults, observer-based fault estimation methods have emerged as a powerful tool, valued for their ability to provide real-time fault information with flexible and simple structures [13–15]. For a class of switched descriptor systems subject to Lipschitz nonlinearities and unknown inputs, a functional observer is proposed in [16] for robust state estimation. Li et al. [17] proposed an integrated estimation observer to achieve fault estimation for a class of nonlinear systems with Lipschitzian nonlinearities and faults.

The aforementioned fault estimation approaches require the observer matching condition to be satisfied, which is often difficult to meet in many practical control systems. Zhu et al. [18] mitigated this limitation through the introduction of an intermediate estimator. Furthermore, prevalent approaches addressing unknown system nonlinearities frequently rely on restrictive assumptions such as global Lipschitz continuity or bounding inequalities. Huang et al. [19] addressed this by proposing a linear transformation technique with an adaptive output feedback controller, relaxing the stringent control matching condition. Building on this, the authors of [20] successfully removed the global Lipschitz constraint and developed a novel state observer. Subsequently, leveraging the observer from , the authors of [21] devised a fault-tolerant control scheme for nonlinear systems subject to unknown time-varying faults and actuator dead zones, achieving robust tracking performance. Despite these advances, the design of computationally efficient, high-performance fault estimators and fault-tolerant controllers continues to pose a significant challenge.

Adaptive backstepping-based tracking control has been widely used in strict-feedback nonlinear systems [22–24]. However, in the closed-loop configuration of such systems, the coupling between the fault estimator and the fault-tolerant controller introduces significant complexity when employing the backstepping approach [25]. Moreover, the conventional backstepping tuning function scheme often fails to guarantee transient performance of system parameters and imposes substantial computational burdens due to the recursive derivative computations required for virtual control laws at each design step. In contrast, the prescribed performance control (PPC) has attracted much attention due to its superior precision and robust real-time performance [26–28]. Specifically, PPC eliminates the need for repeated derivation by error transformation and simplifies Lyapunov analysis by specifying bounds, while achieving higher computational efficiency than conventional backstepping. This method rigorously ensures that the tracking error converges to a user-specified compact set without violating the predefined transient metrics. Building on these advancements, a low-complexity state feedback fault-tolerant control scheme [29] with novel error transformation functions and new update laws was developed. Further advancing this approach, the authors in [30] studied the output tracking problem with prescribed transient and steady-state performance for strict-feedback systems with unknown nonlinear functions and mismatched disturbances. Their solution provides a continuous static low-complexity controller through a novel integration of smooth directional and error transformation functions.

In view of the above discussion, the difficulties faced in this paper are as follows: 1) Is it possible to develop a more generalized fault estimator for system fault estimation? 2) How can the coupling effect between the controller and the fault estimator be eliminated? 3) How can the computational complexity be reduced during the design of the control strategy?

Motivated by the above discussion, this paper studies the adaptive fault estimation and PPC for a class of strict-feedback nonlinear systems with time-varying faults. The main contributions are listed as follows:

1) Different from the fault estimation approaches mentioned above [18, 21, 32], we propose a more general intermediate estimator with time-varying parameter update law, where the added time-varying gain has the property of being monotonically decreasing and greater than zero. This further improves the fault estimation accuracy.

2) Combining the fault estimator with the prescribed performance control, the adaptive fault-tolerant controller is designed without considering the coupling interaction between controller and fault estimator in [18,21]. And, the structure can ensure that the system errors converge to the present ranges.

3) Distinct from existing approaches [14, 18, 21], the proposed control architecture simplifies controller design complexity and reduces computational burden by eliminating the need for iterative intermediate signal derivative calculations. Furthermore, it maintains performance robustness against model uncertainties without introducing complex adaptive structures or inherent approximation errors associated with neural networks or fuzzy systems [25, 28].

The rest of this article is organized as follows: In Section 2, the problem statement and several related assumptions are introduced. The design process of the fault estimator is also given. Section 3 introduces the control process and stability analysis. The numerical simulation results are given in Section 4. Finally, the fifth part draws the conclusion.

2. Problem formulation and preliminaries

2.1. System descriptions

Consider a class of strict-feedback nonlinear systems described by

$$\begin{cases} \dot{x}_1 = x_2, \\ \vdots \\ \dot{x}_{n-1} = x_n, \\ \dot{x}_n = d(x) + gu + f(t), \\ y = x_1, \end{cases} \tag{2.1}$$

where $x = [x_1, x_2, \cdots, x_n]^T \in \mathbb{R}^n$ is the system state vector; $u \in \mathbb{R}$ and $y \in \mathbb{R}$ represent the control input and output, respectively; $d(x) \in \mathbb{R}$ denotes modeling uncertainty or disturbance; $f(t) \in \mathbb{R}$ is an unknown fault signal; and $g \in \mathbb{R}$ is a known constant. In this paper, $f(t)$ can represent various types of faults such as actuator faults and process faults. System (2.1) is assumed to be controllable; therefore, $g \neq 0$.

To develop the systems state observer and the fault estimator, the model (2.1) can be rewritten as

$$\begin{cases} \dot{x} = Ax + Ly + B\left(d(x) + gu + f(t)\right), \\ y = x_1, \end{cases} \tag{2.2}$$

where

$$A = \begin{bmatrix} -l_1 & 1 & 0 & \dots & 0 \\ -l_2 & 0 & 1 & \dots & 0 \\ \vdots & \ddots & \ddots & \ddots & 0 \\ -l_{n-1} & 0 & 0 & \dots & 1 \\ -l_n & 0 & 0 & \dots & 0 \end{bmatrix}, L = \begin{bmatrix} l_1 \\ l_2 \\ \vdots \\ l_{n-1} \\ l_n \end{bmatrix}, B = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix},$$

and L is a matrix to be determined, such that A is a Hurwitz matrix.

Assumption 1. *[28] The target trajectory y_d and its first-order derivative $\dot{y}_d$ are bounded.*

Remark 1. *A large number of systems, such as single-link robots and chaotic systems, can be described by (2.1). Compared with exist works, less knowledge of the system is requested in this study. While prior works like [21] assume that all derivatives of the target trajectory $y_d^{(i)}$ $(i = 1, \dots, n)$ must exist and be measurable, this study reduces derivative dependency – only lower-order derivative information is needed for implementation.*

Assumption 2. *[24] The first derivative of the unknown time-varying fault $f(t)$ is bounded such that $|\dot{f}(t)| \le \bar{f}$, where $\bar{f} \ge 0$ is a known constant.*

Remark 2. *The design of observers—particularly fault observers [14, 21, 24]—typically requires a priori knowledge of the bounds on faults and their derivatives. Assumption 2 is thus rigorously justified by this well-established methodology, establishing a theoretical foundation for fault estimation.*

Lemma 1. *[21] Let $F : \mathbb{R}^n \to \mathbb{R}^q$ be a differentiable function, and $a, b \in \mathbb{R}^n$. Assume that F is differentiable on $C_0(a, b)$. Then, there exist constant vectors $c_1, ..., c_q \in C_0(a, b)$, with $c_i \ne a$ and $c_i \ne b$ for each $i = 1, ..., q$, such that*

$$F(a) - F(b) = \left(\sum_{i,j=1}^{q,n} e_q(i) e_n^T(j) \frac{\partial F_i}{\partial x_j}(c_i) \right)(a - b), \tag{2.3}$$

where $e_q(i) = (0, ..., 0, \underbrace{1}_{ith}, 0, ..., 0) \in R^q$ and $C_0(a, b) = \lambda a + (1 - \lambda)b, 0 \le \lambda \le 1$.

Lemma 2. *If the time-varying function $\rho(t)$ satisfies the following equation*

$$\dot{\rho}(t) = -\rho^2(t), \tag{2.4}$$

and given any specified initial condition with $\rho(0) > 0$, it is ensured that both $\rho(t)$ and its first-order dynamic term $\dot{\rho}(t)$ are bounded. Additionally, $\rho(t)$ meets the condition $\rho(t) \in (0, \rho(0)]$.

Proof. Integrating Eq (2.4) can lead to

$$\rho(t) = \frac{\rho(0)}{\rho(0)t + 1}. \tag{2.5}$$

According to (2.4), $\rho(0) > 0$ and $\rho(t)$ is monotonically decreasing; we can obtain that $\rho(t)$ is bounded and satisfies $\rho(t) \in (0, \rho(0)]$. Moreover, considering the boundedness of $\rho(t)$, along with (2.4), it can be deduced that $\dot{\rho}(t)$ is also bounded. This confirms the validity of Lemma 2.

The problem to be solved is how to design the fault estimator and prescribed performance controller for (2.2) to guarantee the accuracy of fault estimation, the tracking performance, and the stability of the systems, while keeping all the closed-loop signals bounded.

The control objects are that:

1) The fault estimation module can recreate the dynamic process of the fault.

2) The tracking error is limited in a preset area; also, all the closed-loop system signals are bounded.

2.2. *Design of state observer and fault estimator*

In this subsection, the state observer and the system fault estimator will be proposed to deal with the nonlinear system (2.1). Inspired by [21], the state observer is developed as follows:

$$\begin{cases} \dot{\hat{x}} = A\hat{x} + Ly + B\left(d(\hat{x}) + gu + \hat{f}(t)\right), \\ \hat{y} = \hat{x}_1, \end{cases} \tag{2.6}$$

where $\hat{x} = [\hat{x}_1, \hat{x}_2, \cdots, \hat{x}_n]^T \in \mathbb{R}^n$; $\hat{x}_i$ $(i = 1, \ldots, n)$ and $\hat{y}$ denote the observed values of x_i and y; $\hat{f}(t)$ represents the estimated value of the system fault $f(t)$.

The state error $\tilde{x}$ and the fault estimation error $\tilde{f}(t)$ are defined as $\tilde{x} = x - \hat{x}$ and $\tilde{f}(t) = f(t) - \hat{f}(t)$. Invoking (2.2) and (2.6), we obtain

$$\dot{\tilde{x}} = A\tilde{x} + B\left(d(x) - d(\hat{x}) + \tilde{f}(t)\right). \tag{2.7}$$

Considering Lemma 1, we can obtain that

$$d(x) - d(\hat{x}) = h(t)\tilde{x}, \tag{2.8}$$

where $h(t) = \sum_{i=1}^{n} e_n^T(j)\frac{\partial d_i}{\partial x_j}(\xi_i)$, and $\xi_i \in C_0(x(t), \tilde{x}(t))$ for $i = 1, \ldots, n$. Given the expression of $h(t)$, $h(t)$ is bounded. Specifically, there exists a constant H^* such that $|h(t)| \leq H^*$ for all t.

Invoking (2.8), (2.7) can be rewritten as

$$\dot{\tilde{x}} = \overline{A}\tilde{x} + B\tilde{f}(t), \tag{2.9}$$

where $\overline{A} = A + Bh(t)$.

Since A is a Hurwitz matrix, there always exists a symmetric positive definite matrix $P = P^T > 0$ such that, for a suitably chosen positive definite matrix $Q = Q^T > 0$, and considering $\overline{A} = A + Bh(t)$, the following matrix inequality holds:

$$\overline{A}^T P + P\overline{A} \leq -Q < 0. \tag{2.10}$$

In order to realize the estimation of time-varying fault $f(t)$, inspired by [21, 24], a more general intermediate variable is developed as follows:

$$\varepsilon(t) = f(t) - (\rho(t) + \gamma)\, x_n, \gamma > 0, \tag{2.11}$$

where $\rho(t)$ is the designed time-varying function (defined and characterized in detail in Lemma 2, and $\gamma > 4$ is a known bounded constant to be specified later.

Considering Eqs (2.2) and (2.11), we obtain

$$\begin{aligned}\dot{\varepsilon} &= \dot{f}(t) - \dot{\rho}(t)x_n - (\rho(t) + \gamma)\,\dot{x}_n \\ &= \dot{f}(t) - \dot{\rho}(t)x_n - (\rho(t) + \gamma)\,(d(x) + gu + \varepsilon + (\rho(t) + \gamma)x_n) \\ &= \dot{f}(t) - \dot{\rho}(t)x_n - (\rho(t) + \gamma)\,\varepsilon - (\rho(t) + \gamma)\,(d(x) + gu + (\rho(t) + \gamma)x_n)\,.\end{aligned} \tag{2.12}$$

According to (2.2), (2.11), and (2.12), the intermediate variable update law can be designed as

$$\dot{\hat{\varepsilon}} = -\dot{\rho}(t)\hat{x}_n - (\rho(t) + \gamma)\,\hat{\varepsilon} - (\rho(t) + \gamma)\,(d(\hat{x}) + gu + (\rho(t) + \gamma)\hat{x}_n)\,. \tag{2.13}$$

Further, the fault estimator can be designed as

$$\hat{f}(t) = \hat{\varepsilon} + (\rho(t) + \gamma)\,\hat{x}_n. \tag{2.14}$$

To further elucidate the distinctions between the generalized intermediate variable-based fault estimation strategy proposed in this paper, as defined by Eqs (2.13) and (2.14), and those presented in [18, 21], Table 1 is plotted for illustration.

Table 1. Different methods of fault estimation.

Ref.	Fault Estimator Description
This paper	$\begin{cases} \hat{f}(t) = \hat{\varepsilon} + (\rho(t) + \gamma)\,\hat{x}_n \\ \dot{\hat{\varepsilon}} = -\dot{\rho}(t)\hat{x}_n - (\rho(t) + \gamma)\,\hat{\varepsilon} - (\rho(t) + \gamma)\,(d(\hat{x}) + gu + (\rho(t) + \gamma)\hat{x}_n) \end{cases}$
[18, 21]	$\begin{cases} \hat{f}(t) = \hat{\varepsilon} + \gamma\hat{x}_n \\ \dot{\hat{\varepsilon}} = -\gamma\hat{\varepsilon} - \gamma\,(d(\hat{x}) + gu + \gamma\hat{x}_n) \end{cases}$

In addition, the intermediate variable error is as follows

$$\begin{aligned}\tilde{\varepsilon} &= \varepsilon - \hat{\varepsilon} \\ &= (f(t) - (\rho(t) + \gamma)\,x_n) - \left(\hat{f}(t) - (\rho(t) + \gamma)\hat{x}_n\right) \\ &= \tilde{f}(t) - (\rho(t) + \gamma)\,\tilde{x}_n.\end{aligned} \tag{2.15}$$

Differentiating (2.15), we have

$$\begin{aligned}\dot{\tilde{\varepsilon}} &= \dot{\varepsilon} - \dot{\hat{\varepsilon}} \\ &= \dot{f}(t) - \dot{\rho}(t)x_n - (\rho(t) + \gamma)\,\varepsilon - (\rho(t) + \gamma)\,(d(x) + gu + (\rho(t) + \gamma)x_n) \\ &\quad - (-\dot{\rho}(t)\hat{x}_n - (\rho(t) + \gamma)\hat{\varepsilon} - (\rho(t) + \gamma)\,(d(\hat{x}) + gu + (\rho(t) + \gamma)\hat{x}_n)) \\ &= \dot{f}(t) - \dot{\rho}(t)\tilde{x}_n - (\rho(t) + \gamma)\,h(t)x - (\rho(t) + \gamma)\,\tilde{\varepsilon} - (\rho(t) + \gamma)^2\,\tilde{x}_n.\end{aligned} \tag{2.16}$$

Lemma 3. *[30] For bounded initial conditions, if there exists a continuous and positive definite Lyapunov function $V(x)$ satisfying $\pi_1(\|x\|) \leq V(x) \leq \pi_2(\|x\|)$, where $\pi_1, \pi_2 : R^n \to R$ are class K functions, and $\dot{V}(x) \leq -c_1V(x) + c_2$, for some positive constants $c_1, c_2 > 0$, then the solution $x(t)$ is uniformly ultimately bounded.*

Consider the Lyapunov function $V = V(t)$ as

$$V = \tilde{x}^T P \tilde{x} + \frac{1}{2}\tilde{\varepsilon}^2, \tag{2.17}$$

whose first-order time derivative is

$$\begin{aligned}
\dot{V} &= \dot{\tilde{x}}^T P \tilde{x} + \tilde{x}^T P \dot{\tilde{x}} + \tilde{\varepsilon}\dot{\tilde{\varepsilon}} \\
&= \tilde{x}^T \left(\bar{A}^T P + P\bar{A}\right) \tilde{x} + 2\tilde{x}^T PB\tilde{f}(t) + \tilde{\varepsilon}\Big(\dot{f}(t) \\
&\quad - \dot{\rho}(t)\tilde{x}_n - (\rho(t) + \gamma)\, h(t)x - (\rho(t) + \gamma)\, \tilde{\varepsilon} - (\rho(t) + \gamma)^2\, \tilde{x}_n\Big).
\end{aligned} \tag{2.18}$$

Based on Young's inequality and Lemma 2, we obtain

$$\begin{aligned}
\bar{A}^T P + P\bar{A} &\leq -Q, \\
2\tilde{x}^T PB\tilde{f}(t) &\leq 2\|\tilde{x}\|\|PB\|\|\tilde{f}(t)\| \leq \tau^2\|\tilde{x}\|^2 + \tilde{f}^2(t) \\
&\leq \tau^2\|\tilde{x}\|^2 + 2\tilde{\varepsilon}^2 + 2\left(\rho(0) + \gamma\right)^2 \|\tilde{x}\|^2, \\
\tilde{\varepsilon}\dot{f}(t) &\leq \frac{1}{2}\tilde{\varepsilon}^2 + \frac{1}{2}\dot{f}^2(t) \leq \frac{1}{2}\tilde{\varepsilon}^2 + \frac{1}{2}\bar{f}^2, \\
-(\rho(t) + \gamma)h\tilde{\varepsilon}\tilde{x} &\leq \frac{1}{2}\tilde{\varepsilon}^2 + \frac{1}{2}\left(\rho^2(0) + \gamma\right) H^{*2}\tilde{x}^2 \\
&\leq \frac{1}{2}\tilde{\varepsilon}^2 + \frac{1}{2}\rho^2(0)H^{*2}\|\tilde{x}\|^2 + \gamma\rho(0)H^{*2}\|\tilde{x}\|^2 + \frac{1}{2}\gamma^2\|\tilde{x}\|^2, \\
-(\rho(t) + \gamma)^2\tilde{\varepsilon}\tilde{x}_n &\leq \frac{1}{2}\tilde{\varepsilon}^2 + \frac{1}{2}\gamma^2\rho^2(0)x_n^2 \leq \frac{1}{2}\tilde{\varepsilon}^2 + \frac{1}{2}(\rho^2(0) + \gamma)^4\|\tilde{x}\|^2.
\end{aligned} \tag{2.19}$$

Combining (2.18) and (2.19), one can further conclude that

$$\begin{aligned}
\dot{V} &\leq -\tilde{x}^T \left(Q - \bar{\tau}I\right) \tilde{x} - \left(\rho(t) + \gamma - 4\right) \tilde{\varepsilon}^2 + \frac{1}{2}\bar{f}^2 \\
&\leq -\tilde{x}^T \left(Q - \bar{\tau}I\right) \tilde{x} - \left(\gamma - 4\right) \tilde{\varepsilon}^2 + c_1^* \\
&\leq -c_0 V + c_1^*,
\end{aligned} \tag{2.20}$$

where

$$\begin{cases}
c_0 = \min\left(\dfrac{\lambda_{\min}\left(Q - \bar{\tau}I_{n\times n}\right)}{\lambda_{\min}(P)}, \gamma - 4\right), \\
c_1^* = \dfrac{1}{2}\bar{f}^2, \\
\bar{\tau} = \tau^2 + 2\left(\rho(0) + \gamma\right)^2 + \dfrac{1}{2}\rho^2(0)H^{*2} + \gamma\rho(0)H^{*2} + \dfrac{1}{2}\left(\rho(0) + \gamma\right)^4.
\end{cases}$$

Remark 3. *In Section 2.2, this paper addresses the design of a state observer and fault estimator for the strict-feedback nonlinear system (2.1) subject to unknown nonlinearity and time-varying fault. The proposed methodology demonstrates three key advantages over existing strategies: 1. According to (2.20) and Lemma 3, both the state estimation error* $\tilde{x}$ *and fault estimation error* $\tilde{f}(t)$ *are uniformly bounded and converge exponentially at a rate no slower than* $e^{-c_0 t}$*. 2. Compared to existing schemes [18, 21], the introduced time-varying parameter* $\rho(t)$ *yields a more versatile estimator structure while delivering superior performance metrics. 3. Whereas prior works on tracking/stabilization (e.g., [29, 30]) universally require Lipschitz conditions for modeling uncertainties/disturbances, our framework removes this constraint—the adaptive observer's validity is rigorously verified without Lipschitz assumptions via Lemma 1.*

3. Controller design and stability analysis

3.1. Control scheme

In this subsection, we design a low complexity prescribed performance controller, firstly, we define the tracking error e_1 and the state errors e_i as

$$\begin{cases} e_1 &= y - y_d, \\ e_i &= \hat{x}_i - x_{i-1,d}, \quad i = 2, 3, \ldots, n, \end{cases} \tag{3.1}$$

where $x_{i,d}$ is the intermediate control signal to be designed.

Similar to [30], we choose a tangent function

$$\varphi_i = \tan\left(\frac{\pi}{2}\frac{e_i}{k_i}\right), \quad i = 1, 2, \ldots, n, \tag{3.2}$$

as the error transformation, and the prescribed performance function is designed as

$$k_i = (k_{io} - k_{i\infty})e^{-m_i t} + k_{i\infty}, \quad i = 1, 2, \ldots, n. \tag{3.3}$$

The appropriate parameter k_{i0} is then chosen such that

$$|e_i(0)| < k_i(0), \quad i = 1, 2, \ldots, n. \tag{3.4}$$

Referring to [29, 30], the virtual control signal and actual control law are given by

$$\begin{aligned} x_{i,d} &= \lambda_i \eta(\varphi_i)\varphi_i, \\ u &= x_{n,d}, \end{aligned} \tag{3.5}$$

where the positive constant λ_i represents the control gain, $\eta(\cdot)$ can be any function that satisfies the following conditions

$$\limsup_{\varphi_i \to \infty} \eta(\varphi_i) = a_i, \quad \liminf_{\varphi_i \to \infty} \eta(\varphi_i) = -b_i, \tag{3.6}$$

where a_i and b_i are positive constants. For example, $\eta(\varphi_i) = \cos(\varphi_i)$.

Remark 4. *From (3.2), (3.5), and (3.6), we can obtain some important information about $x_{i,d}$*

$$\begin{aligned} &\liminf_{(e_i+k_i)\to 0^+} x_{i,d} = -\infty, \qquad \limsup_{(e_i+k_i)\to 0^+} x_{i,d} = +\infty, \\ &\liminf_{(e_i-k_i)\to 0^-} x_{i,d} = -\infty, \qquad \limsup_{(e_i-k_i)\to 0^-} x_{i,d} = +\infty, \end{aligned} \tag{3.7}$$

where $i = 1, 2, \cdots, n$.

Remark 5. *Compared with existing work, the fault-tolerant control scheme designed based on the prescribed performance function has the following advantages:*
1) Reduced design-stage interaction between the controller and fault estimator. As shown in (3.5), the virtual control signal and actual control law are simplified. Notably, the actual control law is designed independently of the fault estimator. Therefore, the designed controller is easy to implement

and reliable in practical applications.
2) The computational complexity is simplified. No adaptive mechanisms or approximate structures such as neural networks and fuzzy logic systems are employed, regardless of model uncertainty. In addition, the designed control framework omits the iterative computation of intermediate control signal derivatives. Moreover, the control law and Lyapunov analysis are simplified by the prescribed performance function, while retaining the tracking/stability advantage.
3) The need for information about the available derivatives of the reference trajectory y_d is reduced.

3.2. Stability analysis

In this section, stability analysis is given based on the following Lemma 4 and Theorem 1.

Lemma 4. *For each $i \in 1, 2, \cdots, n$, if φ_i, e_i, and $\dot{e}_i$ remain bounded for $t > 0$, then $\dot{x}_{i,d} \in L^\infty$.*

Proof. From (3.5), the derivative of $x_{i,d}$ is given by

$$\begin{aligned} \dot{x}_{i,d} &= \lambda_i \frac{\partial \eta_i}{\partial \varphi_i} \dot{\varphi}_i \varphi_i + \lambda_i \eta_i(\varphi_i) \dot{\varphi}_i \\ &= \lambda_i \dot{\varphi}_i \left(\frac{\partial \eta_i}{\partial \varphi_i} \varphi_i + \eta_i(\varphi_i) \right) \quad i = 1, ..., n. \end{aligned} \tag{3.8}$$

Differentiating (3.2) yields

$$\dot{\varphi}_i = \frac{\pi e_i \left(\dot{e}_i k_i - e_i \dot{k}_i \right)}{k_i^3 \cos\left(\frac{\pi}{2} \frac{e_i^2}{k_i^2} \right)}. \tag{3.9}$$

If $\tan\left(\frac{\pi}{2} \frac{e_i^2}{k_i^2} \right) \in L^\infty$, then $\cos\left(\frac{\pi}{2} \frac{e_i^2}{k_i^2} \right) \in L^\infty$. From (3.3), we can obtain the following inequalities

$$\begin{gathered} k_{i\infty} \le k_i \le k_{i0}, \\ \frac{1}{k_{i0}} \le \frac{1}{k_i} \le \frac{1}{k_{i\infty}}, \\ m_i(k_{i\infty} - k_{i0}) \le \dot{k}_i \le 0. \end{gathered}$$

As a consequence, $\dot{x}_{i,d}$ is bounded in the case where φ_i, e_i, and $\dot{e}_i$, maintain bounded for all $i = 1, ..., n$. This completes the proof.

Theorem 1. *Consider a class of strict-feedback nonlinear systems with actuator faults as described in (2.1). If the initial conditions in (3.4) and Assumptions 1 and 2 are satisfied, then the proposed prescribed performance control scheme guarantees the following:*
1) All closed-loop signals of the system are bounded for $t > 0$.
2) The state errors remain within the prescribed performance bounds, and the system output y is accurately tracked.

Proof. By (2.6), (3.1), and (3.5), we can obtain

$$\begin{aligned} \dot{e}_1 &= e_2 + x_{1,d} + \tilde{x}_2 - \dot{y}_d, \\ \dot{e}_i &= e_{i+1} + x_{i,d} + l_i(y - \hat{x}_1) - \dot{x}_{i-1,d}, \quad i = 2, \ldots, n-1, \\ \dot{e}_n &= d(\hat{x}) + l_n(y - \hat{x}_1) + g x_{n,d} + \hat{f}(t) - \dot{x}_{n-1,d}. \end{aligned} \tag{3.10}$$

To prove the following inequality

$$|e_i(t)| < k_i(t), \quad i \in \{1, ..., n\}, \quad t > 0, \tag{3.11}$$

suppose that there exists at least one state error variable e_j and a time instant t_p such that

$$|e_j(t_p)| \geq k_j(t_p), \quad j \in \{1, \cdots, n\}, \quad p \in \mathbb{Z}^+, \tag{3.12}$$

where the sequence of time instants satisfies $t_p < t_{p+1}$. Let t_1 denote the first time instant at which inequality (3.11) is violated. Therefore, for all $t \in [0, t_1)$, it holds that

$$e_i(t) < k_i(t), \quad i \in \{1, \cdots, n\}. \tag{3.13}$$

This implies that each e_i $(i = 1, \ldots, n)$ is continuous when $t < t_1$. Considering (3.12) and (3.13), there exists at least one e_j such that

$$\lim_{t \to t_1^-} \left| e_j(t) \right| = k_j(t_1), \quad j \in \{1, \cdots, n\}, \tag{3.14}$$

where t_1^- denotes the left-hand limit as t approaches t_1.

It naturally follows that the following conditions must hold

$$\lim_{(e_i - k_i) \to 0^-} \dot{e}_i \geq \dot{k}_i, \qquad \lim_{(e_i + k_i) \to 0^+} \dot{e}_i \leq -\dot{k}_i. \tag{3.15}$$

The subsequent analysis will reveal that the above scenario does not exist.

Step 1. We analyze the dynamic behavior of e_1 when $t < t_1$:

(1) According to Assumption 1, $\dot{y}_d(t)$ is bounded.

(2) From (3.13), we have $e_2 \in L^\infty$.

(3) By (2.20) and Lemma 3, one gets $l_1(y - \hat{x}_1) \in L^\infty$.

In the case of $i = 1$, based on (3.5) and (3.6), it holds

$$\begin{aligned} \lim_{(e_1 - k_1) \to 0^-} \dot{x}_{1,d} &= -\infty, \\ \lim_{(e_1 + k_1) \to 0^+} \dot{x}_{1,d} &= +\infty, \end{aligned} \tag{3.16}$$

and

$$\begin{aligned} \lim_{(e_1 - k_1) \to 0^-} \dot{e}_1 &= -\infty, \\ \lim_{(e_1 + k_1) \to 0^+} \dot{e}_1 &= +\infty. \end{aligned} \tag{3.17}$$

By the contradiction between (3.14) and (3.17), it can be obtained that

$$|e_1| \leq k_1 - c_1, \quad t < t_1, \tag{3.18}$$

where c_1 is a positive constant to be given.

As a consequence of (3.18), the associated error transformation function φ_1 is also bounded on the interval $t \in [0, t_1)$.

Step *i* (2 ≤ *i* ≤ *n* − 1). Similar to Step 1.

(1) According to Lemma 4, we have $\dot{x}_{i-1,d} \in L^\infty$.

(2) From (3.13), $e_{i+1} \in L^\infty$.

(3) By (2.20) and Lemma 3, one gets $l_i(y - \hat{x}_1) \in L^\infty$.

In the case of i, based on (3.5) and (3.6), we have

$$\begin{aligned} \lim_{(e_i-k_i)\to 0^-} \dot{x}_{i,d} &= -\infty, \\ \lim_{(e_i+k_i)\to 0^+} \dot{x}_{i,d} &= +\infty, \end{aligned} \tag{3.19}$$

and

$$\begin{aligned} \lim_{(e_i-k_i)\to 0^-} \dot{e}_i &= -\infty, \\ \lim_{(e_i+k_i)\to 0^+} \dot{e}_i &= +\infty. \end{aligned} \tag{3.20}$$

By the contradiction between (3.14) and (3.20), it has

$$|e_i| \leq k_i - c_i, \quad t < t_1, \tag{3.21}$$

where c_i is a positive constant to be given.

As a result of (3.21), the corresponding error transformation function φ_i is also bounded on $t \in [0, t_1)$.

Step n. Recursively,

(1) according to Lemma 4, we have $\dot{x}_{n-1,d} \in L^\infty$.

(2) From the description related to system controllability, one gets $d(\hat{x}) \in L^\infty$, and $g \in L^\infty$.

(3) From Eq (2.20) and Lemma 3, it follows that both $l_n(y - \hat{x}_1)$ and $\hat{f}(t)$ are bounded.

In the case of $i = n$, based on (3.5) and (3.6), we have

$$\begin{aligned} \lim_{(e_n-k_n)\to 0^-} \dot{x}_{n,d} &= -\infty, \\ \lim_{(e_n+k_n)\to 0^+} \dot{x}_{n,d} &= +\infty, \end{aligned} \tag{3.22}$$

and

$$\begin{aligned} \lim_{(e_n-k_n)\to 0^-} \dot{e}_n &= -\infty, \\ \lim_{(e_n+k_n)\to 0^+} \dot{e}_n &= +\infty. \end{aligned} \tag{3.23}$$

By the contradiction between (3.14) and (3.23), it follows that

$$|e_n| \leq k_n - c_n, \quad t < t_1, \tag{3.24}$$

where c_n is a positive constant to be given.

Based on (3.24), error transformation function φ_n is bounded as $t \in [0, t_1)$.

In summary, all closed-loop signals remain bounded, thus completing the proof.

Remark 6. *The proposed objectives are established via proof by contradiction. Beginning with the false assumption (3.14), we sequentially derive inequalities (3.18), (3.21), and (3.24) at each PPC step. These collective results contradict (3.14), thereby validating (3.11) and guaranteeing bounded state errors. Consequently, Theorem 1 and recursive Steps* 1*–n confirm boundedness of all closed-loop signals.*

Remark 7. *The proof by contradiction is structured as follows: When $e_i - k_i$ approaches the origin from the left, the limit of $\dot{e}_i$ exceeds a positive constant in (3.15). Consequently, the lower bound of $\dot{e}_i$ cannot approach $-\infty$ as posited in (3.23). Symmetrically, when $e_i + k_i$ approaches the origin from the right, $\dot{e}_i$ admits a lower-bounded limit. Thus, (3.20) contradicts (3.15), invalidating assumption (3.12)—i.e., state errors remain constrained within the prescribed performance functions.*

To enhance understanding and facilitate analysis, a control block diagram illustrating the methodology employed in this paper is provided (see Figure 1).

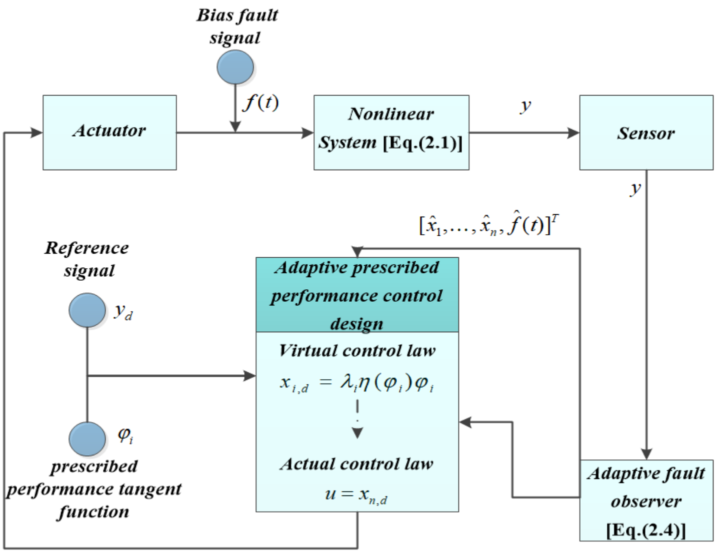

Figure 1. Block diagram of fault estimator-based prescribed performance control.

4. Simulation results

In this section, we give an actual simulation example to further verify the effectiveness of the fault estimation and PPC scheme designed in section 3. Consider a single-link robot system [21] as shown in Figure 2; its motion dynamics can be described as

$$\begin{cases} M\ddot{q} + \dfrac{1}{2} m g_r l \sin(q) = \tau + f_0(t), \\ y = q, \end{cases} \tag{4.1}$$

where $g_r = 9.8\ m/s^2$ is the acceleration due to gravity, M is the inertia, q is the angle position, $\dot{q}$ is the angle velocity, $\ddot{q}$ is the angle acceleration, l is the length of the link, m is the mass of the link, τ is the control force, and $f_0(t)$ denotes the actuator/component fault in the system.

Setting $x_1 = q$, $x_2 = \dot{q}$, and $u = \tau$, then (4.1) can be rewritten as:

$$\begin{cases} \dot{x}_1 = x_2, \\ \dot{x}_2 = d(x) + gu + f(t), \\ \ y = x_1, \end{cases} \tag{4.2}$$

where $d(x) = \frac{-0.5mg_r l \sin(x_1)}{M}$, $g = \frac{1}{M}$, and $f(t) = \frac{f_0(t)}{M}$ denotes the unknown time-varying system fault. For simulation, system parameters are configured as: $m = 1$kg, $M = 0.5$kg m^2, $l = 1m$, and $f(t) = \sin(0.5t) + 0.2\cos(t)$. The observer (2.6) and fault estimator (2.14) parameters are assigned as: $l_1 = 10$, $l_2 = 20$, $\rho(t) = \frac{1}{t+1}$ ($\rho(0) = 1$), $\gamma = 5$. For the prescribed performance control scheme (3.2, 3.3, 3.5), simulation parameters are specified as follows:

$$\begin{aligned} k_1 &= (1 - 0.02)e^{-t} + 0.02, \\ k_2 &= (5 - 2)e^{-1t} + 2, \\ x_{1,d} &= 2\sin(\varphi_1)\varphi_1, \\ x_{2,d} &= 5\cos(\varphi_2)\varphi_2. \end{aligned} \tag{4.3}$$

The initial state conditions are chosen as $x_1(0) = 0.1$, $x_2(0) = -0.2$, $\hat{f}_0(t) = 0$, $\rho(0) = 1$ and the target trajectory is taken as $y_d = 0.5\cos(t)$.

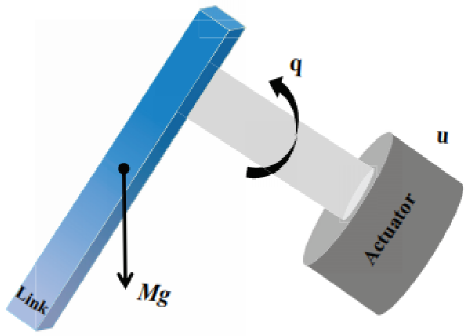

Figure 2. The single-link robot system.

Applying the above fault estimator and fault-tolerant controller, the simulation results are shown in Figures 3–8.

1) Figure 3 illustrates that, despite an initial deviation, the system output effectively tracks the desired output trajectory;

2) Figures 4 and 5 depict the state error e_i response under the performance constraint $k_i(t)$, remaining within the specified performance boundaries. Compared to the method without PPC [21], the proposed strategy demonstrates superior transient convergence and steady-state stability;

3) Figure 6 shows the response curves of system fault $f(t)$ and fault estimate $\hat{f}(t)$, from which it can be seen that the designed generalized intermediate variable estimator has good estimation accuracy compared with [21];

4) Figure 7 shows the corresponding curve of the time-varying gain $\rho(t)$, from which it can be seen that $\rho(t)$ exhibits the properties of being monotonically decreasing and always greater than 0;

5) Figure 8 presents the response curve of the control input signal $u(t)$, from which its boundedness conclusion can be obtained.

Analysis indicates that the proposed generalized intermediate-variable fault estimator not only offers enhanced design generality but also demonstrates significantly superior simulation performance compared to alternative schemes (Figure 6). More importantly, the prescribed performance control strategy based on this estimator effectively guarantees both tracking accuracy (encompassing transient convergence and steady-state stability, Figures 3–5) and global stability (Figures 7 and 8).

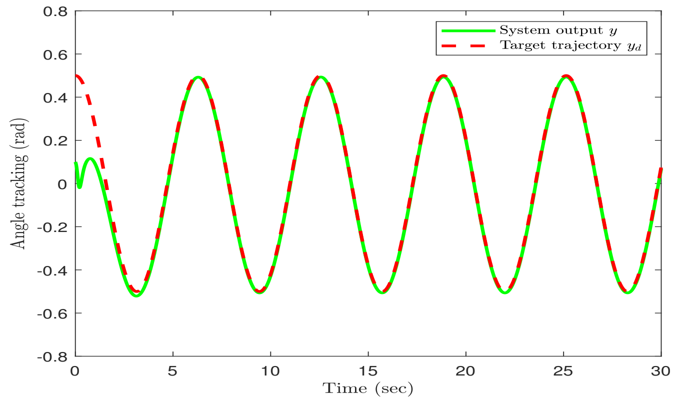

Figure 3. The responses of system output and reference trajectory.

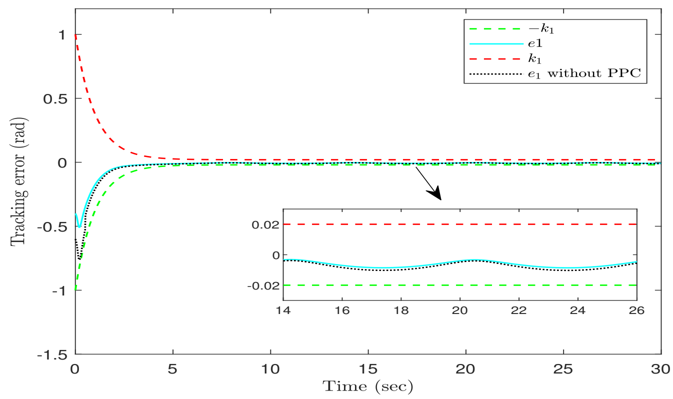

Figure 4. The response of tracking error e_1 under prescribed performance constraint $k_1(t)$.

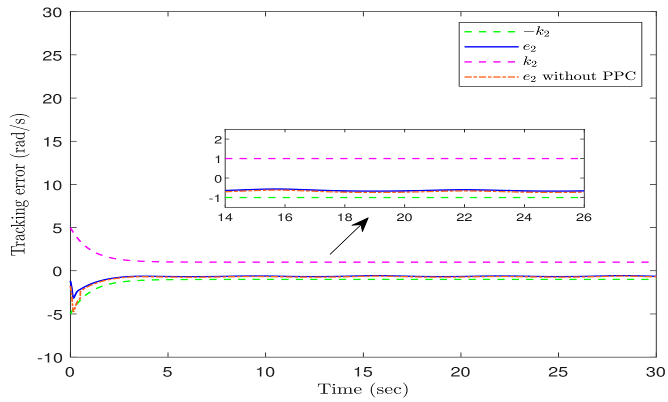

Figure 5. The response of tracking error e_2 under prescribed performance constraint $k_2(t)$.

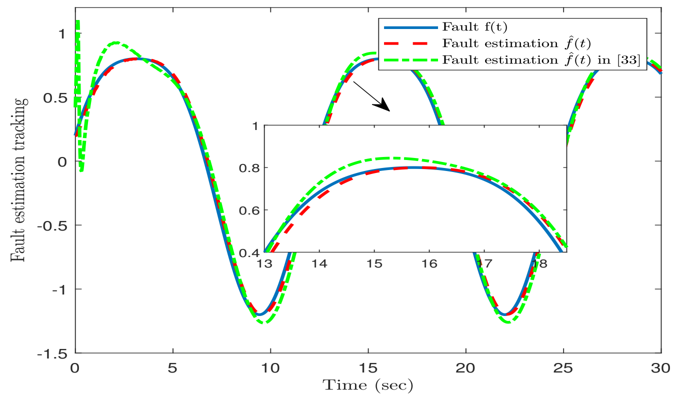

Figure 6. The responses of system fault $f(t)$ and fault estimate $\hat{f}(t)$.

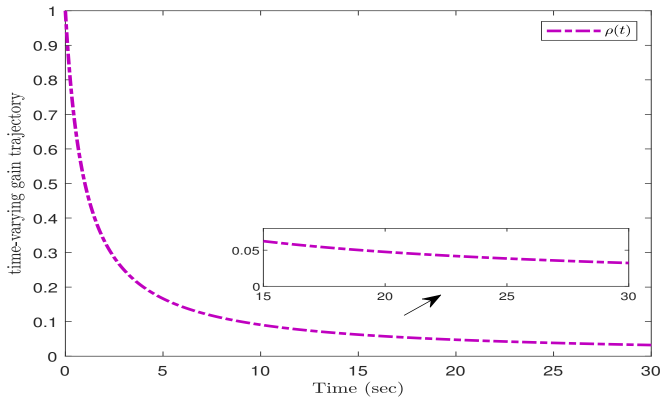

Figure 7. The response of time-varying gain $\rho(t)$.

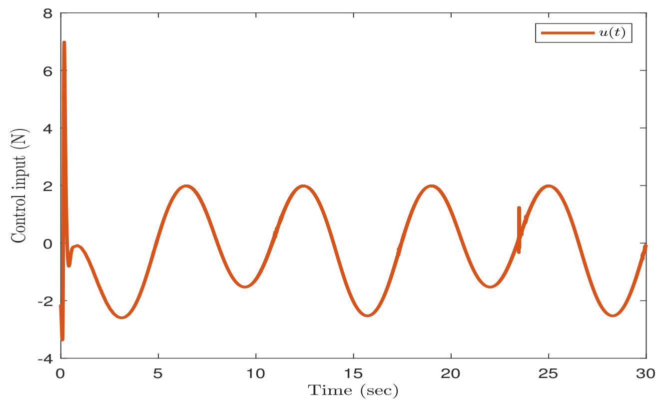

Figure 8. The response of control signal $u(t)$.

5. Conclusions

This paper addresses the adaptive fault-tolerant control problem for a class of strict-feedback nonlinear systems subject to unknown time-varying faults under relaxed matching conditions. An intermediate variable-based adaptive fault estimator and corresponding fault-tolerant controller are developed. The proposed estimator demonstrates enhanced convergence performance, while the prescribed performance control scheme effectively circumvents complex coupling interactions between fault estimation and control modules. Through rigorous proof by contradiction, all closed-loop signals are guaranteed to be uniformly ultimately bounded, with the state tracking error converging to a preset compact set. Simulation results comprehensively validate the effectiveness of the proposed methodology. Future research will extend this framework to actual systems based on intelligent control [31–33] and multi-agent systems based on fault-tolerant control [34, 35].

Author contributions

Xuechao Zhang: Conceptualization, methodology, software, validation, resources, writing–original draft preparation, writing–review and editing, project administration; Shichang Lu: Validation, resources, writing–review and editing, supervision, project administration. All authors reviewed the results and approved the final version of the manuscript.

Use of Generative-AI tools declaration

The authors declare that they have not use Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

All authors declare no conflicts of interest.

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