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Fault Identification Speed Analysis for a Class of Nonlinear Uncertain Systems Using High Gain Observer and Deterministic Learning

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Abstract: In this paper, we propose a novel approach for rapid fault identification (FI) in a class of nonlinear uncertain systems, with a particular emphasis on enhancing the speed of identification. By harnessing the high gain observer technique in tandem with deterministic learning, the proposed method effectively addresses unknown fault dynamics and unmeasurable states. A key contribution of this research is the development of a high gain observer that integrates learning to simultaneously estimate system states and identify faults, thus expediting the FI process. The method ensures satisfaction of a partial persistent excitation (PE) condition, leading to the input-to-state stability of the state and parameter estimation error system. We employ a Lyapunov function to scrutinize the relationship between the identification speed and the PE level of the neural networks. Our findings indicate that the partial PE condition allows the radial basis function (RBF) network to efficiently approximate unknown fault dynamics quickly. The efficiency and learning speed of the FI method are validated through comprehensive simulation studies.

Key Words: high gain observer, fault identification, persistent excitation condition, localized RBF networks

1 Introduction

In recent decades, the design of adaptive observers has emerged as a broad and vibrant area of research.The development and application of adaptive observers have garnered significant attention in the field of control theory, particularly for addressing the intricate problem of joint estimation of missing states and constant parameters within both linear and nonlinear state-space systems. This area of research has played a key role in developing adaptive control strategies and, in fault detection and isolation within dynamic systems.Adaptive observers are not only theoretically significant but also have been successfully implemented across a multitude of disciplines , including industrial control systems, aerospace engineering, robotics, and the critical area of fault diagnostics.[1–10].Despite the progress, rapid and accurate fault identification (FI) in nonlinear uncertain systems remains a considerable challenge. Traditional methods often depend on persistent excitation (PE) conditions, which are difficult to sustain in practical scenarios. Additionally, these methods can be slow to adapt to sudden changes in system dynamics, which is crucial for real-time fault diagnosis and mitigation. Therefore, there is a pressing need for improved fault identification methods that offer faster and more accurate diagnostics, which motivates this research.

The foundational work in adaptive observer design was centered on linear time-invariant systems, with innovative contributions being recognized for their simultaneous estimation of state variables and unknown parameters. This crucial effort laid the groundwork for subsequent advancements in the field [17, 42]. In the early 1980s, researchers began to focus on the design problem of adaptive observers for nonlinear systems. For example, the works of [18–21] have all mentioned that adaptive observers are applicable to a category of nonlinear systems.In [22–24], the construction of adaptive observers is based on Lyapunov functions. Within this framework, specific conditions are meticulously formulated to ensure the asymptotic convergence of the system's state estimates and its undetermined parameter values.A methodical approach introduced in [25] utilizes a coordinate transformation to effectively decouple the system's states from its unknown parameters. Building upon this concept, various adaptive observer configurations have been developed, including sliding mode observer detailed in [26, 27] and high-gain observer in [28]. Farza et al. proposed the idea of the correlation index, enhancing the Persistent Excitation (PE) conditions as discussed in [32]. However, the widespread application of these observers is often limited by the necessity for PE conditions. To address this limitation, an adaptive observer based on an iterative learning approach was designed by Chen et al [29–31].

In [33], a deterministic learning approach for the identification of nonlinear systems was presented in 2006.The objective of deterministic learning is to enable the learning algorithm to accurately discern and identify the system's unknown parameters or dynamic characteristics from its dynamic behavior.In adaptive control, deterministic learning algorithms adjust controller parameters to maintain system stability and performance amidst changing parameters or unknown dynamics.This approach differs from traditional statistical-based learning algorithms (e.g., neural networks or fuzzy logic controllers)[47] in that it does not rely on statistical properties or probability distributions of the data, but rather achieves learning by directly analyzing the dynamic behavior of the system.The deterministic learning methodology emerges as an efficacious solution to the complexities of learning in dynamic environments, with its applications spanning a diverse range that encompasses dynamic pattern recognition [34], the domain of machine vision, and oscilla-

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tion fault diagnosis [35]. When conducting fault identification on a system, the speed of the learning process is crucial. Rapid learning allows for quick responses to address underlying issues effectively.

Research establishes a correlation between the nature of deterministic learning and the persistent excitation (PE) condition, as well as the exponential stability of Linear Time-Varying (LTV) systems, which has propelled progress in LTV system stability.[36–41, 41, 44].In [40], the interrelationship between PE, uniform complete observability (UCO), and exponential stability in LTV systems is adeptly encapsulated. Meanwhile, [41] offers a comprehensive discourse on the PE condition and the issues of parameter convergence.In [42], the exponential convergence performance of various adaptive algorithms is investigated.The stability and convergence properties of a class of nonlinear time-varying (NLTV) systems have been thoroughly investigated, as reported in [43–46]. This examination was facilitated by leveraging contemporary analytical tools, including the application of the classical Lyapunov theorem, and by expanding upon the traditional definition of the persistent excitation (PE) condition.These research enhances adaptive control by enabling online parameter adjustment, contributing to the development of both adaptive control and deterministic learning.

This paper examines how deterministic learning improves fault diagnosis in nonlinear systems, emphasizing the key factors of learning speed. It reveals that higher excitation levels boost learning speed, enabling the radial basis function (RBF) network to better approximate unknown fault dynamics. By analyzing LTV systems, the paper clarifies how design parameters like estimator and learning gains relate to learning performance. It also discusses the role of partial persistent excitation (PE) in designing observer gains for more effective fault approximation and noise reduction. Simulations demonstrate the High Gain Learning Observer's (HGLO) effectiveness in enhancing state estimation and reducing noise sensitivity, offering new insights for fault diagnosis and fault-tolerant control in nonlinear systems and strengthening the theoretical basis for deterministic learning in adaptive control.

The rest of the paper is organized as follows. In Section 2, the problem formulation is presented. In Section 3, the fault identification (FI) scheme utilizing high gain observer (HGO) and deterministic learning (DL) is presented. In Section 4, the convergence analysis utilizing the partial Persistent Excitation (PE) condition is detailed. In Section 5, a simulation example is provided to elucidate the theoretical concepts discussed.

2 Problem Formulation

We consider a class of nonlinear systems of the form

$$\begin{cases} \dot{x} = Ax + B(\phi(x,u) + \omega(t)) \\ y = cx + v(t) \end{cases} \tag{1}$$

where $A = \begin{bmatrix} 0 & I_{n-1} \\ 0 & 0 \end{bmatrix}, B = \begin{bmatrix} 0 & \cdots & 0 & 1 \end{bmatrix}^T, c = \begin{bmatrix} 1 & 0 & \cdots & 0 \end{bmatrix}$, $x \in R^n$ is the state vector, $y \in R$ is the output, $u \in R^m$ is the input vector.Process noise $\omega(t)$ and measurement noise $v(t)$ accompany the function $\phi(x,u)$: $R^{n+m} \mapsto R$, which is an unknown smooth nonlinear function. The function $\phi(x,u)$ characterizes the system dynamics following the occurrence of a fault.

In this paper, we focus on the problem of fault identification. When no fault occurs, identification of unknown system dynamics can be achieved in the same way. The design of the observer needs some assumptions as follows:

Assumption 1 *In the fault modes, the system inputs and states are bounded, i.e., $\forall t \geq t_0$, $(x,u) \in \mathcal{C} \in R^{n+m}$, $\mathcal{C}$ is a compact set. Moreover, (x,u) is in a periodic/periodic-like motion.*

Assumption 2 *The function $\phi(x,u)$ is local Lipschitz about x in $\mathcal{C}$, i.e.,*

$$|\phi(\hat{x},u) - \phi(x,u)| \leq k_\phi |\hat{x} - x| \tag{2}$$

where $k_\phi > 0$ is a constant.

The objectives of this paper are: i) to identify the unknown fault dynamics $\phi(x,u)$ which contains unmeasurable states; ii) to achieve accurate state estimation and FI without resorting to high gain.

3 Fault Identification without PE Condition

3.1 Observer design

Along the system trajectory, the output of $\varphi^T(\hat{x},u)\hat{\theta}$ is mainly affected by the subnetwork $\varphi_\zeta^T(\hat{x},u)\hat{\theta}_\zeta$. Therefore, a high gain learning observer (HGLO) is designed as follows:

$$\begin{cases} \dot{\hat{x}} = A\hat{x} + H\kappa_1(y - c\hat{x}) + h^{-(n+1)}H\Upsilon_\zeta \dot{\hat{\theta}}_\zeta \\ \qquad + B\varphi_\zeta^T(\hat{x},u)\hat{\theta}_\zeta \\ \dot{\hat{\theta}}_\zeta = h^n \Gamma_\zeta \Psi_\zeta^T [y - c\hat{x}] - \sigma \Gamma_\zeta \hat{\theta}_\zeta \end{cases} \tag{3}$$

where $H = \text{diag}\{h, h^2, \cdots, h^n\}$, $h > 0$, $\Upsilon_\zeta \in R^{n_\zeta \times p_\zeta}$, $\Gamma_\zeta \in R^{p_\zeta \times p_\zeta}$ denotes a symmetric positive definite matrix, $\hat{\theta}_\zeta = [\theta_{1_\zeta}, \cdots, \theta_{p_\zeta}] \in R^{p_\zeta}$ is the parameter vector, P is a solution of the following Lyapunov equation:

$$A^T P + PA + P = c^T c \tag{4}$$

$\varphi_\zeta(\hat{x},u) = [\varphi_{1_\zeta}(\hat{x},u), \cdots, \varphi_{p_\zeta}(\hat{x},u)] \in R^{n_\zeta \times m_\zeta} \mapsto R_\zeta^p$, p_ζ is the dimension of φ_ζ, Ψ_ζ is generated by the following filter

$$\begin{aligned} \dot{\Upsilon}_\zeta &= hA_0 \Upsilon_\zeta + hB\varphi_\zeta^T(\hat{x},u) \\ \Psi_\zeta &= c\Upsilon_\zeta \end{aligned} \tag{5}$$

where $\Upsilon_\zeta \in R^{n \times p_\zeta}$.

3.2 Convergence analysis

Set $\tilde{x} = \hat{x} - x$, $\tilde{\theta}_\zeta = \hat{\theta}_\zeta - \theta_\zeta^*$.

Define: $\tilde{z} = H^{-1}\tilde{x}$, $\vartheta = h^{-(n+1)}\tilde{\theta}_\zeta$. Note that $cH = hc, H^{-1}AH = hA$.

$\zeta = H^{-1}B\phi(H\hat{z},u) - H^{-1}B\phi(Hz,u)$, $d' = \kappa_1 v - h^{-n}B(\epsilon + \omega)$. Define $\varepsilon = hA_0\tilde{z} + \Upsilon_\zeta\dot{\vartheta} + hB\varphi_\zeta^T(\hat{x},u)\vartheta + \zeta + d' - \Upsilon_\zeta\vartheta$, then we have

$$\begin{aligned} \dot{\varepsilon} &= hA_0(\varepsilon + \Upsilon_\zeta\vartheta) + hB\varphi_\zeta^T(\hat{x},u)\vartheta - \dot{\Upsilon}_\zeta\vartheta + \zeta + d' \\ &= hA_0\varepsilon + \zeta + d' \end{aligned} \tag{6}$$

Considering Assumption 2, one obtains

$$\|\zeta\| \leq \mu\|\varepsilon + \Upsilon_\zeta \vartheta\| \tag{7}$$

Since $\vartheta = h^{-(n+1)}\tilde{\theta}_\zeta$, it follows that

$$\dot{\vartheta} = -\Gamma_\zeta(\Psi_\zeta^T c\varepsilon + \Psi_\zeta^T \Psi_\zeta \vartheta + \sigma(\vartheta + \vartheta^*) - h^{-1}\Psi_\zeta^T v) \tag{8}$$

where $\vartheta^* = h^{-(n+1)}\theta_\zeta^*$.

4 Fault Identification with Partial PE Condition

In this section, we explore the issue of utilizing a deterministic learning approach to investigate the rate of identification.

Lemma 1 If the subvector $\varphi_\zeta(\hat{x}, u)$ satisfies the persistent excitation condition, then for some constants C_1, C_2, $\delta > 0$, and for all $t \geq t_0$, the vector of signal $\Psi_\zeta(t)$ generated by (5) satisfies

$$C_1 \leq \int_t^{t+\delta} (\Psi_\zeta \bar{\theta}_i)^2 d\tau \leq C_2, \forall\, |\bar{\theta}_i| = 1 \tag{9}$$

Now we investigate the convergence problem of the learning error system ((6) and (8)). First, consider the case with noise of approximat error. With $v = 0, \omega = 0$, the following identification error system can be obtained:

$$\dot{\varepsilon} = f_1(\varepsilon, \vartheta, d_1') = hA_0\varepsilon + \zeta(\varepsilon, \vartheta) + d_1' \tag{10}$$

$$\dot{\vartheta} = f_2(\varepsilon, \vartheta, d_2') = -\Gamma_\zeta \Psi_\zeta^T \Psi_\zeta \vartheta - \Gamma_\zeta \Psi_\zeta^T c\varepsilon + d_2' \tag{11}$$

Theorem 1 *:* Consider the above learning error system with $v = 0, \omega = 0$. If h takes on a sufficiently large value, then we have ε and ϑ converge into small values, with the convergence speed $\frac{\lambda_7}{\lambda_8}$ given as follow

$$\frac{\lambda_7}{\lambda_8} = \frac{\min\left\{h\lambda_1 - 2\mu_1 - \frac{3\mu_2^2 + 3\lambda_6^2}{4\lambda_{\Gamma_\zeta}\lambda_5}, \lambda_{\Gamma_\zeta}\lambda_5\right\}}{\max\{\lambda_2, \delta\}}$$

where λ_1 and λ_2 denote the minimum and maximum eigenvalues of matrix P, respectively, $\mu_1 = 2\mu\lambda_2$, $\mu_2 = \mu_1\bar{\Upsilon}_\zeta$, μ is defined in (7). $\lambda_6 = 2\delta\lambda'_{\Gamma_\zeta}\mu_3$, $\mu_3 := \sup_{t \geq t_0} \|\Psi_\zeta(t)\|$, λ_{Γ_ζ} and λ'_{Γ_ζ} are the minimum and maximum eigenvalues of Γ_ζ, $\lambda_5 > 0$.

Proof: Consider the Lyapunov function $V_1 = \varepsilon^T P\varepsilon$ for the system (10).

The derivative of V_1 satisfies

$$\dot{V}_1 \leq -(h\lambda_1 - \mu_1)\|\varepsilon\|^2 + \mu_2\|\varepsilon\|\|\vartheta\| + 2\lambda_2\|\varepsilon\|\|d_1'\| \tag{12}$$

Define

$$S(t) = \int_t^{t+\delta} \Phi^T(\tau, t)\Phi(\tau, t) d\tau. \tag{13}$$

where $\Phi^T(\tau, t)$ is the state transition matrix of following system.

$$\dot{\vartheta} = f'(\vartheta) = -\Gamma_\zeta \Psi_\zeta^T \Psi_\zeta \vartheta \tag{14}$$

Then design the Lyapunov function

$$V_4 = \vartheta^T(t)S(t)\vartheta(t) \tag{15}$$

for the subsystem (11). , we can prove

$$V_4 \leq \delta\|\vartheta(t)\|^2 \tag{16}$$

Therefore, the derivative of V_4 along the trajectory of system (11) satisfies

$$\begin{aligned}\dot{V}_4(t) =& \dot{\vartheta}^T(t)S(t)\vartheta(t) + \vartheta^T(t)S(t)\dot{\vartheta}(t) + \vartheta^T(t)\dot{S}(t)\vartheta(t) \\ =& \vartheta^T(t)(\Phi^T(t+\delta, t)\Phi(t+\delta, t) - I)\vartheta(t) \\ &+ 2\vartheta^T S(t)(-\Gamma_\zeta \Psi_\zeta^T(t)c\varepsilon(t) + d_2')\end{aligned} \tag{17}$$

It can prove that

$$\begin{aligned}&\vartheta^T(t)\Phi^T(t+\delta, t)\Phi(t+\delta, t)\vartheta(t) - \vartheta^T(t)\vartheta(t) \\ =& \int_t^{t+\delta} \dot{V}_3 d\tau \leq -2\lambda_{\Gamma_\zeta}\lambda_5\|\vartheta(t)\|^2\end{aligned} \tag{18}$$

Therefore, it follows that

$$\dot{V}_4(t) \leq -2\lambda_{\Gamma_\zeta}\lambda_5\|\vartheta(t)\|^2 + \lambda_6\|\vartheta(t)\|\|\varepsilon\| + 2\delta\|\vartheta(t)\|\|d_2'\|$$

Note that

$$\mu_2\|\varepsilon\|\|\vartheta\| \leq \frac{1}{3}\lambda_{\Gamma_\zeta}\lambda_5\|\vartheta(t)\|^2 + \frac{3\mu_2^2\|\varepsilon\|^2}{4\lambda_{\Gamma_\zeta}\lambda_5}$$

$$2\lambda_2\|\varepsilon\|d_1'\| \leq \mu_1\|\varepsilon\|^2 + \frac{\lambda_2^2}{\mu_1}\|d_1'\|^2$$

$$\lambda_6\|\vartheta(t)\|\|\varepsilon\| \leq \frac{1}{3}\lambda_{\Gamma_\zeta}\lambda_5\|\vartheta(t)\|^2 + \frac{3\lambda_6^2\|\varepsilon\|^2}{4\lambda_{\Gamma_\zeta}\lambda_5}$$

$$2\delta\|\vartheta(t)\|\|d_2'\| \leq \frac{1}{3}\lambda_{\Gamma_\zeta}\lambda_5\|\vartheta(t)\|^2 + \frac{3}{\lambda_{\Gamma_\zeta}\lambda_5}\delta^2\|d_2'\|^2$$

So we have

$$\begin{aligned}\dot{V}_1 \leq& -\left(h\lambda_1 - 2\mu_1 - \frac{3\mu_2^2}{4\lambda_{\Gamma_\zeta}\lambda}\right)\|\varepsilon\|^2 + \frac{1}{3}\lambda_{\Gamma_\zeta}\lambda_5\|\vartheta(t)\|^2 \\ &+ \frac{\lambda_2^2}{\mu_1}\|d_1'\|^2\end{aligned} \tag{19}$$

$$\dot{V}_4(t) \leq -\frac{4}{3}\lambda_{\Gamma_\zeta}\lambda_5\|\vartheta(t)\|^2 + \frac{3\lambda_6^2\|\varepsilon\|^2}{4\lambda_{\Gamma_\zeta}\lambda_5} + \frac{3}{\lambda_{\Gamma_\zeta}\lambda_5}\delta^2\|d_2'\|^2 \tag{20}$$

$$\begin{aligned}\dot{V}_1 \leq& -\left(h\lambda_1 - 2\mu_1 - \frac{3\mu_2^2}{4\lambda_{\Gamma_\zeta}\lambda_1}\right)\|\varepsilon\|^2 + \frac{1}{3}\lambda_{\Gamma_\zeta}\lambda_5\|\vartheta(t)\|^2 \\ &+ \frac{\lambda_2^2}{\mu_1}\|d_1'\|^2\end{aligned} \tag{21}$$

$$\dot{V}_4(t) \leq -\frac{4}{3}\lambda_{\Gamma_\zeta}\lambda_5\|\vartheta(t)\|^2 + \frac{3\lambda_6^2\|\varepsilon\|^2}{4\lambda_{\Gamma_\zeta}\lambda_5} + \frac{3}{\lambda_{\Gamma_\zeta}\lambda_5}\delta^2\|d_2'\|^2 \tag{22}$$

Define $V = V_1 + V_4$. Therefore, we get

$$\begin{aligned}\dot{V} \leq& -\left(h\lambda_1 - 2\mu_1 - \frac{3\mu_2^2 + 3\lambda_6^2}{4\lambda_{\Gamma_\zeta}\lambda_5}\right)\|\varepsilon\|^2 - \lambda_{\Gamma_\zeta}\lambda_5|\vartheta(t)\|^2 \\ &+ \frac{\lambda_2^2}{\mu_1}\|d_1'\|^2 + \frac{3}{\lambda_{\Gamma_\zeta}\lambda_5}\delta^2\|d_2'\|^2\end{aligned} \tag{23}$$

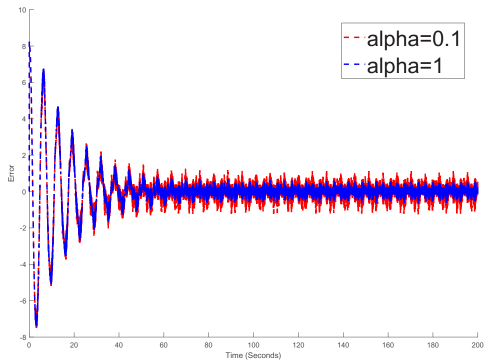

Fig. 1: Fault approximation error.(h=10,alpha=0.1,1)

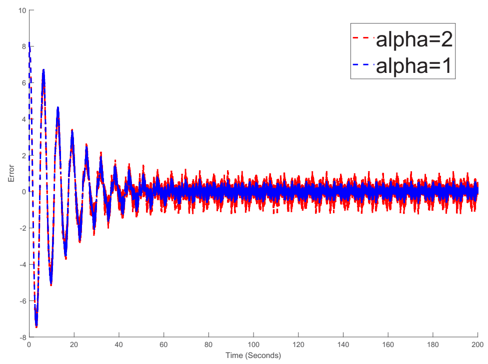

Fig. 2: Fault approximation error.(h=10,alpha=1,2)

$$\text{Let } \lambda_7 = \min\{h\lambda_1 - 2\mu_1 - \frac{3\mu_2^2 + 3\lambda_6^2}{4\lambda_{\Gamma_\varsigma}\lambda_5}, \lambda_{\Gamma_\varsigma}\lambda_5\}$$

Then,we have

$$\dot{V} \leq -\lambda_7 \left(\|\varepsilon\|^2 + \|\vartheta(t)\|^2\right) + \frac{\lambda_2^2}{\mu_1}\|d_1'\|^2 + \frac{3}{\lambda_{\Gamma_\varsigma}\lambda_5}\delta^2\|d_2'\|^2 \tag{24}$$

Given that S(t) is bounded and P is a matrix, there exists a constant λ_8

$$\lambda_8 = \max\{\lambda_2, \delta\}$$

such that

$$V \leq \lambda_8 \left(\|\varepsilon\|^2 + \|\vartheta(t)\|^2\right) \tag{25}$$

Based on (25)

$$\dot{V} \leq -\frac{\lambda_7}{\lambda_8}V + \frac{\lambda_2^2}{\mu_1}\|d_1'\|^2 + \frac{3}{\lambda_{\Gamma_\varsigma}\lambda_5}\delta^2\|d_2'\|^2 \tag{26}$$

This ends the proof.

5 Simulation

To substantiate the efficacy of the suggested observer model, a set of dynamic equations representing a single-link robotic system is utilized for simulation:

$$\begin{aligned}\dot{x}_1 &= x_2 \\ \dot{x}_2 &= \frac{1}{M}(u - 0.5mgl\sin(x_1) - F(x)) + \omega(t) \\ y &= x_1 + v(t)\end{aligned} \tag{27}$$

Here, $u = \tau$ represents the control effort, $x = [x_1\ x_2]^T = [q\ \dot{q}]^T$ is the state vector.The system parameters include the mass $m = 1kg$,link length $l = 1m$ and moment of inertia M,$M = 0.5kgm^2$, with gravitational acceleration g,$g = 9.8m/s^2$ and friction factor F(x), $F(x) = -0.1x_2$. $q, \dot{q}$ and $\ddot{q}$ are the position and velocity. Zero-mean Gaussian noise is represented by $\omega(t)$ and $v(t)$, and u is the input designed to follow a reference trajectory defined by $x_{d1} = sin(t)$, $x_{d2} = cos(t)$. Two observer configurations are simulated: the first being the HGLO as defined by the equation: $\dot{\hat{x}} = A\hat{x} + H\kappa_1(y - c\hat{x}) + h^{-3}H\Upsilon_\varsigma\dot{\hat{\theta}}_\varsigma + B(\varphi_\varsigma^T(\hat{x})\hat{\theta}_\varsigma + u/M)$, where $\dot{\hat{\theta}}_\varsigma$ and Υ_ς are designed according to (3). The localized RBF networks $\varphi_\varsigma^T(\hat{x})\hat{\theta}_\varsigma$ is constructed by Gaussian RBF NNs with nodes $N = 11 \times 11 = 121$. The second observer, a high-gain observer without a neural network, is defined by $\dot{\hat{x}}_o = A\hat{x}_o + Bu/M + H\kappa_o(y - \hat{x}_{o1})$, where $\hat{x}_o = [\hat{x}_{o1}\ \hat{x}_{o2}]^T$.

As depicted in Figs.1 and 2, when h=10, the convergence rate gradually increases with the enlargement of alpha. Continuing to increase the value of alpha does not significantly alter the convergence rate. Higher alpha values can accelerate the learning speed, but may also lead to excessive system response, resulting in oscillations or instability.As illustrated in Figs. 3, when alpha=0.2, the convergence rate increases as h becomes larger. After h reaches a certain level (h=10), the convergence rate remains essentially constant. This indicates that a larger value of h implies a faster response but may also enhance the system's sensitivity to noise.

6 Conclusion

In this paper, we employ a method for rapid fault identification (FI) in a class of nonlinear uncertain systems, with a focus on exploring the speed of identification. By integrating the high gain observer technique with deterministic learning, this approach effectively addresses the issues of unknown fault dynamics and unmeasurable states. A key contribution of this research is the development of a high gain observer that incorporates learning to simultaneously estimate system states and identify faults, thereby accelerating the FI

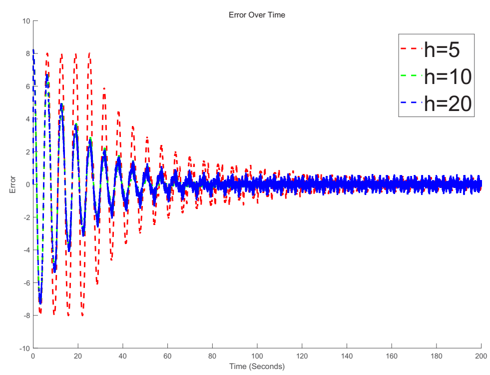

Fig. 3: Fault approximation error.(alpha=0.2,h=5,10,20)

process. This method guarantees fulfillment of the partial persistent excitation (PE) criterion, thereby achieving input-to-state stability for the system of state and parameter estimation errors. Our findings indicate that the partial PE condition allows the radial basis function (RBF) network to efficiently approximate unknown fault dynamics more quickly and with reduced observer gain and noise sensitivity. The effectiveness of the proposed scheme in enhancing the speed of fault identification is emphasized.

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