

基于自适应观测器的一类非线性系统鲁棒故障诊断¹⁾

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摘要 针对一类含有不确定性的非线性系统,对于执行器故障情形,提出了一种新的鲁棒故障诊断方法.首先设计了自适应观测器结构,并利用最小二乘法给出了故障估计递推算法.对系统中的不确定性,算法中采用域值处理技术以实现鲁棒故障估计.在此基础上,分析了该方法的鲁棒性,可检测性和稳定性.最后,给出了仿真实例,结果证明了该方法的有效性.

关键词 故障诊断,非线性,自适应观测器,执行器,鲁棒性

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Robust Fault Diagnosis Using Adaptive Observer Technique for a Class of Nonlinear Systems

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Abstract A new robust actuator fault diagnosis method for nonlinear systems with modeling uncertainties is proposed in this paper. First, an adaptive observer structure is designed. And an iterative algorithm of the fault estimation is given according to least minimum square theory. For modeling uncertainties of the system, dead region value treatment technique is adopted to realize robust fault evaluation in the algorithm. Robustness, sensitivity and stability of the method are analyzed. Finally, a simulation example is used to illustrate the effectiveness of the method.

Key words Fault diagnosis, nonlinear, adaptive observer, actuator, robust

1 引言

现代科技的发展使得控制系统的规模不断扩大,对系统的可靠性要求越来越高.尽早地

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诊断出系统中出现的故障对于先进控制系统的设计和应用具有重要意义. 目前故障诊断的方法主要是信息冗余方法, 其中基于模型方法研究较多. 它是利用观测器或滤波器估计系统的状态, 进而得出输出残差, 根据残差信息检测、诊断故障. 该方法在线性领域得到了广泛地发展, 在非线性领域则处于起步阶段, 研究相对较少^[1~4]. 另外, 无论是线性领域, 还是非线性领域, 由于建模误差和未知干扰输入的存在, 故障诊断的鲁棒性研究具有必要性和实际意义^[5].

针对于非线性系统, 为解决故障的估计问题, 文献[6~9]提出了自适应观测器故障诊断方法, 而文献[10~12]则对故障诊断的鲁棒性进行了研究, 其中文献[12]针对传感器偏差型故障设计了鲁棒自适应观测器. 本文针对文献[12]提出的非线性系统, 对于发生执行器故障情形, 设计了自适应观测器结构, 给出了故障的在线鲁棒估计算法, 同时对观测器的稳定性、鲁棒性以及故障的可检测性进行了分析. 最后给出了仿真验证结果.

2 系统描述

考虑如下离散非线性系统

$$\mathbf{x}(k+1) = A\mathbf{x}(k) + B\bar{\mathbf{u}}(k) + \xi(C\mathbf{x}(k), \bar{\mathbf{u}}(k)) + \zeta(\mathbf{x}(k), \bar{\mathbf{u}}(k), k), \mathbf{x}(0) = \mathbf{0} \quad (1a)$$

$$\mathbf{y}_m(k) = C\mathbf{x}(k) + \varsigma(\mathbf{x}(k), \bar{\mathbf{u}}(k), k) \quad (1b)$$

上式中 $\mathbf{x}(k) \in R^n$ 为状态变量; $\bar{\mathbf{u}}(k) = (I + \text{diag}(f_1^*, \dots, f_m^*))\mathbf{u}(k)$, $\mathbf{u}(k) \in R^m$ 为无故障的控制输入矢量, $\mathbf{u}(k) = f_c(\mathbf{y}_{gd}(k), \mathbf{y}_m(k))$, $f_c(\cdot)$ 为控制器函数; $\mathbf{y}_{gd}(k) \in R^p$ 为系统期望输出; $\mathbf{y}_m(k) \in R^p$ 为系统输出测量值; $\mathbf{f}^* = (f_1^*, \dots, f_m^*)^T$, $\mathbf{f}^* \in R^m$ 为系统执行器增益型故障, 当 $\mathbf{f}^* = \mathbf{0}$ 时, 表示系统无故障发生, 当 $\mathbf{f}^* \neq \mathbf{0}$ 时, 表示系统有故障发生; $\xi(C\mathbf{x}(k), \bar{\mathbf{u}}(k))$ 为系统非线性部分; $\zeta(\mathbf{x}(k), \bar{\mathbf{u}}(k), k)$, $\varsigma(\mathbf{x}(k), \bar{\mathbf{u}}(k), k)$ 为系统不确定部分, 为简单起见, 后面分别用 ζ , ς 代替; 矩阵 A, B, C 具有适当维数.

为进一步分析, 假设下面条件成立.

假设 1. (A, C) 是可观测的.

假设 2. 非线性函数 $\xi(\alpha, \beta)$ 满足 Lipschitz 条件, 即

$$|\xi(\alpha_1, \cdot) - \xi(\alpha_2, \cdot)| \leq L_1 |\alpha_1 - \alpha_2|, \quad |\xi(\cdot, \beta_1) - \xi(\cdot, \beta_2)| \leq L_2 |\beta_1 - \beta_2|.$$

假设 3. 模型不确定性函数满足 $|\zeta| \leq \lambda_1$, $|\varsigma| \leq \lambda_2$.

假设 4. 系统输入是有界的, 即 $|\mathbf{u}(k)| \leq \mathbf{u}_d$.

假设 5. 系统状态在发生故障后仍保持有界, 即 $\mathbf{x} \in l_\infty$.

3 故障诊断

对于系统(1), 当不考虑故障发生时, 系统状态估计由如下观测器给出

$$\hat{\mathbf{x}}(k+1) = A\hat{\mathbf{x}}(k) + B\mathbf{u}(k) + \xi(\mathbf{y}_m(k), \mathbf{u}(k)) + G(\hat{\mathbf{y}}_m(k) - \mathbf{y}_m(k)), \hat{\mathbf{x}}(0) = \mathbf{0} \quad (2a)$$

$$\hat{\mathbf{y}}_m(k) = C\hat{\mathbf{x}}(k) \quad (2b)$$

式中 $\hat{\mathbf{x}}(k) \in R^n$ 为状态变量估计值, $\hat{\mathbf{y}}_m(k) \in R^p$ 为系统输出估计值, $G \in R^{n \times p}$ 为观测器增益矩阵, 保证 $A+GC$ 稳定.

当考虑系统可能发生故障时, 在观测器(2)中加入故障估计部分, 得如下自适应观测器结构

$$\hat{x}(k+1) = A\hat{x}(k) + Bu(k) + \xi(y_m(k), u(k)) + G(\hat{y}_m(k) - y_m(k)) + M(k)\hat{f}(k-1) - A_0M(k-1)\hat{f}(k-2) \quad (3a)$$

$$\hat{y}_m(k) = C\hat{x}(k) \quad (3b)$$

式中 $A_0 = A + GC$, $M(k)$ 满足下式

$$M(k) = \phi(k) + A_0M(k-1), \quad M(-1) = 0_{n \times m}, \quad \phi(k) = B \text{diag}(u_1(k), \dots, u_m(k)) \quad (4)$$

令 $N(k) = CM(k)$, 则依据最小二乘法, 得如下故障估计算法

$$\hat{f}(k) = \hat{f}(k-1) + \frac{N^T(k)D(e_y(k+1))}{\epsilon_0 + \|N(k)\|_2^2}, \quad \hat{f}(-1) = \hat{f}(-2) = 0_{m \times 1} \quad (5)$$

上式中 $e_y(k+1) = y_m(k+1) - \hat{y}_m(k+1)$, 为系统输出估计误差; ϵ_0 为正数, 起稳定算法作用; $D(\cdot)$ 为死区控制算子, 其表达式为

$$D(e_y(k+1)) = \begin{cases} 0, & \text{if } \|e_y(k+1)\| < e \\ e_y(k+1), & \text{otherwise} \end{cases} \quad (6)$$

式中 e 为鲁棒算法阈值.

4 性能分析

4.1 鲁棒性分析

一般情况下, 确定性系统故障诊断通过检测系统状态或输出估计误差是否为零. 当为零时, 表示系统无故障; 不为零时, 表示有故障. 对于不确定系统来说, 为了提高故障诊断的可靠性, 降低误报警率, 需要采用鲁棒技术. 通常有两种方法: 当系统含未知干扰输入时, 可采用未知输入观测器解耦技术; 当不确定性部分为一有界未知函数时, 采用阈值限定技术. 基于此, 本文采用第二种方法, 即如式(6)所示, 当系统输出估计误差小于某一值时, 估计算法不予更新, 当大于此值时才开始更新. 下面确定该值 e 的大小.

定理 1. 当系统(1)满足假设 1 至假设 5, 利用观测器(3)估计系统状态, 则当故障未发生时, 输出残差满足如下方程

$$\|e_y(k)\| < h(L_1\lambda_2 + \lambda_1 + \|G\|_2\lambda_2) + \lambda_2 = e \quad (7)$$

式中 h 为满足 $\left\| \sum_{i=0}^{\infty} CA_0^i \right\| < h$ 的正常数.

证明. 由于没有故障发生, 并假设 k 时刻以前误差方程满足式(7), 则由式(1), (3)和(5)得, 系统状态误差方程及输出残差方程为

$$e_x(k+1) = A_0e_x(k) + \xi(Cx(k), \bar{u}(k)) - \xi(y_m(k), u(k)) + \zeta + G\varsigma \quad (8a)$$

$$e_y(k) = Ce_x(k) + \varsigma \quad (8b)$$

式中 $e_x(k) = x(k) - \hat{x}(k)$ 为状态变量估计误差, $e_x(k) \in R^n$.

于是得 $k+1$ 时刻

$$e_y(k+1) = C \sum_{i=0}^k A_0^{k-i} (\xi(Cx(i), u(i)) - \xi(y_m(i), u(i)) + \zeta + G\varsigma) + \varsigma$$

$$|e_y(k+1)| \leq \left| C \sum_{i=0}^k A_0^{k-i} (\xi(Cx(i), u(i)) - \xi(y_m(i), u(i))) \right| + \left| C \sum_{i=0}^k A_0^{k-i} (\zeta + G\varsigma) + \varsigma \right| \leq$$

$$\sum_{i=0}^k \|CA_0^{k-i}\|_2 (L_1\lambda_2 + \lambda_1 + \|G\|_2\lambda_2) + \lambda_2 <$$

$$h(L_1\lambda_2 + \lambda_1 + \|G\|_2\lambda_2) + \lambda_2 = e \quad (9)$$

由归纳法知,当无故障时,系统输出残差始终满足方程(7),定理得证.

证毕.

上述定理给出系统无故障时输出残差上限计算方法.该值是最坏情形的一种估计,实际应用中,可以选取比该值小的上限.

4.2 可检测性分析

故障可检测性就是多大的故障可以检测出或不能够被检测出的一种分析.对于本文提出的故障诊断方法,故障的检测范围由下述定理给出.

定理 2. 当系统(1)满足假设 1 至假设 5,利用观测器(3)估计系统状态,并由式(5)对故障进行估计,则故障 f^* 满足 $|f(f^*)| > 2e$ 时可检测.

$$f(f^*) = C \sum_{i=k_1}^k A_0^{k-i} \phi(i) f^* + C \sum_{i=k_1}^k A_0^{k-i} (\xi(y_m(i), \bar{u}(i)) - \xi(y_m(i), u(i)))$$

证明. 当系统发生故障后,但输出估计误差满足式(7)时,系统状态误差方程及输出残差方程为

$$e_x(k+1) = A_0 e_x(k) + \xi(Cx(k), \bar{u}(k)) - \xi(y_m(k), u(k)) + \zeta + G\varsigma + \phi(k) f^* \quad (10a)$$

$$e_y(k) = C e_x(k) + \varsigma \quad (10b)$$

于是有

$$e_y(k+1) = C \sum_{i=0}^k A_0^{k-i} (\xi(Cx(i), \bar{u}(i)) - \xi(y_m(i), u(i))) + C \sum_{i=0}^k A_0^{k-i} \phi(i) f^* +$$

$$C \sum_{i=0}^k A_0^{k-i} (\zeta + G\varsigma) + \varsigma$$

利用三角不等式关系,可得

$$|e_y(k+1)| \geq \left| C \sum_{i=0}^k A_0^{k-i} (\xi(Cx(i), \bar{u}(i)) - \xi(y_m(i), \bar{u}(i))) \right| - \left| C \sum_{i=0}^k A_0^{k-i} (\zeta + G\varsigma) \right| -$$

$$|\varsigma| + |f(f^*)| > -h(L_1\lambda_2 + \lambda_1 + \|G\|_2\lambda_2) - \lambda_2 + |f(f^*)| = -e + |f(f^*)|$$

可见,当 f^* 满足 $|f(f^*)| > 2e$ 时, $|e_y(k+1)| > e$,故障诊断算法将启动,故障可估计.

证毕.

4.3 稳定性分析

定理 3. 当系统(1)满足假设 1 至假设 5,利用观测器(3)估计系统状态,并由式(5)对故障进行估计,则算法稳定.

证明. 当系统在某一时刻 K 发生可检测故障时,得

$$e_x(k+1) = A_0 e_x(k) + M(k) \tilde{f}(k-1) - A_0 M(k-1) \tilde{f}(k-2) +$$

$$\xi(Cx(k), \bar{u}(k)) - \xi(y_m(k), u(k)) + \zeta + G\varsigma \quad (11a)$$

$$e_y(k) = C e_x(k) + \varsigma \quad (11b)$$

式中 $\tilde{f}(k) = f^* - \hat{f}(k)$ 为故障估计误差.令 $\gamma(k+1) = e_x(k+1) - M(k) \tilde{f}(k-1)$, 且 $v_1(k)$,

$v_2(k)$ 和 $v_3(k)$ 为如下差分方程的解

$$v_1(k+1) = A_0 v_1(k) + \zeta + G\zeta, \quad v_1(K) = 0$$

$$v_2(k+1) = A_0 v_2(k), \quad v_2(K) = e_x(K) - M(K-1)\tilde{f}(K-2)$$

$$v_3(k+1) = A_0 v_3(k) + \xi(Cx(k), \bar{u}(k)) - \xi(y_m(k), u(k)), \quad v_3(K) = 0$$

从而 $e_y(k+1) = N(k)\tilde{f}(k-1) + Cv_1(k+1) + Cv_2(k+1) + Cv_3(k+1) + \zeta$

设计 Lyapunov 函数为

$$V(k+1) = \frac{1}{2} \tilde{f}^T(k) \tilde{f}(k) + \sum_{i=k+2}^{\infty} \frac{4(|Cv_2(i)|^2 + |Cv_3(i)|^2)}{\epsilon_0 + \|N(i)\|_2^2} \quad (12)$$

则有

$$\begin{aligned} \Delta V(k+1) &= V(k+1) - V(k) = \\ &= -\tilde{f}^T(k-1) \frac{N^T(k)D(e_y(k+1))}{\epsilon_0 + \|N(k)\|_2^2} + \frac{1}{2} \left(\frac{N^T(k)D(e_y(k+1))}{\epsilon_0 + \|N(k)\|_2^2} \right)^T \left(\frac{N^T(k)D(e_y(k+1))}{\epsilon_0 + \|N(k)\|_2^2} \right) - \\ &= \frac{4(|Cv_2(k+1)|^2 + |Cv_3(k+1)|^2)}{\epsilon_0 + \|N(k)\|_2^2} \end{aligned} \quad (13)$$

当 $\|e_y(k+1)\| < e$ 时, $D(e_y(k+1)) = \mathbf{0}$, $\Delta V(k+1) \leq 0$; 当 $\|e_y(k+1)\| \geq e$ 时, 有以下结果

$$\Delta V(k+1) \leq \frac{(-0.375e_y(k+1) + Cv_1(k+1) + \zeta)^T e_y(k+1)}{\epsilon_0 + \|N(k)\|_2^2} \quad (14)$$

由上式可以看出, 当 $\|e_y(k+1)\| \geq \left\| \frac{8}{3} Cv_1(k+1) + \zeta \right\|$ 时, $\Delta V(k+1) \leq 0$. 结合假设 5, 系统所有信号和参数保持有界, 故障诊断算法稳定.

5 仿真研究

考虑如下非线性系统

$$A = \begin{bmatrix} 1 & -0.6 \\ 0.8 & -1 \end{bmatrix}, \quad B = \begin{bmatrix} 1 & -0.2 \\ 0 & -0.5 \end{bmatrix}, \quad C = \begin{bmatrix} 2.01 & 1.04 \\ 1 & 1 \end{bmatrix}$$

$$\xi(Cx(k), \bar{u}(k)) = \begin{bmatrix} 0.0025 & 0 \\ 0 & 0 \end{bmatrix} (Cx(k))^2 + \begin{bmatrix} 0 \\ -0.1 \sin(\bar{u}(k)) \end{bmatrix}$$

$\zeta(k)$, $\zeta(k)$ 为分别满足 $\|\zeta(k)\| \leq \lambda_1 = 0.03$ 和 $\|\zeta(k)\| \leq \lambda_2 = 0.05$ 的有界噪声. 执行器 1 在 $k=80$ 时刻发生故障, $f_1^* = 0.2$; 执行器 2 在 $k=340$ 时刻发生缓变型故障, $f_2^* = -0.3 \times (k-340)/260$.

对上述系统进行仿真, 故障诊断结果如图 1 所示, 输出估计误差如图 2 所示. 可见, 在

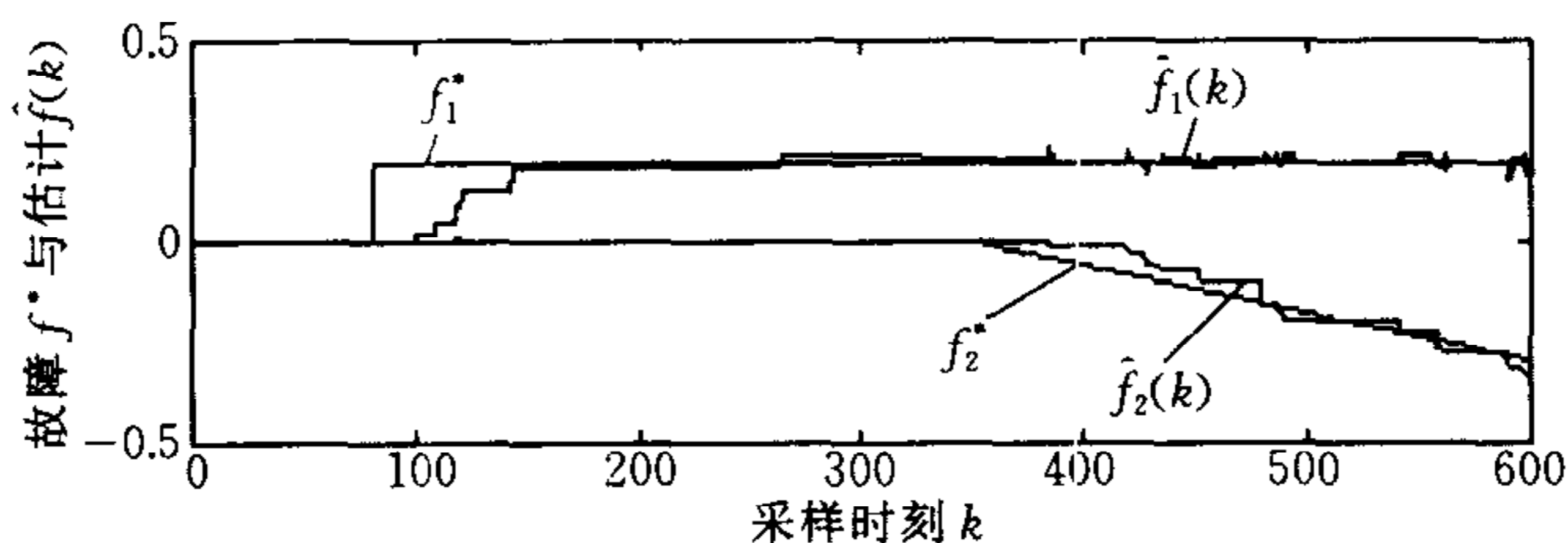


图 1 故障诊断结果

Fig. 1 The diagram of results of the fault diagnosis

$k=100$ 时刻检测到了执行器 1 故障,在 $k=356$ 时刻检测到了执行器 2 故障,而故障较为准确的估计则有相应的延时,故障估计误差较小. 仿真结果说明提出的诊断方法不仅能对跳变型故障进行诊断,对缓变型故障也具有诊断能力.

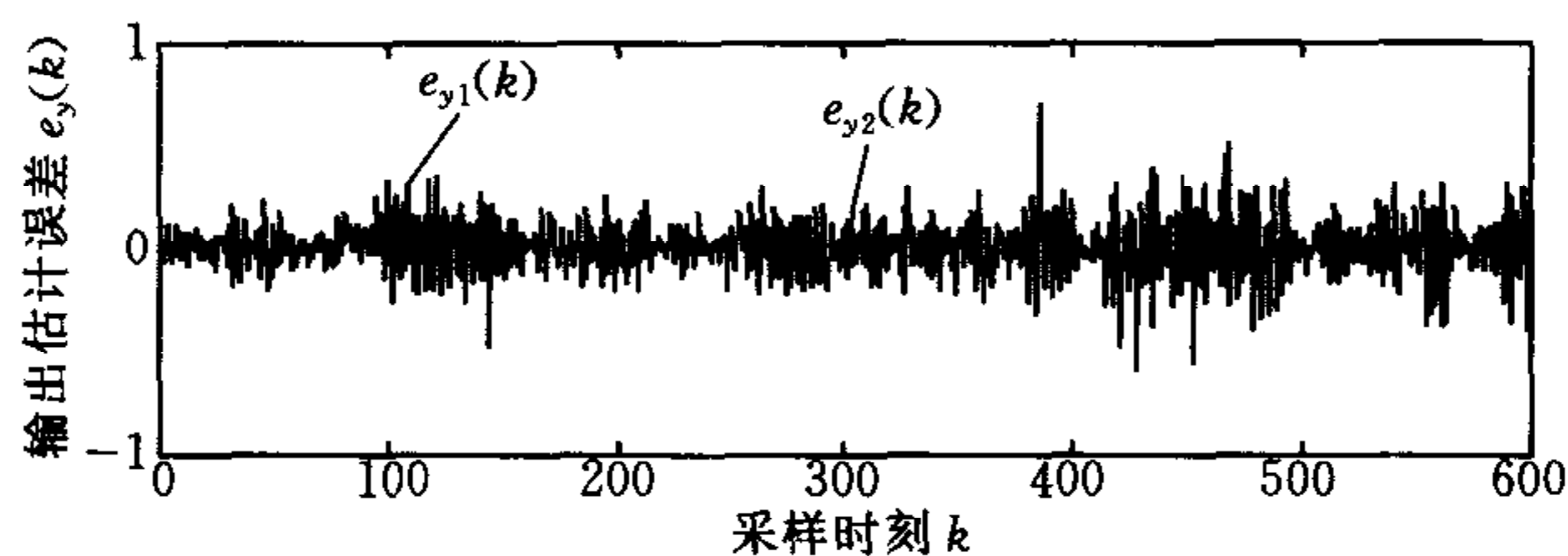


图 2 输出估计误差

Fig. 2 The diagram of output estimation error

6 结论

本文提出了一类非线性系统执行器故障检测与诊断的新方法. 针对系统存在不确定性, 给出了自适应观测器及故障估计算法. 该方法具有一定鲁棒性, 对于可检测故障可以进行有效估计, 算法稳定. 仿真结果说明该方法是有效的.

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