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Online Diagnosis of Faults Using Sliding Fault-Tolerant Fit for SISO Process *

HU Feng and SUN Guoji
(The State Key Laboratory of Manufacturing System Engineering, Xi'an Jiaotong University · Xi'an, 710049, P. R. China)

Abstract: A sliding fault-tolerant (SFT) algorithm is built for fitting trajectories of a SISO process when some pulse-type faults arise from output components of the process. Based on the SFT algorithm, a series of practical program is given to online detect pulse-type faults in process and to identify magnitudes of these faults. Simulation results show that these new methods are efficient.

Key words: fault-tolerant fit; fault detection; fault magnitude identification
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SISO 过程突发性故障基于滑动容错拟合的在线诊断

胡 峰 孙国基
(西安交通大学制造系统工程国家重点实验室·西安, 710049)

摘要: 以 SISO 过程输出环节脉冲型故障为研究对象, 建立了过程轨线具有容错功能的滑动容错拟合算法. 以滑动容错拟合算法为基础, 构造了一组适用于多故障过程脉冲型故障的在线检测方法, 以及故障幅度的统计辨识算法. 通过理论分析和仿真计算, 证实了本文滑动容错拟合和故障在线诊断方法的有效性.

关键词: 容错拟合; 故障检测; 故障幅度辨识

1 Introduction

In many fields such as process safety and dynamic system surveillance, it is a valuable and widely applicable task to detect whether there exist any faults occurred at a running process or not and to conclude the magnitudes of the faults. In order to detect and diagnose faults of a process or a system, most of the typical approaches include detecting filters, analysis of influence function, residual analysis, parity equation, parity space, probability ratio, generalized likelihood ratio (LR), innovation analysis of Kalman filter and some classical statistical diagnosis, etc. Paper [1 ~ 5] summarized the evolution of fault detection and diagnosis (FDD) from different viewpoints.

Summing up recent reference on FDD, we may find out that most of the approaches were based on the least squared (LS) estimators of process parameters, the LS fitting of process trajectories, the LR function, or an equivalent transformation of process model, etc.

Generally, these approaches stated above possess excellent properties when the process run properly. So, these detection algorithms can be efficiently used to online detect the first fault and to offline detect multi-faults, when a dynamic process run out of the way. But some classical statistics (such as the LS estimators, the Kalman filter and the LR test, etc) lack of the fault-tolerance against the bad influence from faults arose before the monitoring time. In other words, these detection algorithms have bad behavior and may make false decision[2 ~ 6] in online monitoring the process that has historical faults.

In practice, when a dynamic process run for a long time, it is possible that there may exist some distinct faults occurred at different times in the running process. In this case, it is important to discuss how to online monitor the state of the dynamic process with historical faults. In this paper, we build a series of practical algorithms to detect pulse-type faults online and to estimate

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magnitudes of these faults. Our algorithms have strong fault-tolerance to faults. Some simulations will show validity of the new algorithms given in this paper.

2 The SLS fitting and the SFT fitting

Assume that the output $\{y(t), t \in T\}$ of a continuous variable dynamic system is a measurable stochastic process and that the expectant trajectory $\{\mu(t), t \in T\}$ of the output is squared integrable and smooth piecewise in all of the finite intervals. Basing on the famous Weierstrass approximation theorems and their generalized results[3], we conclude that the function $\mu(t)(t \in [t_a, t_b] \subseteq T)$ can be approximated by the linear combination of a series of reasonably selected base $\{x_j(t) \in L^2[t_a, t_b], j = 1,2,3,\cdots\}$. Namely,

$$\sum_{j=1}^{s} a_j x_j(t) \to \mu(t)(s \to +\infty), \tag{1}$$

where $\{a_j \in \mathbb{R}, j = 1,2,3,\cdots\}$ are real constants.

Considering the compensating error principle, formula (1) can be expressed as

$$y(t) = \sum_{j=1}^{s} a_j x_j(t) + \varepsilon(t), \tag{2}$$

where process error $\{\varepsilon(t), t \in T\}$ is an aggregate of stochastic noise and error from fitting model.

Let's set a coefficient vector $\boldsymbol{\alpha} = (a_1, \cdots, a_s)^{\tau}$. The key problem is how to identify or estimate the coefficient vector $\boldsymbol{\alpha}$ when we use model (2) to fit the output of a monitored process. The classical statistics for estimating $\boldsymbol{\alpha}$ are the LS estimators, the recursive least-squared (RLS) estimators and the sliding least-squared (SLS) estimators.

2.1 The SLS fitting

In engineering fields, many of the dynamic processes must run for a long time generally and involve complicated dynamic properties and produce a large number of measurement data. In order to cut down the truncated error and to avoid the problem of data saturation, the sliding fitting must be applied.

Now, let's use the following notations

$$\begin{cases} H_{i\to j} = \begin{bmatrix} x_1(t_i) & \cdots & x_s(t_i) \\ \vdots & & \vdots \\ x_1(t_j) & \cdots & x_s(t_j) \end{bmatrix}, \\ \boldsymbol{h}_i = \begin{bmatrix} x_1(t_i) \\ \vdots \\ x_s(t_i) \end{bmatrix}, \quad Y_{i\to j} = \begin{pmatrix} y(t_i) \\ \vdots \\ y(t_j) \end{pmatrix}, \end{cases} \quad (1 \leqslant i \leqslant j), \tag{3}$$

and build a series of recursive SLS estimators for coefficients of the fitting model. In fact based on the measurement data set $D_{(i+1\to i+n)} = \{y(t_{i+1}), \cdots, y(t_{i+n})\}$, it can be proved that the LS estimator of $\boldsymbol{\alpha}$

$$\hat{\boldsymbol{\alpha}}_{\mathrm{LS}(i+1\to i+n)} = J_{(i+1\to i+n)} H^{\tau}_{(i+1\to i+n)} Y_{(i+1\to i+n)}, \tag{4}$$

where

$$J_{(i+1\to i+n)} = (H^{\tau}_{(i+1\to i+n)} H_{(i+1\to i+n)})^{-1}, \quad n \geqslant s.$$

With the system's running up progressively, formula (4) satisfies a recursive algorithm as follows:

$$\begin{aligned} &\hat{\boldsymbol{\alpha}}_{\mathrm{LS}(i+1\to i+n)} = \\ &\hat{\boldsymbol{\alpha}}_{\mathrm{LS}(i\to i+n-1)} - J_{(i+1\to i+n)} \boldsymbol{h}_i (y(t_i) - \boldsymbol{h}_i^{\tau} \hat{\boldsymbol{\alpha}} D_{\mathrm{LS}(i\to i+n-1)} + \\ &F_{(i+1\to i+n)} (y(t_{i+n}) - \boldsymbol{h}_{i+1}^{\tau} \hat{\boldsymbol{\alpha}}_{\mathrm{LS}(i\to i+n-1)}), \end{aligned} \tag{5}$$

where

$$F_{(i+1\to i+n)} = \frac{J_{(i+1\to i+n)} \boldsymbol{h}_{i+n}}{1 + \boldsymbol{h}_{i+n}^{\tau} J_{(i+1\to i+n)} \boldsymbol{h}_{i+n}}.$$

Using formula (4), we can educe that the SLS fit for process trajectories at time t is equal to

$$\hat{y}_{\mathrm{LS}(i+1\to i+n)}(t) = \sum_{j=1}^{s} \hat{a}_{j,\mathrm{LS}(i+1\to i+n)} x_j(t), \tag{6}$$

when the process runs properly. Correspondingly, the one-step predictor for the process output $y(t_{i+n+1})$ is $\hat{y}_{\mathrm{LS}(i+1\to i+n)}(t_{i+n+1})$. Let us note the predicting error as

$$\hat{\varepsilon}_{\mathrm{LS}(i+n+1|i+1\to i+n)} = y(t_{i+n+1}) - \hat{y}_{\mathrm{LS}(i+1\to i+n)}(t_{i+n+1}). \tag{7}$$

Theorem 1 If the mean and variance of process $\{\varepsilon(t_i): i = 1,2,\cdots\}$ are equal to zero and σ^2 respectively, then variance of the predicting error $\{\hat{\varepsilon}_{\mathrm{LS}(i+n+1|i+1\to i+n)}\}$ is equal to

$$\begin{aligned} &\mathrm{var}(\hat{\varepsilon}_{\mathrm{LS}(i+n+1|i+1\to i+n)}) = \\ &(1 + \boldsymbol{h}_{i+n+1}^{\tau} J_{(i+1\to i+n)} \boldsymbol{h}_{i+n+1}) \sigma^2. \end{aligned} \tag{8}$$

Proof Combining the LS estimators $\hat{\boldsymbol{\alpha}}_{\mathrm{LS}(i+1\to i+n)}$ with (6) into formula (7) and do some reduction, we can obtain formula (8). Some detailed procedures are omitted here.

2.2 Fault-tolerant improvement of the SLS fitting

Generally, the recursive SLS estimators given in (5) are piecewise optimal unbiased linear estimators of the fitting coefficients when the process runs properly and exports output without faults. So, the SLS fitting possesses some excellent statistical properties. But, the SLS fitting has the same weakness as the ordinary LS fitting. Many results have shown that the practical fitting results are unsatisfactory and can break down estimating algorithms in the case there exist abrupt faults occurred at the running process. In fact, if there exists a fault occurred at time t_{i_0}, whose magnitude is $\lambda(t_{i_0})$, namely

$$\tilde{y}(t) = \begin{cases} y(t), & t \neq t_{i_0}, \\ y(t) + \lambda(t), & t = t_{i_0}, \end{cases} \tag{9}$$

then the predicting error of the SLS predictor can be expressed as follows

$$\begin{aligned} &\tilde{\hat{\varepsilon}}_{LS(i+n+1|i+1\to i+n)} = \\ &\hat{\varepsilon}_{LS(i+n+1|i+1\to i+n)} + \\ &\begin{cases} 0, & t_{i_0} \leqslant t_i \text{ or } t_{i_0} > t_{n+i+1}, \\ \omega(t_{i+n+1}, t_{i_0}), & t_{i+1} \leqslant t_{i_0} \leqslant t_{n+i}, \\ \lambda(t_{i_0}), & t_{i_0} = t_{n+i+1}, \end{cases} \end{aligned} \tag{10}$$

where

$$\begin{aligned} &\omega(t_{i+n+1}, t_{i_0}) = \\ &-\boldsymbol{h}^{\tau}_{i+n+1}(H^{\tau}_{(i+1\to i+n)}H_{(i+1\to i+n)})^{-1}\boldsymbol{h}_{i_0}. \end{aligned}$$

Expression (10) shows that pulse-type faults occurred at a running process may result in evidently magnifying the predictor error, the numerical values of which are not equal to any constants at different sliding interval. On the other hand, we can view the $\hat{\boldsymbol{\alpha}}_{LS(i+1\to i+n)}$ in formula (5) as a modification of $\hat{\boldsymbol{\alpha}}_{LS(i\to i+n-1)}$ by the SLS filtering residual

$$\hat{\varepsilon}_{LS(i|i\to i+n-1)} = y(t_i) - \boldsymbol{h}_i^{\tau}\hat{\boldsymbol{\alpha}}_{LS(i\to i+n-1)}$$

and the predicting error $\hat{\varepsilon}_{LS(i+n+1|i+1\to i+n)}$. So we may conclude that a pulse-type fault occurred at time t_{i+n} can not only unconventionally magnify the predicting error $\hat{\varepsilon}_{LS(i+n+1|i+1\to i+n)}$, but also evidently change the estimators $\hat{\boldsymbol{\alpha}}_{LS(i+1\to i+n)}$ and even break down the algorithm (5).

In order to overcome all of the bad influence from exceptional change brought by a pulse-type fault on the recursively sliding estimators of the model coefficients, we set a re-descending[8] ϕ -function as follows:

$$\phi_{rd}(x) = \begin{cases} x, & |x| < c_1, \\ c_1\operatorname{sgn}(x), & c_1 \leqslant |x| < c_2, \\ \dfrac{c_2 - |x|}{c_2 - c_1}c_1, & c_2 \leqslant |x| < c_3, \\ 0, & |x| \geqslant c_3, \end{cases} \tag{11}$$

where (c_1, c_2, c_3) are constants, and use this kind of ϕ -function to cut down the bad influence of informal predicting error on the sliding identification algorithms. By ϕ -function (11), we construct the following sliding fault-tolerant (SFT) algorithm:

$$\begin{aligned} &\hat{\boldsymbol{\alpha}}_{\phi(i+1\to i+n)} = \\ &\hat{\boldsymbol{\alpha}}_{\phi(i\to i+n-1)} - J_{(i+1\to n+i)}\boldsymbol{h}_i\tilde{y}_{(i|i\to i+n-1)} + \\ &F_{(i\to i+n-1)}d_{(i\to i+n-1)}\phi_{rd}\left(\frac{\tilde{y}_{(i+n|i\to i+n-1)}}{d_{(i\to i+n-1)}}\right), \end{aligned} \tag{12}$$

where

$$d_{(i\to i+n-1)} = \sqrt{1 + \boldsymbol{h}^{\tau}_{i+n}J_{(i\to i+n-1)}\boldsymbol{h}_{i+n}};$$

$$\tilde{y}_{(j|i\to i+n-1)} = y(t_j) - \boldsymbol{h}_j^{\tau}\hat{\boldsymbol{\alpha}}_{\phi(i\to i+n-1)}.$$

Theorem 2 If $\{\varepsilon(t), t \in T\}$ of model (2) is stationary and its distribution is symmetrical, whose mean and variance are equal to zero and σ^2 respectively, the estimators $\{\hat{\boldsymbol{\alpha}}_{\phi(i+1\to i+n)}, i = 1,2,3,\cdots\}$ are unbiased in the case that there are not any faults occurred before the time t_{n_0} $(n_0 > \min\{s, n-1\})$[6], and that initial value $\hat{\boldsymbol{\alpha}}_{\phi(n_0-n+1\to n_0)}$ of the algorithm (12) is selected as $\hat{\boldsymbol{\alpha}}_{LS(n_0-n+1\to n_0)}$.

Proof Distinctly, $\hat{\boldsymbol{\alpha}}_{\phi(n_0-n+1\to n_0)}$ is an unbiased estimator of the parameter vector $\hat{\boldsymbol{\alpha}}$. Using the property that the integral of an odd function on symmetrical interval is equal to zero, we can also prove the statistic $\hat{\boldsymbol{\alpha}}_{\phi(n_0-n+2\to n_0+1)}$ being unbiased. Similarly, we can prove that all of the estimators are unbiased by mathematical induction.

Now, let us expatiate on the rationality of the new algorithm (12). Using a term "innovation" in [7], we regard the one-step predicting error $\varepsilon_{LS(i+n|i\to i+n-1)}$ as innovation brought by the measuring data at time t_{i+n}. It is obviously reasonable for us to substitute $\phi(x) = x$ implied in (5) for the re-descending ϕ -function given in (11), because of the following reasons:

1) When an innovation of new sampling data fall into the anticipative bound, we think that these new sampling data are reasonable and are supposed to make full use of them;

2) When the innovations of new sampling data go beyond selected bound but do not overtop a lot, we must use the reasonable influence and confine the bad influence from these sampling data;

3) We must escalate the restriction on making use of information from the distrustful sampling data;

4) When the innovations distinctly depart from the

normal value and are exceptionally large, we must quite eliminate bad influence from them.

Considering the explanations stated above, we find out that the modified algorithm (12) can more reasonably use the innovation from sampling data $y(t_{i+n})$ to update the identification of parameters than the recursive SLS estimators (5), when there exists large discrepancy between a sampling data $y(t_{i+n})$ and the predictor $\hat{y}(t_{i+n}) = \boldsymbol{h}_{i+n}^{\tau}\hat{\boldsymbol{\alpha}}_{\phi(i\to i+n_1-1)}$.

Distinctly, the modified algorithm (12) improves the reliability of estimators with losing a little optimality of the old algorithm. In other words, it is a compromise between statistical optimality and fault-tolerance ability.

3 The SFT detection for process fault

Generally, if there do not exist any faults before the time t_{i+n} and the process $\{\varepsilon(t), t \in T\}$ is white and stationary Gaussian noise, then the predicting error $\epsilon_{LS(i+n+1|i+1\to i+n)}$ obeys the normal distribution $N(0, d_{(i+1\to i+n)}\sigma)$ as we have pointed out before. Basing on this property, we may use the following detecting statistic

$$R_{LS}(t_{i+n+1}) = \frac{y(t_{i+n+1}) - \boldsymbol{h}_{i+n+1}^{\tau}\hat{\boldsymbol{\alpha}}_{LS(i+1\to i+n)}}{d_{(i+1\to i+n)}}, \tag{13}$$

and the famous "3σ-criterion" to diagnose whether there is a fault occurring at time t_{i+n+1} or not. But many theoretical analysis and practical applications show that $R_{LS}(t_{i+n+1})$ can not be used in the case there exist one or more faults occurring before the time (t_{i+n+1}) because the detection statistic (13) is based on the LS estimating algorithms and is hypersensitive to outliers[8] in sampling data. Namely, algorithm (13) can not be used in monitoring multiple faults of a dynamic process.

In order to protect a detection statistic against any bad influence of historical faults, it is one reasonable means to substitute the SFT estimators for the recursive SLS estimators in (13).

In Section 2.2, it has pointed out that the estimators $\hat{\boldsymbol{\alpha}}_{\phi(i+1\to i+n)}$ given by formula (12) have the ability to overcome bad influence coming from outliers and to make sure the reliability of estimators. So we replace $\hat{\boldsymbol{\alpha}}_{LS(i+1\to i+n)}$ in expression (13) by $\hat{\boldsymbol{\alpha}}_{\phi(i+1\to i+n)}$. This means is a practical technical approach without failure for online monitoring dynamic process in the case there are multiple faults having occurred before the sampling moment detected.

According to all of the analysis stated above, we build a series of detecting strategies which are based on the recursive SFT estimators:

1) Selecting $n_0 > \min\{s, n-1\}$ and using the robust-LR detection algorithm given in [8], let us do some offline detection to diagnose whether there are any faults before the time t_{n_0} or not.

2) All of the outliers detected at step 1) must be corrected with interpolation.

3) The $\hat{\boldsymbol{\alpha}}_{LS(n_0-n+1\to n_0)}$ calculated with (4) is set as the initial value of the recursive algorithm (12).

4) According to algorithm (12), a series of sliding calculation is done to obtain $\hat{\boldsymbol{\alpha}}_{\phi(i+1\to i+n)}$.

5) The detection statistic is built as follows

$$R_{\phi}(t_{i+n+1}) = \frac{y(t_{i+n+1}) - \boldsymbol{h}_{i+n+1}^{\tau}\hat{\boldsymbol{\alpha}}_{\phi(i+1\to i+n)}}{d_{(i+1\to i+n)}}. \tag{14}$$

6) A judgement is done: if $|R_{\phi}(t_{i+n+1})| \geq c$, there is a fault occurred at time t_{i+n+1}; otherwise, the sampling data is normal and the process is running without fault, where the constant c is a bound selected properly (The default value is suggested as 3σ).

7) With the process running continuously, four steps 3) ~ 6) are done again and again.

4 The SFT estimators of fault magnitudes

Setting $\boldsymbol{h}_{i+n+1}^{\tau}\hat{\boldsymbol{\alpha}}_{\phi(i+1\to i+n)}$ as a predicting value of $y(t_{i+n+1})$, a statistic is constructed as follows

$$\hat{\lambda}_{\phi}(t_{i+n+1}) = \epsilon_{\phi(i+n+1|i+1\to i+n)} = |y(t_{i+n+1}) - \boldsymbol{h}_{i+n+1}^{\tau}\hat{\boldsymbol{\alpha}}_{\phi(i+1\to i+n)}| \tag{15}$$

to estimate the magnitude of a fault.

Theorem 3 Assuming that the process $\{\varepsilon(t), t \in T\}$ is stationary and the distribution of $\varepsilon(t)$ is $N(0, \sigma^2)$.

1) If there exists a pulse-type fault occurred at time t_{i+n+1}, then mathematical expectation of the statistic $\hat{\lambda}_{\phi}(t_{i+n+1})$ is equal to $\lambda(t_{i+n+1})$, the magnitude of the fault.

2) If the dynamic process runs properly, then the mathematical expectation of $\hat{\lambda}_{\phi}(t_{i+n+1})$ is zero.

Proof The result of the theorem can be educed by Theorem 2 and expression (15) obviously.

5 Simulation

The simulation model is selected as a polynomial

$$y(t) = a + bt + ct^2 + \varepsilon(t), \varepsilon(t) \sim N(0, \sigma^2).$$

Setting the coefficients $a = 100, b = 10, c = -0.25$ and $\sigma^2 = 1$, we get 100 sampling data at time set

$$D = \{t_i = t_0 + ih \mid t_0 = 0, i = 1, \cdots, 100, h = 1\text{s}\}$$

by using the Monte Carlo method.

By intentionally shifting some sampling data about $(-1)^{i+1}100\sigma$ at the time set $D_{out} = \{t_i \mid i = 50 \sim 54, 75\}$, we get a new series of output data with long patchy outliers and an isolated outlier as in Fig. 1.

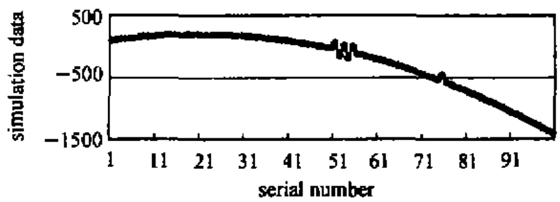

Fig. 1 Simulation with two kinds of outliers

Intuitively, the magnitudes of the isolated outlier and the patchy outliers are not prominent to all appearances shown in Fig. 1.

5.1 The behavior of SFT estimators

Set the length of sliding interval $n = 20$. Fig. 2 and Fig. 3 show the recursive SLS estimators and the SFT estimators of three coefficients of the simulation model given above respectively, using the simulation data shown in Fig. 1.

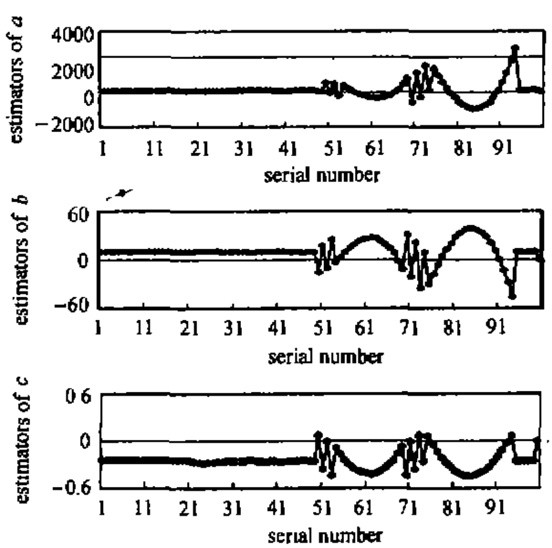

Fig. 2 The recursive SLS estimators of coefficients

Comparing Fig. 2 with Fig. 3, we are convinced that the recursive SLS estimators of model coefficients are influenced badly by outliers and that the SFT algorithm (12) have commendable resistance to outliers.

5.2 Detecting and identifying outliers

Using the estimators shown in Fig. 2 and Fig. 3 respectively, we obtain two different kinds of prediction residuals and show these two series of prediction residuals in the Fig. 4 and Fig. 5, respectively.

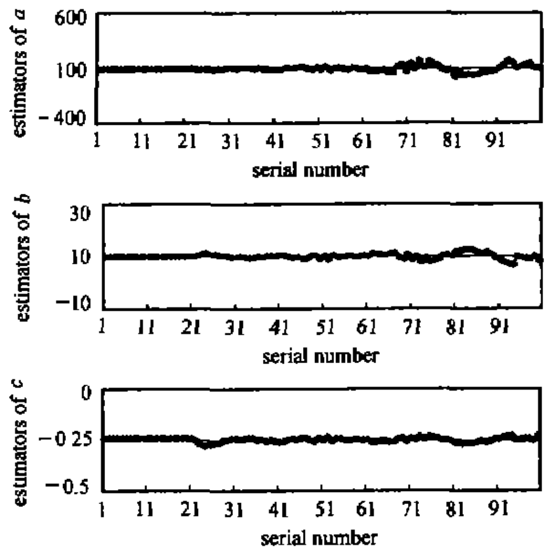

Fig. 3 The SFT estimators of coefficients

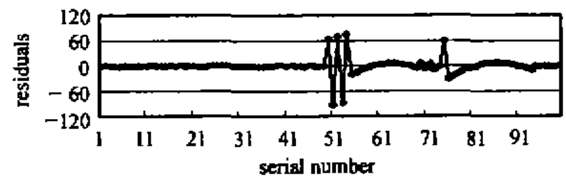

Fig. 4 Residuals of prediction using the recursive SLS

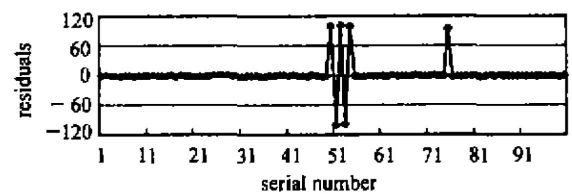

Fig. 5 Residuals of prediction using SFT

Fig. 4 shows that the bad influence of outliers on residuals of the SLS predictors is descending step by step. Evidently, if these prediction residuals were used to detect the outlier online, then the sampling data $\{y(t_i) \mid i = 55, 56, 76, 77\}$ would be diagnosed falsely as informal data although these data are normal. In this example, the ratio of false detection is 40% and the ratio of losing outliers is 0.

Fig. 5 shows that shapes and magnitudes of the residuals are very close to outlying data inside the time set D_{out}. What is more, the prediction residuals rapidly descend to zero or close to zero outside the time set D_{out}, respectively. So, the residuals of the SFT algorithm can exhibit the patterns of faults excellently. In this example, the ratio of false detection is 40% and the ratio of losing outliers is 0 too.

Talble 1 The estimators of fault magnitudes

Serial Number i_0	50	51	52	53	54	75
The SLS estimators $\hat{\lambda}(t_{i_0})$	64.960	-93.207	71.422	-87.617	75.259	61.238
The SFT estimators $\hat{\lambda}_\phi(t_{i_0})$	101.326	-99.744	102.063	-99.317	100.613	95.416

The estimating values of magnitudes for the six outliers are calculated and shown in Table 1, with the recursive SLS algorithms and the SFT algorithms respectively. According to Table 1, we may educe that the SFT estimators $\hat{\lambda}_\phi(t_{i_0})$ are markedly closer to the values that are designed for simulation than the recursive SLS estimator $\hat{\lambda}(t_{i_0})(i_0 = 50 \sim 54, 75)$.

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本文作者简介

胡 峰 1964年生.高级工程师.2000年获西安交通大学博士学位.现为制造系统工程国家重点实验室访问学者,兼中国科联研究员、《飞行器测控学报》编委.近期主要研究方向为系统建模,过程监控与容错处理技术,已出版专著一本,发表论文70多篇.获得部委级或军队级科技进步二、三等奖8项.

孙国基 1936年生.教授.1966年获得苏联科学技术系统副博士学位.现为西安交通大学博士生导师,全国系统仿真学会副理事长,《系统仿真学报》等期刊编委.近期主要从事CIMS仿真和虚拟现实在仿真中应用研究,出版著作多本,发表研究论文90多篇.获得全国科学大会奖及部委级科技进步奖多项.