第 15 卷第 3 期
1998 年 6 月
控制理论与应用
CONTROL THEORY AND APPLICATIONS
Vol. 15, No. 3
Jun., 1998

A New Technique Integrated Steady-State Estimation and Dynamic Identification for a Class of Nonlinear Systems

HUANG Zhengliang and LI Zhongli
(Southwest Institute of Technology · Sichuan Mianyang, 621002, PRC)
WAN Baiwu
(Institute of systems Engineering, Xi'an Jiaotong University · Xi'an, 710049, PRC)

Abstract: In this paper, a new identification technique is presented. The new technique uses both steady-state and dynamic information to identify the nonlinear gain and impulse responses of linear subsystem of the Hammerstein system, respectively, and the estimates obtained are of strong consistence. Besides, the paper also studies the asymptotic distributions and convergence rate of estimation error of nonlinear gain. Simulation results show that the new technigue is very efficient and practical.

Key words: nonlinear gain; impulse response; linear subsystem; Hammerstein system; identification

1 Introduction

A wide variety of controlled plants with nonlinear actuators can be described by the Hammerstein system which consists of a zero memory nonlinear gain followed by a linear dynamic subsystem, although identifying the Hammerstein system has received considerable attention[1~3], so far, identification techniques proposed have not given the strong consistence estimates of unknown parameters of the nonlinear gain and impulse response of the linear subsystem of the Hammerstein system.

In this paper, a new identification technique integrated steady-state estimation and dynamic identification is presented. Under conditions of knowing the construction of the nonlinear gain, the strong consistence estimates of unknown parameters of the nonlinear gain and impulse response are obtained, and the asymptotic distribution of the estimation error and the convergence rate of the errors are obtained.

2 Steady-State Identification

Consider now a discrete-time Hammerstein system showed by Fig. 1, where $u(k)$ and $y(k)$ are the input and output of the system at the time k, respectively; $w(k)$ is the output of the zero memory nonlinear gain, and unmeasured; $\zeta(k)$ and $\eta(k)$ are the noises of the system.

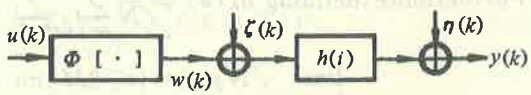

Fig. 1 Hammerstein system

The system mentioned above can be described as follows

Manuscript received Dec. 26, 1995, revised Aug. 22, 1997.

$$y(k) = \sum_{i=0}^{\infty} h(i)\Phi[u(k-i)] + \varepsilon(k), \tag{1}$$

$$\varepsilon(k) = \sum_{i=0}^{\infty} h(i)\zeta(k-i) + \eta(k). \tag{2}$$

For simplification, the following assumptions about the system and the noise are made.

Assumption 1 $\eta(k)$ and $\zeta(k)$ are mutually independent white noise with zero mean and varianced r_1^2 and r_2^2, respectively, and there exists constant $\delta > 0$ such that $E|\eta(k)|^{2+\delta}$ and $E|\zeta(k)|^{2+\delta}$ are uniform boundness.

Assumption 2 The linear subsystem is strictly stable, i. e.,

$$\sum_{k=0}^{\infty} k|h(k)| < \infty \quad \text{and} \quad \lambda = \sum_{k=0}^{\infty} h(k) \neq 0.$$

Assumption 3 $\Phi[\cdot]$ is piecewise continuous with boundary M on the real variable interval of the $u(k)[a,b]$.

The input signal here is a step function, that is, when $k \geqslant 0, u(k) = \sigma$, where $\sigma \in [a,b]$ is a continuous point of $\Phi[\cdot]$, and when $k < 0, u(k)$ may take arbitrary value belong to $[a,b]$. The total number of sampled data is N. According to (1), we have

$$\frac{1}{N}\sum_{k=1}^{N} y(k+T) = \frac{1}{N}\sum_{k=1}^{N}\sum_{i=0}^{k+T} h(i)\Phi[\sigma] + \frac{1}{N}\sum_{k=1}^{N}\sum_{i=k+T+1}^{\infty} h(i)\Phi[u(k+T-i)] + \frac{1}{N}\sum_{k=1}^{N}\varepsilon(k+T), \tag{3}$$

where T denotes the steady-state time. Furthermore, according to (1) and Assumption 2 we find that

$$\lim_{N\to\infty} \frac{1}{N}\sum_{k=1}^{N}\varepsilon(k+T) = 0 \quad (\mathrm{q}), \tag{4}$$

where (q) represents the convergence in mean square. So, from (3) and (4) it follows that

$$\lim_{N\to\infty} \frac{1}{N}\sum_{k=1}^{N} y(k+T) = \lambda\Phi[\sigma] \quad (\mathrm{q}), \tag{5}$$

Let $F(\sigma) = \lambda\Phi[\sigma]$, $F_N(\sigma) = \frac{1}{N}\sum_{k=1}^{N} y(k+T)$, and $\delta_N(\sigma) = F_N(\sigma) - F(\sigma)$, from (5) we know that $F_N(\sigma)$ is the strongly consistency estimate of the $F(\sigma)$, and one has

$$\delta_N(\sigma) = \frac{1}{N}\sum_{k=1}^{N}\sum_{i=k+T+1}^{\infty} h(i)(\Phi[u(k+T-i)] - \Phi[\sigma]) + \frac{1}{N}\sum_{k=1}^{N}\varepsilon(k+T). \tag{6}$$

Furthermore, defining $\mu_N(\sigma) = \frac{1}{N}\sum_{k=1}^{N}\sum_{i=k+T+1}^{\infty} h(i)(\Phi[u(k+T-i)] - \Phi[\sigma])$ then

$$\begin{aligned}
\lim_{N\to\infty} |\sqrt{N}\mu_N(\sigma)| &\leqslant 2M \lim_{N\to\infty} \frac{1}{\sqrt{N}}\sum_{k=1}^{N}\sum_{i=k+T+1}^{\infty} |h(i)| \\
&= 2M \lim_{N\to\infty} \sum_{i=N+T+1}^{\infty} |h(i)| / |\sqrt{N} - \sqrt{N-1}| \\
&\leqslant 4M \lim_{N\to\infty} \sum_{i=N+T+1}^{\infty} i|h(i)| = 0.
\end{aligned} \tag{7}$$

By the central limit theorem, we obtain

$$\lim_{N\to\infty} \frac{1}{\sqrt{N}} \sum_{K=1}^{N} \eta(k+T) = \eta \quad (W)$$

$$\sim N(0, r_1^2), \tag{8}$$

$$\lim_{N\to\infty} \frac{1}{\sqrt{N}} \sum_{K=1}^{N} \zeta(k+t-i) = \zeta_i \quad (W)$$

$$\sim N(0, r_2^2), \tag{9}$$

where (W) represents the distribution convergence. Let $\xi_{N,i} = \frac{1}{\sqrt{N}} \sum_{K=1}^{N} \zeta(k+T-i)$, then $\forall\, N - |i-j| \geqslant 1$, we have

$$E\zeta_{N,i}\zeta_{N,j} = \frac{1}{\sqrt{N}} \sum_{K=1}^{N} \sum_{s=1}^{N} E\zeta(k+T-i)\zeta(s+T-j)$$

$$= \frac{1}{\sqrt{N}} \sum_{i=1}^{N-|i-j|} r_2^2$$

$$= (N - |i-j|) r_2^2 / N, \tag{10}$$

so

$$E\zeta_i\zeta_j = \lim_{N\to\infty} E\zeta_{N,i}\zeta_{N,j} = r_2^2. \tag{11}$$

Because the arbitrary linear combination of normal random variables is also a normal random variable, and the limit of the normal random series in mean square as well, then

$$\lim_{N\to\infty} \frac{1}{N} \sum_{k=1}^{N} \varepsilon(k+T) = \lim_{N\to\infty} \left(\frac{1}{N} \sum_{k=1}^{N} \eta(k+T) + \frac{1}{N} \sum_{k=1}^{N} \sum_{i=0}^{N} h(i)\zeta(k+T-i) \right)$$

$$= \eta + \sum_{i=0}^{\infty} h(i)\zeta_i \quad (W)$$

$$\sim N\left(o, r_1^2 + \left(\sum_{i=0}^{\infty} h(i)\right)^2 r_2^2\right). \tag{12}$$

Hence, from (6), (7) and (12) it follows

$$\lim_{N\to\infty} \sqrt{N}\,\delta_N(\sigma) \sim N\left(o, r_1^2 + \left(\sum_{i=0}^{\infty} h(i)\right)^2 r_2^2\right). \tag{13}$$

In the following, we shall analyse the convergence rate of the $\delta_N(\sigma)$. We have

$$E(\sqrt{N}\sigma_N(\sigma))^2 = E\left(\sqrt{N}\mu_N(\sigma) + \frac{1}{N} \sum_{k=1}^{N} \varepsilon(k+T)\right)^2$$

$$= (\sqrt{N}\mu_N(\sigma))^2 + E\left(\frac{1}{\sqrt{N}} \sum_{k=1}^{N} \varepsilon(k+T)\right)^2. \tag{14}$$

Due to (7) and (12), it follows that

$$\lim_{N\to\infty} E(\sqrt{N}\delta_N(\sigma))^2 = r_1^2 + \left(\sum_{i=0}^{\infty} h(i) r_2\right)^2. \tag{15}$$

So

$$(E\delta_N^2(\sigma))^{\frac{1}{2}} = O\left(\frac{1}{\sqrt{N}}\right). \tag{16}$$

Theorem 1 If assumptions 1, 2 and 3 hold, then $F_N(\sigma)$ is the strong consistence estimate of the $F(\sigma)$,and the asymptotic distribution of the estimation error is normal. Furthermore, the convergence rate of the error is the same as $\frac{1}{\sqrt{N}}$.

Taking σ_i from $[a,b](i = 1,2,\cdots,p)$ such that $\lambda\Phi[\sigma_i]$ is not mutually equal and σ_i is the continuous points of the $\Phi[\cdot]$. Making p number of times open-loop steady-state estimative experiments, we may obtain the strong consistence estimates of the $\lambda\Phi[\sigma_i]$. If both λ and the construction of nonlinear gain are known, then we may get the strong consistence estimates of the unknown parameters of the nonlinear gain, otherwise, we may construct a polynomial to approximate the nonlinear gain by using the $(\sigma_i, \lambda\Phi[\sigma_i])$,and the estimated precision will become highter with the increase of p .

3 Dynamic Identification

Taking up independent and identical distribution random variables sequence $\{u(k)\}$ as the input signals, and the probability distribution of the $u(k)$ is the uniform distribution on the discrete point set $\{\sigma_i | i = 1,2,\cdots,p\}$. Although we can not measure the $F(\sigma_i)(= \lambda\Phi[\sigma_i]$, by using the results obtained from open-loop steady-state estimated experiments, we may get the strong consistence estimates of the $F(\sigma_i)$. In fact, when $k \geqslant 0$, $\{\widetilde{w}(k)\} = \{\lambda\Phi[u(k)]\}$ is the independent and identical distribution random variables sequence on discrete point set $\{\lambda\Phi[\sigma_i] | i = 1,2,\cdots,p\}$. Hence (1) may be rewritten as follows

$$y(k) = \sum_{i=0}^{\infty} h^*(i)\widetilde{w}(k-i) + \varepsilon(k), \tag{17}$$

where $h^*(i) = h(i)/\lambda$. Obviously, $y(k)$ is not a stationary (wide sense) process . Thus, Construct another system as follows

$$\widetilde{y}(k) = \sum_{i=0}^{\infty} h^*(i)\widetilde{w}(k-i) + \varepsilon(k), \tag{18}$$

where $\widetilde{w}(k) = \lambda\Phi[\widetilde{u}(k)]$, $\{\widetilde{u}(k)\}$ is the independent and identical distribution stationary process whose probability distribution is the uniform distribution on point set $\{\sigma_i | i = 1,\cdots,p\}$, and when $k \geqslant 0$ one has $\widetilde{u}(k) = u(k)$. It is obvious that $\widetilde{y}(k)$ is a stationary process

Constructing a continuous function $G(\cdot)$ with boundary M_1 such that

$$EG[\widetilde{u}(k)] = \frac{1}{P}\sum_{i=1}^{P} G(\sigma_i) = 0, \tag{19}$$

$$m = E\widetilde{w}(k)G[\widetilde{u}(k)] = \frac{1}{P}\sum_{i=1}^{P} F(\sigma_i)G(\sigma_i) \neq 0. \tag{20}$$

Obviously, $\{G[\widetilde{u}(k)]\}$ is the independent and identical distribution stationary process, and mutually independent with $w(s)(s \neq k)$,then we have

$$E\widetilde{y}(k+j)G[\widetilde{u}(k)] = h^*(j)m, \tag{21}$$

$$h^*(j) = E\widetilde{y}(k+j)G[\widetilde{u}(k)]/m. \tag{22}$$

Now, the key problem is how to calculate the $E\widetilde{y}(k+j)G[\widetilde{u}(k)]$. In the following, we shall prove that $\forall\ j \geqslant 0$, $\widetilde{z}_j(k) = \widetilde{y}(k+j)G[\widetilde{u}(k)]$ is an ergodic stationary process. Since

$$\widetilde{z}_j(k) = \sum_{i=0}^{\infty} h^*(i)\widetilde{w}(k+j-i)G[\widetilde{u}(k)] + \varepsilon(k+j)G[\widetilde{u}(k)], \tag{23}$$

then

$$E\tilde{z}_j(k) = h^*(j)m. \tag{24}$$

Hence $\forall\ t > 0$. We have

$$\begin{aligned} E\tilde{z}_j(k+t)\tilde{z}_j(k) &= \sum_{i=0}^{\infty}\sum_{l=0}^{\infty} h^*(i)h^*(l)E\tilde{w}(k+j-i)G[\tilde{u}(k)] \\ &\quad \cdot \tilde{w}(k+j+t-l)G[\tilde{u}(k+t)] \\ &= \begin{cases} h^*(j-t)h^*(j+t)m^2 + h^{*2}(j)m^2, & j \geqslant t, \\ h^{*2}(j)m^2, & j < t. \end{cases} \end{aligned} \tag{25}$$

It follows that $\tilde{z}_j(k)$ is a stationary process and the correlation function has the following form

$$\begin{aligned} R_j(t) &= E[\tilde{z}_j(k+t) - h^*(j)m][\tilde{z}_j(k) - h^*(j)m] \\ &= E\tilde{z}_j(k+t)\tilde{z}_j(k) - h^*(j)m^2 \\ &= \begin{cases} h^*(j-t)h^*(j+t)m^2, & j \geqslant t, \\ 0, & j < t. \end{cases} \end{aligned} \tag{26}$$

Hence

$$\lim_{N\to\infty} \frac{1}{N}\sum_{t=0}^{N-1} R_j(t) = 0. \tag{27}$$

So, Applying the ergodic theorem, we have

$$E\tilde{y}(k+j)G[\tilde{u}(k)] = \lim_{N\to\infty}\frac{1}{N}\sum_{k=1}^{N}\tilde{y}(k+j)G[\tilde{u}(k)]. \quad (q) \tag{28}$$

Defining $h_j^*(N) = \frac{1}{mN}\sum_{k=1}^{N}\tilde{y}(k+j)G[\tilde{u}(k)]$, ,from (24) and (28) we find that

$$\lim_{N\to\infty} h_j^*(N) = h^*(j). \quad (q) \tag{29}$$

Since $\tilde{y}(k)$ is unmeasured, we can only measure the $y(k)$. According to (17) and (18) we have

$$\begin{aligned} |\tilde{y}(k) - y(k)| &= \sum_{i=k+1}^{\infty} |h(i)||\tilde{w}(k-i) - w(k-i)| \\ &\leqslant 2|\lambda|M\sum_{i=k+1}^{\infty}|h(i)|. \end{aligned} \tag{30}$$

So

$$\lim_{k\to\infty}(\tilde{y}(k) - y(k)) = 0. \tag{31}$$

Defining $h_j(N) = \frac{1}{mN}\sum_{k=1}^{N} y(k+j)G[u(k)]$, we have

$$\begin{aligned} h_j^*(N) - h_j(N) &= \frac{1}{mN}\sum_{k=1}^{N}(\tilde{y}(k+j)G[\tilde{u}(k)] - y(k+j)G[u(k)]) \\ &= \frac{1}{mN}\sum_{k=1}^{N}[\tilde{y}(k+j) - y(k+j)]G[u(k)]. \end{aligned} \tag{32}$$

From (30), it follows that

$$\lim_{N\to\infty} h^*(N) = \lim_{N\to\infty} h_j(N). \quad (q) \tag{33}$$

Since $w(k)$ is unmeasured, if both the nonlinear gain and impulse response are not restricted by another conditions, then we cannot identify them at all. Thus, without loss generality, we suppose that $h(1)=1$. Hence from $h^*(j) = h(j)/\lambda$, one has $\lambda = 1/h^*(1)$ and

$$\lambda(N) = \left(\frac{1}{mN}\sum_{k=1}^{N} y(k+1)G[u(k)]\right)^{-1} \tag{34}$$

is the strong consistence estimate of λ. So,

$$h_j(N) = h_j^*(N)\lambda(N)$$
$$= \sum_{k=1}^{N} y(k+j)G[u(k)] / \sum_{k=1}^{N} y(k+1)G[u(k)] \tag{35}$$

is the strong consistence estimate of $h(j)$.

Theorem 2 If the Assumptions 1,2 and 3 hold, then the estimates $\lambda(N)$ and $h_j(N)$ given by (34) and (35) are the strong consistence estimates of λ and $h(j)$, respectively.

In the following, we shall give the asymptotic distribution and convergence rate of the estimate error. At first, because $h_j(N)$ is the unbiased estimate of $h(j)$, thus one has

$$E[h_j^*(N) - h^*(j)]^2 = Eh^{*2}_j(N) - h^{*2}(j), \tag{36}$$

$$m^2 Eh^{*2}_j(N) = \frac{1}{N^2}\sum_{i=0}^{\infty}\sum_{t=0}^{\infty} h^*(i)h^*(t)\sum_{k=1}^{N}\sum_{s=1}^{N} E\tilde{w}(k+j-i)G[\tilde{u}(k)],$$

$$\tilde{w}(s+j-t)G[\tilde{u}(s)] + \frac{1}{N^2}\sum_{k=1}^{N} E\varepsilon^2(k+j)G^2[\tilde{u}(k)]$$

$$= \frac{1}{N^2}\sum_{i=0}^{\infty}\sum_{t=0}^{\infty} h^*(i)h^*(t)\sum_{k=1}^{N} E\tilde{w}(k+j-i)\tilde{w}(k+j-t)G^2[\tilde{u}(k)] + \frac{1}{N}q$$

$$+ \frac{1}{N^2}\sum_{i=0}^{\infty}\sum_{t=0}^{\infty} h^*(i)h^*(t)\sum_{k=1}^{N}\sum_{s\neq k}^{N} E\tilde{w}(k+j-i)\tilde{w}(s+j-t)G[\tilde{u}(k)]G[\tilde{u}(s)], \tag{37}$$

$$\frac{1}{N^2}\left|\sum_{i=0}^{\infty}\sum_{t=0}^{\infty} h^*(i)h^*(t)\sum_{k=1}^{N} E\tilde{w}(k+j-i)\tilde{w}(k+j-t)G^2[\tilde{u}(k)]\right|$$

$$\leqslant (MM_1\sum_{i=0}^{\infty}|h(i)|)^2/N, \tag{38}$$

$$\frac{1}{N}q = \frac{1}{N^2}\sum_{k=1}^{N} E\varepsilon^2(k+j)G^2[\tilde{u}(k)] \leqslant M_1^2 r^2/N, \quad (r^2 = E\varepsilon^2(k)), \tag{39}$$

$$\frac{1}{N^2}\sum_{i=0}^{\infty}\sum_{t=0}^{\infty} h^*(i)h^*(t)\sum_{k=1}^{N}\sum_{s\neq k}^{N} E\tilde{w}(k+j-i)\tilde{w}(s+j-t)G[\tilde{u}(k)]G[\tilde{u}(s)]$$

$$= (N-1)h^{*2}(j)m^2/N + \frac{1}{N^2}\sum_{i\neq j}^{2j} h^*(i)(2j-i)\sum_{k=a}^{N} E\tilde{w}(k+j-i)$$

$$\cdot\, \tilde{w}(k)G[\tilde{u}(k+j-i)]G[\tilde{u}(k)], \tag{40}$$

where $a = \max\{o, i-j\}$. Furthermore, we obtain

$$E[h_j^*(N) - h^*(j)]^2 \leqslant h^{*2}(j)/N + (\sum_{i=0}^{\infty}|h(i)|)^2/N\lambda^2$$

$$+ (MM_1\sum_{i=0}^{\infty}|h(i)|)^2/Nm^2 + M_1^2 r^2/Nm^2, \tag{41}$$

$$(E[h_j^*(N) - h^*(j)]^2)^{½} = O\left(\frac{1}{\sqrt{N}}\right). \tag{42}$$

According to (33), it follows that

$$E[h_j(N) - h(j)]^2)^{1/2} = O(\frac{1}{\sqrt{N}}). \qquad (43)$$

Hence, we may get the following theorem

Theorem 3 If the assumptions 1, 2 and 3 hold, then the convergence rate of $h_j(N) - h(j)$ is the same as $\frac{1}{\sqrt{N}}$.

Studying the asymptotic distribution of $h_j(N) - h(j)$ is very difficult, even if $\varepsilon(k) = \eta(k)$.

Total identification may be described as follows

1° Pick up p numbers of σ_i, and make out p number of times open-loop steady-state experiments and calculate the $F_N(\sigma_i)$ according to the following formula

$$F_N(\sigma_i) = \frac{1}{N}\sum_{k=1}^{N} y(k+T).$$

2° Construct G(•) and Calculate the m

$$\frac{1}{p}\sum_{i=1}^{p} G(\sigma_i) = 0,$$

$$m = \frac{1}{p}\sum_{i=1}^{p} F_N(\sigma_i)G(\sigma_i)) \neq 0.$$

3° According to the following formulae, calulate λ and $h(j)$

$$\lambda = (\frac{1}{mN}\sum_{k=1}^{N} y(k+1)G[u(k)])^{-1},$$

$$h(j) = \frac{1}{mN}\sum_{k=1}^{N} y(k+j)G[u(k)]/\lambda.$$

4° Calculate the $\Phi[\sigma_i]$, according to the following formula

$$\Phi[\sigma_i] = F_N(\sigma_i)/\lambda.$$

4 Simulation Studies of the Classical Systems

Example 1 Linear system of nonlinear input with dead band

$$\Phi[u(k)] = \begin{cases} ru(k) - \Delta \operatorname{sgn}[u(k)], & |u(k)| \geqslant \Delta, \\ 0, & |u(k)| < \Delta, \end{cases}$$

$$y(k) = \frac{q^{-1}(1 + 0.2q^{-1})}{1 - 0.5q^{-1}}[w(k) + \zeta(k) + \eta(k)],$$

Where q^{-1} denotes the backward shift operator, the variances of $\eta(k)$ and $\zeta(k)$ are 1. In the course of the simulation, we take $\sigma_1 = -2, \sigma_2 = -1, \sigma_3 = 0, \sigma_4 = 1$, and $\sigma_5 = 2$, and pick up $G(u) = u, T = 100$ and $N = 1000$. The estimates of r and Δ are given by the following formulae

$$r(N) = [F_N(-1) + F_N(2)]/\lambda(N),$$

$$\Delta(N) = [2F_N(-1) + F_N(2)]/\lambda(N),$$

$$\lambda(N) = (\frac{1}{mN}\sum_{k=1}^{N} y(k+1)G[u(k)])^{-1}.$$

The simulation results are given in table 1.

Table 1 Numerical results of example 1

Parameter	λ	r	Δ	$\lambda\Phi(-2)$	$\lambda\Phi(-1)$	$\lambda\Phi(0)$	$\lambda\Phi(1)$	$\lambda\Phi(2)$
True values	2.4	1	0.5	−3.6	−1.2	0	1.2	3.6
Estimated values	2.4129	0.9949	0.4976	−3.6001	−1.1997	−0.0002	1.2004	3.6004
Parameter	$h(1)$	$h(2)$	$h(3)$	$h(4)$	$h(5)$	$h(6)$	$h(7)$	$h(8)$
True values	1.0000	0.7000	0.3500	0.1750	0.0875	0.0438	0.0219	0.0109
Estimated values	1.0000	0.7153	0.3612	0.1642	0.0819	0.0492	0.0246	0.0113

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稳态估计与动态辨识相结合的辨识非线性系统的新方法

黄正良 李众立

(西南工学院·四川绵阳,621002)

万百五

(西安交通大学系统工程研究所·西安,710049)

摘要：本文针对 Hammerstein 系统，提出了一种辨识非线性增益和脉冲响应的新方法，该方法同时利用稳态和动态两种信息，所得到的估计是强一致性的. 并且还研究了非线性增益估计误差的渐近分布和收敛速度. 仿真结果说明了该方法的有效性和实用性.

关键词：非线性增益；脉冲响应；线性子系统；Hammerstein 系统；辨识

本文作者简介

黄正良 1962 年生. 1992 年毕业于西安交通大学系统所，获工学博士学位. 现为西南工学院院长助理，教授. 江油市副市长. 研究方向为系统辨识，自适应控制.

李众立 1948 年生，1982 年毕业于西南工学院信息控制系. 现为西南工学院信息控制系主任，副教授. 主要从事计算机过程控制系统研究.

万百五 1928 年生，1951 年交通大学电信研究所研究生毕业，现为西安交通大学教授. 主要研究方向为大系统优化递阶控制，智能控制.