International Journal of Intelligent Information and Management Science

Volume 7, Issue 2, April, 2018

http://www.hknccp.org

Publisher: HongKong New Century Cultural Publishing House
Address: Unit A1, 7/F, Cheuk Nang Plaza, 250 Hennessy Road, Wanchai, Hong Kong

---

International Journal of Intelligent Information and Management Science
ISSN: 2307-0692, Volume 7, Issue 2, April, 2018

Contents

HK.NCCP
International Journal of Intelligent Information and Management Science
ISSN: 2307-0692, Volume 7, Issue 2, April, 2018

Recursive Identification Methods for a Hammerstein System

Wentian Liu
College of Automation and Electrical Engineering, Qingdao University, Qingdao, 266071, China

Abstract: The maximum likelihood algorithm has extensive applications in dynamic nonlinear systems with colored noise. This paper proposes recursive identification methods based on maximum likelihood algorithm for a multivariable Hammerstein system with controlled autoregressive moving average noises. The result from simulation indicates that the estimates of system are consistent with their true values and the proposed methods have well stability, feasibility and validity.

Keywords: Maximum likelihood; Multivariable; Hammerstein

1. Introduction

The research on modeling identification [1] of linear systems is formulated perfectly at present. Since non-linear factors cannot be avoided in practical systems, and large errors are existed in the using linear identification methods analyzing non-linear systems, researches on the non-linear systems are getting more and more attention by domestic and foreign experts and scholars. Hammerstein system [2] is a kind of modular nonlinear system model where a nonlinear static sub-module is followed by a linear dynamic sub-module, which can effectively reflecting the dynamic characteristic of most practical systems, and has been widely applied in the fields of military, astronomy, socioeconomic, space, and communication [3].

Many identification methods for Hammerstein systems have been presented, including recursive identification methods, iterative identification methods, instrumental variable methods, and blind identification methods. For example, *Laurain et al. proposed* instrumental variable methods for a Hammerstein model with a Box-Jenkins linear part; Bai et al. studied iterative algorithm to identify Hammerstein models with independent identically distributed inputs and presented a blind identification approach for a Hammerstein-Wiener model with a general nonlinear structure ; Narendra *et al. developed* an iterative method for nonlinear systems using a Hammerstein model in the presence of noise ; Voros et al. designed an iterative method for parameter identification of Hammerstein systems with two-segment nonlinearities and presented recursive identification methods for Hammerstein systems with discontinuous nonlinearities containing dead-zones .

Different from the conventional identification methods [4-5]. The estimators of the parameters by using the methods have good statistical properties, e.g., consistency, asymptotic normality, validity, etc. This paper proposes recursive identification methods based on maximum likelihood algorithm to obtain parameter estimation values of a multivariable Hammerstein controlled autoregressive moving average system by decomposing the system into m (m is the number of the system output) subsystems which are easier to identify [6].

The rest of this paper is organized as follows. Section 2 gives the system description and identification mode of the multivariable Hammerstein CARMA system. Section 3 introduces the maximum likelihood principle and derives recursive identification methods based on maximum likelihood algorithm for the Hammerstein CARMA system. Section 4 provides a illustrative example to confirm the validity of the proposed method.

2. System Identification Model

Let us introduce some notations. The superscript denotes the matrix/vector transpose; the symbol stands for an identity matrix of appropriate size [7].Consider the following multivariable Hammerstein CARMA system in Fig. 1 :

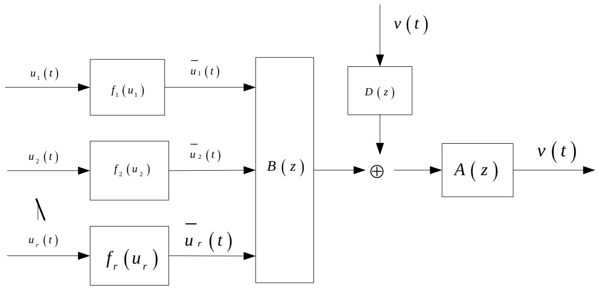

Figure 1. The multivariable Hammerstein CARMA system

3. The Recursive Identification Methods based on Maximum Likelihood Algorithm research

For a set of measurements $\{\mathbf{u}_N := [u(1), u(2), \cdots, u(N)]\}$ and $\{\mathbf{y}_N := [y(1), y(2), \cdots, y(N)]\}$, the joint probability density function $p\left(\mathbf{y}_{jN} \middle| \mathbf{u}_{j(N-1)}, \boldsymbol{\theta}_j\right)$ ($j = 1, 2, \cdots, m$) is just a function to $\boldsymbol{\theta}_j$ and thus the likelihood function $L_j\left(\mathbf{y}_{jN} \middle| \mathbf{u}_{j(N-1)}, \boldsymbol{\theta}_j\right)$ ($j = 1, 2, \cdots, m$) equals the joint probability density function $p\left(\mathbf{y}_{jN} \middle| \mathbf{u}_{j(N-1)}, \boldsymbol{\theta}_j\right)$. In addition, the measurements $\{\mathbf{u}_N, \mathbf{y}_N\}$ and the parameter vector $\boldsymbol{\theta}_j$ are unrelated with $v_j(t)$, the likelihood function $L_j\left(\mathbf{y}_{jN} \middle| \mathbf{u}_{j(N-1)}, \boldsymbol{\theta}_j\right)$ can be written as:

$$\begin{aligned} L\left(y_{jN} \middle| u_{j(N-1)}, \theta_j\right) &= p\left(y_{jN} \middle| u_{j(N-1)}, \theta_j\right) \\ &= p\left(y_{jN} \middle| y_{j(N-1)}, u_{j(N-1)}, \theta_j\right) p\left(y_{j(N-1)} \middle| u_{j(N-1)}, \theta_j\right) \\ &= \prod_{t=1}^{N} p\left(y_j(t) \middle| y_{j(t-1)}, u_{j(t-1)}, \theta_j\right) \\ &= \prod_{t-1}^{N} p\left(\sum_{i=1}^{n_b} B_{ij} F(t-i) c + \Psi_j^T(t) \middle| y_{j(t-1)}, \theta + v_j(t) \middle| y_{j(t-1)}, u_{j(t-1)}, \theta_j\right) \end{aligned}$$

According to the maximum likelihood principle [8-9], the maximum likelihood estimate of makes ,then the recursive identification methods based on maximum likelihood algorithm for the multivariable Hammerstein CARMA system can be summarized as :

$$\hat{\boldsymbol{\theta}}_j(t) = \hat{\boldsymbol{\theta}}_j(t-1) + \mathbf{K}_j(t) \hat{v}_j(t)$$

The flowchart of computing the parameter estimates $\hat{\boldsymbol{\theta}}_j(t)$ in the algorithm is shown in Fig. 2.

4. Example

Consider the following multivariable Hammerstein CARMA system:

$$A(z)\mathbf{y}(t) = \mathbf{B}(z)\bar{\mathbf{u}}(t) + D(z)\mathbf{v}(t)$$

$$\mathbf{y}(t) = \begin{bmatrix} y_1(t) \\ y_2(t) \end{bmatrix}, \mathbf{v}(t) = \begin{bmatrix} v_1(t) \\ v_2(t) \end{bmatrix}$$

$$\bar{\mathbf{u}}(t) = \begin{bmatrix} \bar{u}_1(t) \\ \bar{u}_2(t) \end{bmatrix} = \begin{bmatrix} c_1 u_1(t) + c_2 u_1^2(t) \\ c_1 u_2(t) + c_2 u_2^2(t) \end{bmatrix} = \begin{bmatrix} 0.32 u_1(t) - 0.59 u_1^2(t) \\ 0.32 u_2(t) - 0.59 u_2^2(t) \end{bmatrix}$$

$$A(z) = 1 + a_1 z^{-1} + a_2 z^{-2} = 1 + 0.35 z^{-1} - 0.22 z^{-2}$$

$$\mathbf{B}(z) = \mathbf{B}_1 z^{-1} + \mathbf{B}_1 z^{-2} = \begin{bmatrix} -1.43 & 0.70 \\ 0.35 & -1.43 \end{bmatrix} z^{-1} + \begin{bmatrix} 0.38 & -1.37 \\ 0.93 & -1.59 \end{bmatrix} z^{-2}$$

$$D(z) = 1 + d_1 z^{-1} + d_2 z^{-2} = 1 + 0.09 z^{-1} - 0.10 z^{-2}$$

In simulation, the input $\{\mathbf{u}(t)\}$ is taken as an uncorrelated stochastic signal sequence with zero mean and unit variance, $\{\mathbf{v}(t)\}$ as a white noise sequence with zero mean and variances $\sigma^2 = 1.00^2$ and $\sigma^2 = 2.00^2$. We adopt the data length , applying the algorithm presented in this paper to estimate the parameters of the systems, From the simulation results in , we can draw the following conclusions:

As the length of data increases, the errors of the parameter estimates decrease and tend to zero.

The algorithm has a high convergence speed, and the smaller noise variance, the faster convergence rate is.

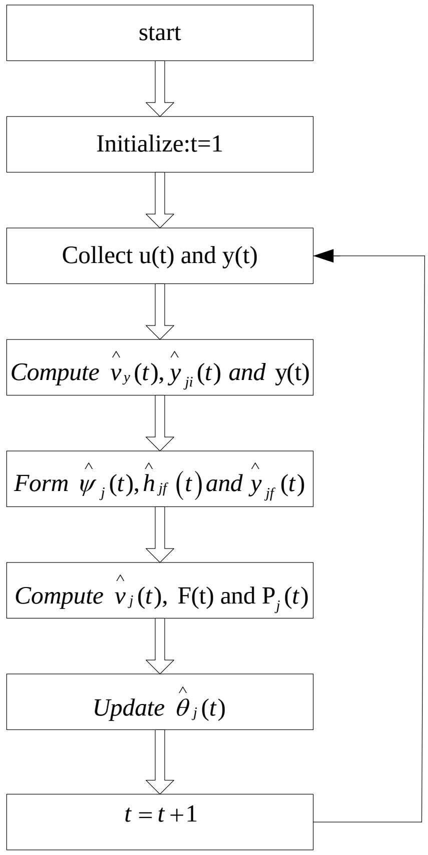

Figure 2. The flowchart of computing the parameter estimates $\hat{\boldsymbol{\theta}}_j(t)$

5. Conclusion

Recursive identification methods based on maximum likelihood algorithm for the multivariable Hammerstein controlled autoregressive moving average systems are proposed in this paper. The simulation result shows that the proposed methods could precisely identify the estimates of the system with colored noises. Also, their use will be further promoted and they will benefit in more fields by combining other identification methods.

References

[1] S.N Taylor, L.A Basile, M Ebeling, C.L Wagner. Intestinal Permeability in Preterm Infants by Feeding Type: Mother's Milk Versus Formula[J]. Breastfeeding Medicine the Official Journal of the Academy of Breastfeeding . U. K.,2009: v4111-15.

[2] P.G Gallman. A comparison of two Hammerstein model identification algorithms[J]. IEEE Transactions on Automatic Control. U.S., 1976: v211124-126.

[3] P Stoica. On the convergence of an iterative algorithm used for Hammerstein system identification[J]. IEEE Transactions on Automatic Control. U.S.,1981:v24967-969.

[4] X Chen, H.T Fang. Recursive Identification for Hammerstein Systems with State-space Model[J]. Acta automatic Sinica. C.N.,2010:v1361460-1467.

[5] H Boutayeb，M Darouach. Recursive identification method for MISO Wiener-Hammerstein model[J]. IEEE Transactions on Automatic Control. U.S., 1995:v14287-291.

[6] E.W Bai, D Li. Convergence of the iterative Hammerstein system identification algorithm[J]. Automatica. U.S.,2004:v1491929-1940.

[7] J.W Hogan, T Lancaster. Instrumental variables and inverse probability weighting for causal inference from longitudinal observational studies[J]. Statistical Methods in Medical Research. C.N.,2004: v13117-48.

[8] D.Y Riabkov. Analysis of blind identification methods for estimation of kinetic parameters in dynamic medical imaging[J]. Journal of Submicroscopic Cytology & Pathology. U.S.,2003:v254359-371.

[9] J.F Cardoso. Blind signal separation: statistical principles[J]. Proceedings of the IEEE. U.S.,2009:v4212009-2025.